Neglecting Uncertainties Leads to Suboptimal Decisions
About Home-Owners Flood Risk Management

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Key points:

● We analyze strategies to elevate a house to manage flood risks under deep uncertainties.
● Accounting for deep uncertainties can considerably increase the projected risks, change the economically optimal elevation, and yield drastically different recommendations compared to the current guidance from the U.S. Federal Emergency Management Agency (FEMA).
● The analysis requires an integrated approach as the uncertainty in the projected net costs is driven by a complex interaction between uncertainties associated with Earth, social, and engineering sciences.

Keywords:
National Flood Insurance Program; Federal Emergency and Management Agency; house elevation; flood mitigation; deep uncertainty; flood hazard uncertainty
Abstract

Homeowners around the world elevate houses to manage flood risks. Deciding how high to elevate the house poses a nontrivial decision problem. The U.S. Federal Emergency Management Agency (FEMA) recommends elevating a house to the Base Flood Elevation (the elevation of the 100-yr flood) plus a freeboard. This recommendation neglects many uncertainties. Here we use a multi-objective robust decision-making framework to analyze this decision in the face of deep uncertainties. We find strong interactions between the economic, engineering, and Earth science uncertainties, illustrating the need for an integrated analysis. We show that considering deep uncertainties surrounding flood hazards, the discount rate, the house lifetime, and the fragility increases the economically optimal house elevation to values well above FEMA’s recommendation. An improved decision-support for home-owners has the potential to drastically improve decisions and outcomes.

1. Introduction

Floods affect billions of people worldwide1. From 1900 to 2015, the U.S. had 35,000 disasters out of which 40 percent were floods2. Between 1970 and 2019, over 68 billion U.S. dollars have been claimed by the National Flood Insurance Program (NFIP) policyholders3. The average damage to households has been over 30,000 U.S. dollars per event3.

At the building level, structural and non-structural mitigation measures are commonly used to reduce flood risks4. These plans generally fall into three categories of wet-floodproofing, dry-floodproofing, and structure modification (e.g. relocating or elevating)5. Dry-proofing prevents water from entering the building by closing the openings such as windows and doors or filling the basement. Wet-proofing allows water to flow inside the building, but reduces the vulnerability of the structure, for example, by moving valuable contents to higher floors5,6. Generally, non-structural measures are more effective for low inundation depths and structural measures are more effective for extreme floods6.

The projected flood risks are deeply uncertain7. Elevating a house to reduce these risks requires nontrivial investments. How high to elevate a house poses a nontrivial decision problem. One key guideline to this decision is provided by the U.S. Federal Emergency Management Agency (FEMA). FEMA recommends elevating houses in 100-yr flood zones to at least the Base Flood Elevation (BFE) (the flood level with an annual exceedance chance of 1%) plus at least one foot of freeboard. This recommendation is unspecific as it provides just a lower bound. In addition, this recommendation ignores key factors such as house size, house value, the monetary value of future damages (i.e. discount rate), and their associated uncertainties8.

Cost-Benefit Analysis (CBA) is a common approach to identifying the least-cost strategy5,8. A CBA compares the investment cost (i.e. cost of elevating the structure) with the current (i.e. discounted) value of the expected benefits (i.e., the expected savings in future flood damages). The estimated benefits are deeply uncertain9–12 because they depend on deeply uncertain inputs such as projected flood hazards, building vulnerability, discount rates, and the building lifespan7,13,14. Deep uncertainty occurs, for example, when the decision-makers cannot agree on a single probability density function for a variable or a model parameter15–18.
CBA seeks a strategy that minimizes the total discounted expected costs. However, stakeholders can have additional (and potentially conflicting) objectives. For example, homeowners may intrinsically value the safety of the house and the robustness of the strategy in the face of deep uncertainty. Thus, analyzing the house elevation decision as a multi-objective problem can provide useful insights\textsuperscript{19,20}.

Previous work\textsuperscript{8} on this problem has provided valuable insights, but has been largely silent on the effects of uncertainties in the objectives and their potential trade-offs\textsuperscript{6}. We identify and assess the effects of uncertainty sources on the house elevation decision and quantify the trade-offs between key objectives in the face of deep uncertainty. We especially focus on four strategies: (1) repairing flood damages as they occur, (2) elevating the house to FEMA’s minimum recommended height, (3) elevating the house to the cost-optimal heightening strategy neglecting uncertainty, and (4) elevating the house to the optimal height considering uncertainty.

We demonstrate the approach for a rural location in Pennsylvania (PA). Between 1959 and 2005, PA ranked 2nd, 10th, and 14th in the U.S. in the frequency of flash flood-related fatalities, injuries, and casualties, respectively\textsuperscript{21}. In the same period, two from the ten deadliest events in the U.S. (excluding hurricane Katrina) have happened in PA, resulting in over 50 fatalities\textsuperscript{21}. Within 1975 to 2019, FEMA paid $953 million to NFIP participants in Pennsylvania for property damages\textsuperscript{3}. In response to these floods, some PA house owners have elevated their houses. Even though elevated to FEMA’s standards, these houses still had over 29 million U.S. dollars in flood damages. Specifically, we choose Selinsgrove, a town by the Susquehanna River Basin, flowing into the Chesapeake Bay where frequent and severe floods are a major concern.

2. Results

We consider four key sources of uncertainty (Figure S1). First, we quantify the chance of being flooded in any given year. Ignoring uncertainty can drastically underestimate flooding probability by a factor of 10% (Figure 1d-e). The downwards bias is exacerbated for floods with higher return periods. This underestimation drives also an underestimation of Annual Expected Damages (EAD) (Figure 1a-c). Second, we quantify the uncertainties surrounding the monetary discount rates. Uncertainty in future discount rates increases the Net Present Value (NPV) of projected flood damages (Figure 2a). The discount rate is an important factor in this assessment, as it translates futures costs to today\textsuperscript{13}. Flood risk management studies often use a constant and perfectly known future rate, for example, 4% per year\textsuperscript{8}. However, the observed historical discount rates are highly stochastic (Figure 2b). We quantify the uncertainty surrounding projected discount rates using past observations of discount rates. Results show that neglecting the uncertainty surrounding future discount rates can drastically underestimate future damages (Figure 2). Third, we quantify the uncertainty surrounding the damages for a certain depth of water in a house. Damage models (also known as depth-damage functions) are often used to estimate the damages to a house given certain water depth. These damage models are deeply uncertain because there is no single agreement on these models. Finally, we sample the uncertainty surrounding the house lifetime. The house lifetime is uncertain because it is impacted by uncertain factors such as its structural durability, social acceptability, change in land value,
and change in occupant needs\textsuperscript{14,22}. Flood risk studies often use a deterministic value between 30 to 100 for residential buildings’ lifetime and ignore the surrounding uncertainty\textsuperscript{5,8,23–25}.

We consider and quantify all the aforementioned sources of uncertainty in the estimation of an optimal strategy. For flooding probability and house lifetime we use a probability density function (PDF) to represent the uncertainty. For items discount rate and damage model, since there is no agreement on a single PDF, we consider them deeply uncertain and use multiple PDFs to quantify their uncertainty.

We start with analyzing a hypothetical 2,000 ft\(^2\) house with worth of \$320,000 and with the lowest level at four feet below the BFE. Total costs include investment cost plus the net present value of expected damages. If this house is not elevated, total costs could be more than two times the house value (V). With 90\% probability, these costs are between 0.3V and 2.22V with an expected value of 1V (Figure 3a). Total costs drop to \(~\)0.82V if the house is elevated by 14 feet (ten feet above the BFE). The optimal elevation that minimizes the expected total costs is 8.5 feet (4.5 ft above the BFE). At this heightening strategy, total costs are expected to be 0.73V. These costs are less than the house value with high probability.

Ignoring uncertainty changes the optimal elevation (Figure 3a). Ignoring uncertainty, the total cost for no elevation is less than 0.21V. Ignoring uncertainty implies that the expected damages are cheap and the cost-benefit analysis suggests not to elevate the house. Considering uncertainty changes the decision to elevate the house by 8.5 ft. Considering uncertainties leads to a higher optimal elevation because it increases the expected damages while leaving the costs unchanged. By adopting the recommendation that neglects uncertainty, the house owner risks \$319,631 (NPV), which is considerably higher than the cost of elevating the house (i.e. \(~\)\$193,000). The FEMA recommendation suggests elevating this house by at least 5.5 feet (the minimum freeboard recommended by FEMA in Selinsgrove is 1.5 feet). This costs the homeowner \$187,000. Implementing FEMA’s recommendation reduces the expected total costs from 1V to 0.83V. However, this strategy is suboptimal.

In summary, implementing the strategies derived by neglecting uncertainty, following FEMA, and considering uncertainty costs the homeowner zero, 0.58V, and 0.60V, respectively. The NPVs of the expected total costs of these strategies are 1V, 0.83V, and 0.73V, respectively. Thus, implementing the strategy recommended by the considering-uncertainty assumption costs marginally more but these extra costs are more than offset in future damages.

Next, we evaluate the benefit-to-cost ratio to ensure that the implemented strategy passes the cost-benefit (CB) test. If the homeowner elevates the house by more than three feet, the benefits are greater than the costs (strategy passes the cost-benefit test) with high probability (Figure S2). The expected Benefit-to-Cost Ratio (BCR) of the optimal strategy is 1.44. The optimal strategy is expected to pass the CB test. Ignoring uncertainty implies that elevating this house is never cost-effective. The FEMA-recommended strategy has a BCR of 1.29 and passes the CB test (Figure S2).

Another homeowner’s objective may be maximizing reliability, the probability of not flooding over the house lifetime. Expected reliability is more than 50\% for all heightening strategies greater than three feet (Figure S3). If the house is not elevated, its reliability is 20\%,
which means that there is an 80% chance that it will be flooded at least once during the next 30 years. This chance drops to 17% if the house is elevated to the optimal elevation under uncertainty. The expected reliability of the FEMA-recommended strategy is 69%. Ignoring uncertainties overestimates the reliability and underestimates the chance of being flooded. This leads to a false sense of security.

A robust decision is insensitive to the deep uncertainties, for example about the model parameters or model structures\textsuperscript{26}. Following previous work\textsuperscript{15}, we evaluate the robustness as the fraction of parameter samples (each referred to as a state-of-the-world or SOW) for which one or all objectives are within the decision-makers’ acceptable ranges. If the house is elevated to three feet or more, 40% of SOWs lead to an acceptable benefit-to-cost ratio (Figure 3b). If the house owner decides not to elevate the house, none of the SOWs are within the acceptable range of reliability and only 40% of SOWs are within the acceptable range of total cost. However, if elevated by 10 feet or more, the robustness of reliability grows to 100%. Overall, the decision not to heighten at all is 0% robust, the FEMA-recommended strategy is 20% robust, the optimal strategy is 40% robust (Figure 3b).
Figure 1: EAD is the area under the EPL curve (damage versus flood probability) (b). EPL curves under the considering-uncertainty (red line and bounds) and ignoring-uncertainty (blue line) assumptions are compared in panel a. The resulting EADs are compared in panel c. The shaded red area (in a) indicates the 90% confidence intervals of the considering-uncertainty assumption. The narrow line on the red bar indicates the range of uncertainty in EAD. Return levels of the two assumptions are compared in panel d. Panel e exhibits the comparison for 500-yr flood.
Figure 2: Impact of different discount rate models on estimates of the net present value of expected damages for the typical house. Box plots show the dispersion of the damage estimates for the three considered stochastic models (b) Historical (1800-2018) and projected discount rate time series. The shaded areas indicate uncertainty in projected discount rates.
Figure 3: (a) Total cost and the optimal elevation under assumptions of ignoring-uncertainty (dashed red line and the hollow point) and considering-uncertainty (solid red line, shaded bounds, and the filled red point). This house is worth $320,000, is four feet below the BFE, has an area of 2,000 ft$^2$. Under the ignoring-uncertainty assumption, the house lifetime and discount rate are assumed to be 30 years and 4 % per year, respectively. The vertical line indicates the FEMA-recommended heightening strategy. The hatched gray area on the left refers to elevating the house by less than three feet which we assume is impractical in this study. (b) Robustness of heightening policies. Robustness of different objective are shown by dashed lines. The solid red line indicates the robustness of all objectives.
2.3 Trade-off Analysis

The considered objectives show strong trade-offs. Reliability and upfront costs are two competing objectives in the house elevation decision (Figure 4 and Figure S4). It is infeasible to have perfect reliability with zero upfront costs (star in Figure 4). A small heightening strategy has a low upfront cost and low reliability. A large heightening corresponds to relatively high reliability, but require high investments that might not be affordable. Ignoring uncertainty moves the estimated Pareto front into the infeasible zone in the case when the uncertainties are considered. One key reason for this is that considering uncertainty reduces reliability (Figure S3).

![Figure 4: Trade-offs between the upfront cost and reliability with and without uncertainty quantification. Trade-off under the considering-uncertainty and ignoring-uncertainty assumptions are shown by red and blue, respectively. Along each line, the dashed parts indicate that the policy does not pass the cost-benefit test (i.e. the benefit-to-cost ratio is less than one). Heightening policies of 0-3 feet are blocked by the gray area as we assume that it is impractical to elevate a house by less than three feet. “not elevating” policies are shown by dots and the optimal elevations are shown by squares.](image-url)
2.4. Which uncertainty drives the variance in objectives?

In order to guide future research as well as to simplify the decision framework, we identify the most influential uncertainty sources. To this end, we use a global sensitivity analysis. The uncertainty in the output is explained either from changes to individual inputs or parameters (i.e. first-order sensitivities) or from their interactions (i.e. second-order sensitivities, if the variance in the output results from interactions between two inputs). There are two sources of deep uncertainty including the damage model with two options and the discount rate model with three options. Thus, there are a total of six scenarios.

For all scenarios, the expected damages are sensitive to a complex interplay of uncertainties surrounding the discount rate, damage function, house lifetime, and flood frequency (Figure S5). The shape parameter for the flood distribution has the largest effect on the damage uncertainty. This is, perhaps, expected, as the expected probability of flooding in any given year has a direct impact on the expected annual damages and consequently on the lifetime expected damages. After the flood frequency model parameters, lifetime and damage model uncertainties play the most important roles. The dominant second-order interactions are between the frequency model parameters. For the most likely scenario, out of five statistically significant second-order interactions, two are with the house lifetime uncertainty (Figure 5). Furthermore, for the majority of scenarios, there is a statistically significant second-order interaction between the discount rate and lifetime uncertainty (Figure S5). If we consider a case with higher house lifetimes, different discount rate models diverge even more (Figure S6). For such houses, the discount rate model structure plays an even more important role. For houses with a lower lifetime, the discount rate models do not result in considerably different projections.

Sensitivity analysis also allows us to assess the relative importance of different model structures in factors that are deeply uncertain. Thus, we assess the relative importance of the discount rate model structure and the depth-damage function structure (Figure S7). By considering deep uncertainties, the depth-damage model structure becomes more significant and the frequency model parameters become less significant.

These results are based on a sample house that is worth $320,000, is 2,000 ft\(^2\) and is four feet below the BFE. To account for house vulnerability factors, we re-evaluated these sensitivities for a set of hypothetical houses (Figure S8) under the most likely scenario. For all the cases, the uncertainties in the flood probability, house lifetime, discount rate, and depth-damage function play statistically significant roles for the variance in projected damages, regardless of house vulnerability factors. Interactions between the uncertain factors become more complicated for the houses that are farther below the BFE. Additionally, the flood frequency model becomes less important for houses that are farther below the BFE.

One important takeaway is that neglecting discount rate uncertainty can considerably underestimate the damages. If a fixed discount rate is used, its value becomes the most important factor that explains the variance in the damages (Figure S9). However, if an uncertain stochastic model is used, its uncertainty becomes less important (Figure 5) and the model choice has much less of an effect on the projected damages (Figure S7).
2.3. House vulnerability analysis

House vulnerability factors such as house size, value, the lowest level elevation play an important role in the risk mitigation decisions. The analysis thus far focused on objectives and uncertainties for a single sample house. In this section, we address the effects of house vulnerability factors on the mitigation decision. To this end, we analyze the multi-objective robust decision framework described above for 1,000 hypothetical houses (Table S3) that sample vulnerability factors. Ignoring uncertainty decreases the optimal elevation for all considered
houses (Figure S10). For nearly 80% of the houses, the optimal elevation is higher than FEMA’s recommendation (Figure S11). On average, the optimal elevation is two feet higher than FEMA’s recommendation. This means that if the house owners raise their houses by a few feet higher than the FEMA-recommended elevation, they save more in future damages. For around 46% of the buildings, the optimal elevation is zero but FEMA recommends elevating them. In all of those houses, FEMA’s recommendation would not pass the cost-benefit test. In about 4% of the houses, the optimal elevation is less than FEMA’s recommendation. In almost all of them, FEMA’s recommendation does not pass the cost-benefit test. In all the houses with different elevations, sizes, and values, the optimal elevation passes the cost-benefit test. However, in only 30% percent of houses, the FEMA-recommended strategy passes the cost-benefit test. Given their characteristics, the benefits of elevating 70% of these houses are marginal in our analysis. However, FEMA’s recommendation would still suggest elevating them.

3. Discussion

One common flood risk mitigation strategy is to elevate a building in flood-prone regions. For the considered case study in Selinsgrove (PA, USA) the FEMA recommendation suggests elevating at-risk houses to at least one foot (1.5 ft in Selinsgrove) above the Base Flood Elevation (BFE), the water elevation associated with the 100-year flood. This recommendation still leaves open the question of whether (and if so, by how much) to elevate the houses.

This problem is typically addressed in a single objective cost-benefit framework that often neglects key uncertainties. Traditional approaches seek an optimal strategy that minimizes the total cost, which is the net present value of expected damages plus the investment cost. To calculate the total cost, one needs to estimate the flooding probability, the damage function, the discount rate (to calculate the present value of future damages), and the expected house lifetime. Traditional approaches often adopt deterministic values for all of these components. Often, a fixed value of 4 [%/year] and 30 [years] are assigned to the discount rate and the house lifetime, respectively. For the damage model, depth-damage functions by FEMA are often used. For flooding probability, it is common to use a probability distribution but the uncertainty in the parameters of that distribution is often ignored. Ignoring these uncertainties creates a bias in the estimation of expected damages. This, in turn, leads to drastic changes in the decision outcomes.

Some stakeholders have monetary preferences such as maximizing the benefit-to-cost ratio, minimizing the total cost, or minimizing the upfront costs. Others put a higher weight on the reliability and prefer to elevate the house high enough to increase the probability of no floods. Some stakeholders might pay more attention to the robustness of their decision to unforeseen future conditions. We quantify and assess these objectives. We identify considerable trade-offs between objectives and that neglecting uncertainties leads to a false sense of security.

We use a multi-objective decision analysis that considers key uncertainties. We show that flood frequency model parameters, the house lifetime, discount rate, and the depth-damage function are all uncertain and influence the uncertainty of the discounted expected damages. The FEMA-recommended heightening policy is often neither cost-effective nor cost-optimal. Currently, FEMA’s recommendation is only based on the zone and elevation with respect to the
BFE. Our findings suggest that taking house characteristics such as house value, house size, and initial elevation into account can lead to improved decisions. In most cases, the homeowners can save more in future damages if they raise the house by a few feet above the FEMA recommendations.

Our study is subject to several caveats that point to research needs. For one, we consider houses without flood insurance. NFIP policyholders receive premium incentives for an elevated building, an effect not considered in this study. Seconds, we neglect uncertainty surrounding the elevation costs as well as changes in house value after elevation. Third, we neglect nonstationarity in flood hazards. Last, but not least, we consider a one-shot decision to be implemented now or not at all and hence neglect the option to postpone the elevation.

In conclusion, we identify the key drivers of poor outcomes in the decision of elevating a house to manage flood risks. What seems like a simple risk mitigation decision can turn rather complex, once deep uncertainties and their interactions are considered. Our findings suggest that accounting for uncertainties in the discount rate, the depth-damage functions, and house lifetime can be fruitful avenues to improve this decision.

4. Methods

We use a Multi-Objective Robust Decision Making (MORDM) framework to analyze the house elevation decision\textsuperscript{15,17} (Figure S1). Exogenous uncertain factors in our framework are flooding frequency, discount rate, depth-damage curve, and house lifespan. The decision lever (i.e. actions that the decision-maker can take) is heightening (i.e. the added height to the house). We consider five objectives: (1) minimizing the total costs, (2) maximizing the benefit-to-cost ratio, (3) minimizing the upfront cost with respect to the initial value of the house, (4) maximizing reliability (i.e. the probability of no floods during the house lifetime), and (5) maximizing the robustness of the design to deviations from the best-guess parameters\textsuperscript{26}.

The closest U.S. Geological Survey (USGS) gage to Selinsgrove is USGS gage 01554000 collecting water data at Susquehanna River at Sunbury, Pennsylvania. Daily discharge data at this location are available for the period of 1937 to 2019 but daily gage height data are limited to 2000-2019. Thus, in order to take advantage of the rather long record of discharge data, we use the USGS stage-discharge rating curve for this location to convert discharge to gage height.

4.1. Uncertainties

4.1.1. Flooding probability

We quantify the uncertainty surrounding flood probabilities using a Generalized Extreme Value (GEV) distribution combined with a Markov Chain Monte Carlo (MCMC) sampling for parameter estimation. Using the maximum \textit{a posteriori} estimates of GEV parameters (as opposed to the full parameter sample) underestimates the flood hazard (Figure 1d-e). This effect is driven by the right-skewed nature of the return level distribution where the mode is smaller than the mean (Figure 1b). This underestimation drives also an underestimation of the Annual Expected Damages (EAD) (Figure 1a-c). EAD is the area under the Exceedance-Probability Loss (EPL) curve that represents the damages versus exceedance probability (Figure 1a). Comparing
The EPL curves neglecting and considering uncertainty (Figure 1a) illustrates how ignoring uncertainty underestimates EAD.

The GEV distribution is frequently used for modeling annual maximum daily water level (maximum daily water level in the course of a year) and is recommended by FEMA. We hence approximate the annual maximum floods distribution using a GEV distribution. To estimate the GEV parameters, we use MCMC sampling within a Bayesian framework. We adopt the mode of MCMC samples for each parameter as the “best guess” estimate of that parameter. To account for the uncertainty of flooding frequency, we consider the full ensemble of samples.

The Cumulative Distribution Function (CDF) of GEV (i.e. the probability of annual maximum water level; AMWL; not exceeding level $h$) is

$$Pr (H \leq h) = \exp \left\{-\left[1 + \xi \left(\frac{h - \mu}{\sigma}\right)\right]^\frac{-1}{\xi}\right\}, \quad (1)$$

where $H$ is a random variable representing AMWL. $\mu$, $\sigma$, and $\xi$ are location, scale, and shape parameters, respectively. Prior distributions for $\mu$, $\sigma$, and $\xi$ are normal distributions centered at zero. For posterior sampling, we use one MCMC chain initialized at five, one, and 0.1. Our sample size is 50,000.

### 4.1.2. Discount rate

We expand on previous work and quantify the uncertainty surrounding projected discount rates using the observed record and time-series models. The observed historical discount rates are highly stochastic (Figure 2b). To account for deep model structural uncertainty, we follow previous work and consider three autoregressive models, fitted to the logarithms of the discount rates, as there is no historical evidence of negative discount rates in the U.S. reflecting deep model structural uncertainty. Following ref., the first model is a random walk and the second model is mean-reverting. We additionally consider a model with a background linear trend (on the log-scale). Accounting for this discount rate uncertainty results in a higher discount factor and increases the net present value of projected benefits and costs (Figure 2a).

We estimate uncertain discount rate dynamics using an extension of the data from ref. As in that paper, we obtained estimates of expected inflation from a ten-year moving average of Livingston Survey Consumer Price Index (CPI) forecasts. We subtract these estimates from annual nominal yields on 20-year Treasuries to produce a series of historical discount rates. We follow ref. by then converting these rates to their continuously compounded equivalents and using a three-year moving average to smooth short-term fluctuations. The resulting discount rate time series, denoted $d_t$, is shown in Figure 2b.

Our discount rate models are autoregressive AR(3) time series models fit to this data, which maximizes the Akaike Information Criterion, AIC. We use logarithms of the discount rates to ensure that the time series remains positive, due to the lack of evidence of negative rates in the United States. Following ref., we consider three models, reflecting deep model structural uncertainty. The first model is a random walk,
\[ \ln(d_t) = \rho_{t-1}d_{t-1} + \rho_{t-2}d_{t-2} + \rho_{t-3}d_{t-3} + \varepsilon, \quad \Sigma_t \rho_t = 1. \] (2)

The second model is mean-reverting with constant mean,
\[ \ln(d_t) = \eta + \rho_{t-1}(d_{t-1} - \eta) + \rho_{t-2}(d_{t-2} - \eta) + \rho_{t-3}(d_{t-3} - \eta) + \varepsilon, \quad \Sigma_t \rho_t < 1. \] (3)

The third model is a mean-reverting model with trend,
\[ \ln(d_t) = \eta + \beta t + \rho_{t-1}(d_{t-1} - (\eta + \beta(t - 1))) + \rho_{t-2}(d_{t-2} - (\eta + \beta(t - 2))) + \rho_{t-3}(d_{t-3} - (\eta + \beta(t - 3))) + \varepsilon, \quad \Sigma_t \rho_t < 1. \] (4)

We show the estimated coefficients for all three models in Table S1. The random walk and mean-reverting models have AIC values (Table S2) which are statistically equivalent, as AIC differences less than 2 indicate similar levels of evidence for the compared models\(^\text{41}\). The background trend model has stronger support based on AIC\(^\text{41}\), but a similar Bayesian Information Criterion (BIC) value to the mean-reverting model with constant mean\(^\text{42}\). As a result, we include all models in our analysis.

### 4.1.3. Damage curve

Depth-Damage functions determine the susceptibility of entities at risk to floods and are key to damage estimation\(^\text{12,43}\). Depth-damage functions estimate potential damages for a certain amount of water (usually in the form of depth) in a house. There is a wide variety of published sources to obtain these curves\(^\text{43}\). These depth-damage functions show considerable structural uncertainties\(^\text{43}\).

A common source of depth-damage functions in damage assessment studies in the U.S. is Hazard U.S. (HAZUS) provided by FEMA. In an attempt to aggregate various depth-damage curves, the Joint Research Centre (JRC) of the European Commission’s science and knowledge service presented consistent global depth-damage functions\(^\text{44}\).

To account for the depth-damage function uncertainty, most studies have used multiple functions\(^\text{11,45}\). Other studies have used parametric distributions to quantify the damage model uncertainty\(^\text{12}\). In this study, we combine both approaches to represent the deep uncertainty in the damage curve. We use two different sources of depth-damage function. We represent the uncertainty of each function by assuming a uniform uncertainty of 30% around the curve\(^\text{27}\). Figure S12 presents both curves and the uncertainty around each model.

### 4.1.4. House lifetime

It is crucial to estimate the anticipated lifetime of a structure for mitigation decisions\(^\text{14}\). The lifespan of a house is uncertain. The lifetime of a building is impacted by uncertain structural and social factors\(^\text{14,22}\). Many flood damage studies do not address the actual lifetime of a building and assume a typical value (i.e. 30 or 50 years)\(^\text{5,8,14,25}\). These studies ignore the surrounding uncertainty\(^\text{5,8,23–25}\). To the best of our knowledge, this is the first time that house lifetime uncertainty is considered in a flood mitigation study.
A study based on U.S. residential building stock data (provided by the U.S. Census Bureau under the 2009 American Housing Survey microdata) finds that the average residential building lifetime is 61 years with a standard deviation of 25 years\(^{14}\) (Figure S13). With 90\% confidence, lifetime is expected to be between 21 and 105 years\(^{14}\). The distribution of building lifetime is best represented by Weibull distribution with shape and scale parameters of 2.8 and 73.5, respectively. In this study, we use the model suggested by that paper to quantify the uncertainty of house lifetime. We compare this distribution with previously published literature in Figure S13. We adopt the Weibull distribution for the “considering uncertainty” assumption and the fixed value of 30 years for the “ignoring uncertainty” assumption.

4.2. Objectives

4.2.1. Upfront cost to house value

The first objective is the ratio of the upfront cost (cost of elevating the house) to house value \(\left(\frac{C_h}{V}\right)\), where \(V\) is the current value of the house (before elevating) and \(C_h\) is the cost of elevating the building by \(h\) feet. The cost of elevating a single-family house is interpolated from the Coastal Louisiana Risk Assessment Model (CLARA)\(^{45}\). According to this model, the unit cost of elevating a house by 3–7, 7–10, and 10–14 feet is $82.5, $86.25, and $103.75 per square feet with a $20,745 initial fee. The initial fee includes administration, survey, and permits. Figure S14 depicts the interpolated construction costs for three hypothetical 1,000-, 2,000-, and 3,000-square feet houses.

4.2.2. Total discounted costs

Total cost \(\left(\frac{O_{2h}}{V}\right)\) is the upfront cost of lifting a house (by \(h\) feet) plus the present value of lifetime expected damages (LED) if elevated by \(h\) feet. LED is a function of expected annual damages (EAD) and is calculated by

\[
LED_h = \sum_{n=0}^{\infty} EAD_h \times F_t ,
\]

where \(EAD_h\) is the expected annual damages when a house is elevated by \(h\) feet. \(n\) is the house lifetime, and \(F_t\) is the discount factor at year \(t\).

Previous studies have either substitute EAD with NFIP insurance premiums\(^{8}\) or calculated the expected damages\(^{5,6,46}\). The former method implies that NFIP premiums reflect the actual risk. However, NFIP was designed to subsidize the cost of flood insurance on existing houses\(^{47–50}\) and is not risk-based especially for structures that were built before the FEMA flood maps. To reflect the actual expected damages, we follow the latter method and calculate EAD as the area under the EPL curve that represents damages against exceedance probability. EAD is defined as

\[
EAD = \int_{p_{min}}^{p_{max}} D(p) \ dp ,
\]

where \(p\) is exceedance probability derived from GEV distribution. \(D(p)\) is the damage caused by a flood with an exceedance probability of \(p\). We calculate the damages using the depth-damage function.
Under the ignoring-uncertainty assumption, we derive \( D \) from the HAZUS depth-damage function and the house lifetime is 30 years. Under this assumption, \( p \) is from a GEV model, parameters of which are the maximum \textit{a posteriori} likelihood estimations (the mode of the posterior distribution). Discount factor is
\[
F_t = \exp(-\sum_{t=0}^{\infty} r),
\]
with an \( r \) value of 4\% per year.

Under the considering-uncertainty assumption, \( O_{2h} \) becomes an ensemble and the mean of that ensemble is the expected total cost under uncertainty. Under uncertainty \( O_{2h} \) becomes
\[
O_{2h, \text{unc}} = E[O_{2h}^i] = E[C_h + LED_h^i],
\]
where
\[
LED_h^i = \sum_{t=0}^{\infty} EAD_h^i * F_t^i.
\]
In these equations, \( i \) indicates an index in the state space. Each state vector in the state space is called a State of the World (SOW). We create the state space by random sampling (using the Latin Hypercube Sampling\textsuperscript{51} method). Samples are drawn from sources identified in section 4.1. In cases where the type of uncertainty is deep, we randomly switch samples from different models.

The elevations that minimize the total discounted costs with and without uncertainty are
\[
h_{opt} = \text{Arg Min}_{h \in [0,14]}(O_{2h}),
\]
and
\[
h_{opt, \text{unc}} = \text{Arg Min}_{h \in [0,14]}(O_{2h, \text{unc}}),
\]
respectively.

### 4.2.2. Benefit-to-cost ratio

In our cost-benefit analysis (CBA), the cost is the upfront cost \((C_h)\) of elevating a house by \( h \) feet. The benefits \((B_h)\) are the net present value of the savings after elevating the house by \( h \) feet. The benefit-to-cost ratio is \( O_{3h} = \frac{B_h}{C_h} \) where \( B_h = LED_h - LED_0 \).

When uncertainty is ignored, we calculate \( LED \) using Eq. 5 with values discussed in the previous section. When uncertainty is considered, \( O_{3h} \) becomes an ensemble. We use the mean of this ensemble as the expected benefit-to-cost ratio under uncertainty.

### 4.2.4. Reliability

We define reliability as the probability of no flooding during the house lifetime. For a building that is elevated by \( h \) feet, reliability is
\[
O_{4h} = \prod_{t=1}^{n} Pr(Pr(X \leq h) = (CDF_h)^t),
\]
where \( n \) is the house lifespan and \( CDF \) denotes the probability that the annual maximum water level does not exceed the house’s lowest level. Under uncertainty, reliability is the expected value of the ensemble of reliabilities for all SOWs.
4.2.5. Robustness

Robustness is often measured using the concepts of satisficing and regret. Satisficing-based measures focus on outcomes that are within acceptable ranges defined for each objective. Regret-based criteria, on the other hand, focus on the deviations in performance caused by incorrect assumptions/decision\textsuperscript{15,26}. In this study, we assess the robustness of heightening strategies using a satisficing-based criterion\textsuperscript{26,52} called the domain measure.\textsuperscript{20} This satisficing index measures the fraction of SOWs in which one or more objectives fall within the acceptable range. The acceptable ranges in our analysis are $[1,\infty)$ for the benefit-to-cost ratio, $[0,0.75]$ for the ratio of the total cost to house value, and $[0.5,1]$ for reliability.

4.3. Sensitivity analysis

We use global sensitivity analysis (GSA) to quantify the relative importance of uncertainty sources in determining expected damages.\textsuperscript{53-54} Unlike one-at-a-time (OAT)\textsuperscript{55} sensitivity analysis approach that varies each factor separately, GSA allows variation of all the factors at the same time. This allows for understanding the effects of interactions between factors.\textsuperscript{27} If $y = f(x_1, x_2, \ldots, x_j, \ldots, x_k)$, the relative importance of an individual factor ($x_j$) (also known as first-order sensitivity index) is $S_j = \frac{\text{var}(E(y|x_j))}{\text{var}(y)}$, which is the variance of the expected value of $y$ conditioned on $x_j$ divided by the unconditional variance.\textsuperscript{54} Sobol' sensitivity analysis identifies a subset of factors that accounts for most of the variance in output.\textsuperscript{56} The total variance of the output is decomposed into elements that come from individual parameters and their interactions.\textsuperscript{53} Sobol’’s first-order index indicates the effects of a single parameter on the model output. The total-order effect is the combination of the first-order effect and all the interactions with other parameters. Since Sobol’’s method becomes computationally expensive in high parameter spaces, Saltelli’s method, which uses fewer simulations, is often used for high-order indices.\textsuperscript{54} Saltelli proposes two theorems.\textsuperscript{54} The first theorem calculates the full set of first- and total-order indices at the computational cost of $n(k+2)$. The second theorem calculates first-, second-, and total-order indices at the cost of $n(2k+2)$, where $n$ is the number of Monte Carlo samples and $k$ is the number of parameters. In this study, we use Saltelli’s second theorem to quantify the first-, second-, and total-order indices. We use the R package “sensitivity”\textsuperscript{57}.

Data availability

USGS water level and streamflow data can be accessed at https://waterdata.usgs.gov/nwis/uv?site_no=01554000. USGS rating curve can be accessed at https://waterwatch.usgs.gov/?m=mkrc&sno=07050500. Discount rate time series and all data used in this paper are available, under the GNU license, at https://github.com/scrim-network/Zarekarizi-flood-home-elavate.git

Code availability

All code used in this paper are available, under the GNU license, at https://github.com/scrim-network/Zarekarizi-flood-home-elavate.git
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Author contribution

M.Z. and K.K. designed the study. M.Z. led the calculations, in collaboration with V.S. V.S. led the development of the discounting models and implemented them (section 4.1.2). M.Z. wrote the initial draft of the paper. All authors revised and edited the paper.

Competing interests

The authors declare no competing financial or nonfinancial interests.

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S1. Supplementary tables

Table S1: Parameters of the discount rate models.

| Parameter                     | Random Walk | Mean-Reverting | Background Trend |
|-------------------------------|-------------|----------------|------------------|
| Mean                          |             | 3.405          |                  |
| log-Mean standard error       |             | 0.3457         |                  |
| Intercept                     | 1.9289 (0.1728) |                | 1.9289 (0.1728) |
| Trend                         | -0.0058 (0.0014) |                |                  |
| AR1                           | 1.7429 (0.0648) | 1.7371 (0.0649) | 1.6965 (0.0655) |
| AR2                           | -1.0455 (0.1160) | -1.0270 (0.1175) | -0.9755 (0.1181) |
| AR3                           | 0.3010 (0.0674) | 0.2806 (0.0710) | 0.2388 (0.0738) |
| $\sigma^2$                    | 0.0034       | 0.0034         | 0.0033           |

Tables S2: AIC and BIC of discounting models. The model with the lowest AIC and BIC is in bold.

| Discount rate model | AIC   | BIC   |
|---------------------|-------|-------|
| Random Walk         | -617  | -603  |
| Mean-Reverting      | -617  | -600  |
| Background Trend    | -624  | -604  |
Table S3: Characteristics of the hypothetical pool of houses for the vulnerability study. We sample from plausible ranges as indicated below. We create a pool of 1,000 hypothetical buildings using Latin Hypercube Sampling.

| Variable                                      | Minimum | Maximum  |
|-----------------------------------------------|---------|----------|
| House value ($)                               | 10,000  | 1,000,000|
| House size (ft²)                              | 100     | 5000     |
| lowest level elevation with respect to BFE (ft)| -10     | 0        |

S2. Supplementary figures

Figure S1: An XLRM diagram that shows the decision framework. The orange element is the lever (L) (i.e. how high to elevate a house). Red components represent exogenous uncertain factors (X) that impact the decision and are out of control of the decision-maker. Objectives or metrics (M) represent how success is measured. System relationships (R) shows how levers and uncertainties translate into objectives.
Figure S2: The benefit-to-cost ratio under assumptions of ignoring-uncertainty and considering-uncertainty for the typical house studied in this paper. The blue vertical line indicates the FEMA-recommended heightening strategy. The green vertical line indicates the strategy recommended by the considering-uncertainty assumption. The hatched gray area on the left refers to elevating the house by less than three feet which we ignore in this study.

Figure S3: Reliability under assumptions of ignoring-uncertainty and considering-uncertainty for the typical houses studied in this paper. The vertical line indicates the FEMA-recommended heightening strategy. The green vertical line indicates the strategy recommended by the considering-uncertainty assumption. The hatched gray area on the left refers to elevating the house by less than three feet which we ignore.
Figure S4: Tradeoffs between different decision-makers’ preferences. Each line indicates a heightening policy. The left-out line indicates the not-elevating policy (a policy recommended by the ignoring-uncertainty assumption). The infeasible ideal policy yields a horizontal line on the top of the axes. Green lines represent lower lifting policies and blue lines indicate higher lifting policies. Policies with high (low) reliability are associated with low (high) expected damages, high (low) upfront costs, and high (low) benefit-to-cost ratio.
Figure S5: Similar to Figure 5 but for different scenarios. Scenarios are defined based on combinations of discount rate and depth-damage model options.
Figure S6: 100-year-period discount factors of three stochastic models as compared with the discount factor of a constant positive discount rate. Shaded bounds indicate the uncertainties in the stochastic models.
S7: Same as Figure 5 but for deep uncertainties. Here, the discount rate node indicates the model structure uncertainties. Samples for this node are drawn uniformly from the vector of (1,2,3). Each element represents a model choice. For depth-damage function, samples are drawn uniformly from two model choices as discussed in the methods.
Figure S8: same as Figure 5 but for different house vulnerability factors such as size, value, and the lowest level elevation. Small: 500 ft$^2$ large: 3,000 ft$^2$ cheap:$100,000$ expensive:$600,000$
S9: Same as Figure 5 but with a different sampling approach for the discount rate. Here, we draw samples randomly from the [1%,10%] range.
Figure S10: Comparision of economically-optimal elevations under two assumptions of ignoring-uncertainty and considering-uncertainty. Each point represents a house. Houses in which one or both of the optimal elevations are more than house value are indicated by red.
In 79% of the houses, FEMA recommended height is lower than cost optimal height.

In 5% of the houses, FEMA recommended height is higher than cost optimal height.

In 15% of the houses, FEMA recommends elevating but it is not cost optimal.

**Figure S11:** The economic optimal elevation versus FEMA’s recommendation. Each dot represents a house (a total of 1,000 houses). Red dots indicate that FEMA’s recommended policy does not pass the cost-benefit test (i.e., the benefit is less than the cost). The diagonal green line is the 1:1 line.
Figure S12: Two depth-damage functions used in this study. The damage model in blue is obtained from FEMA HAZUS and the damage curve shown in green is obtained from the European Commission’s science and knowledge service. Shallow uncertainty in each function is represented by 30% uniform bounds.

Figure S13: The uncertainty in house lifetime considered in this study (the shaded blue distribution) and some deterministic values commonly used in the literature (vertical black lines).
Figure S14: Construction cost for three sample houses with sizes of 1,000, 2,000, and 3,000 ft$^2$. The gray area indicates an elevation of fewer than three feet which we assume to be impractical. These cost estimates are adopted from the CLARA model. Units are in 2017 US$ value.