Estimating the Greenhouse Gas Emissions from Flood Damages

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January 18, 2024

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**Keywords:** flood risk, resilience, life cycle cost analysis, environmental impact analysis, cost-benefit analysis

Abstract

Summarize purpose, methods, and results. (300 words).

# 1. Introduction

Floods and storms are the most frequent and devastating natural hazards worldwide and are becoming increasingly so due to climate change ([CRED and Guha-Sapir, 2023](#ref-cred2023a); [Pörtner et al., 2022](#ref-portner2022)). From 2013 to 2022 in the United States alone, more than 2.7 million people were affected by flood and storm disasters which caused an inflation-adjusted total of US$540.2 Billion according to the Centre for Research on the Epidemiology of Disasters (CRED)’s Emergency Events Database (EM-DAT)[[1]](#footnote-1) ([2023](#ref-cred2023a)). Even if immediate and dramatic efforts are implemented to reduce greenhouse gas (GHG) emissions, flood losses in the U.S. are expected to increase by 24-29% by 2050 due to climate change alone and as much as 97% when considering both climate and population change, disproportionately affecting Black and low-income communities ([Wing et al., 2022](#ref-wing2022)). Cost benefit analyses for flood risk management (FRM) projects rely on deterministic damage functions to estimate the monetary damages caused by floods ([Davis and Skaggs, 1992](#ref-davis1992); [Dawson, 2003](#ref-dawson2003); [U.S. Water Resources Council, 1983](#ref-u.s.waterresourcescouncil1983)). This approach limits planners in developing FRM solutions by failing to account for uncertainty in flood risk assessments and failing to consider flood impacts beyond monetary losses such as greenhouse gas (GHG) emissions. The purpose of this study is to answer the following develop damage functions that can be used by FRM planners to estimate the GHG emissions from floods. To this end we seek to answer the following research questions:

1. What is the carbon footprint embodied within components of structures susceptible to damage from floods?
2. What quantity of greenhouse gas emissions is produced due to damages from a 100-year flood event and to what extent do these emission affect the valuation of risk from this flood event?
3. To what extent does including the impacts of greenhouse gas emissions affect the distribution of risk from a 100-year flood event?

Much of the research assessing the GHG emissions caused by floods has focused on impacts to natural ecosystems and their contribution to the carbon cycle. For example, Gebremichael et al. ([2017](#ref-gebremichael2017)) assessed the effect of flooding on European coastal grassland ecosystems and found that longer-term flooding was associated with a net increase in CO2 emissions produced by soil microbes. Oram et al. ([2020](#ref-oram2020)) found that flooding significantly increased the GHG emissions from managed grasslands in the Netherlands and showed that certain plant species can mitigate against this. Increased urbanization in flood prone areas is expected to be a primary driver future flood risk Wing et al. ([2022](#ref-wing2022)), yet there has been little effort to assess the how flood impacts on the built environment contribute to GHG emissions.

There is an abundance of research assessing the life cycle environmental impacts of residential construction and material selections to support more sustainable building practices ([Haddad et al., 2023](#ref-haddad2023); [Hosseinijou et al., 2014](#ref-hosseinijou2014); [Kong et al., 2010](#ref-kong2010); [Megange et al., 2019](#ref-megange2019); [Nagireddi et al., 2022](#ref-nagireddi2022); [Napolano et al., 2015](#ref-napolano2015); [Salazar and Sowlati, 2008](#ref-salazar2008); [Schneider-Marin et al., 2022](#ref-schneider-marin2022); [H. Wang et al., 2020](#ref-wang2020a)). Likewise, many studies have assessed the environmental impacts of material choice for maintenance and repairs to residential structures ([Caruso et al., 2020](#ref-caruso2020); [Dong et al., 2018](#ref-dong2018); [McGrath et al., 2013](#ref-mcgrath2013); [Y. Wang et al., 2020](#ref-wang2020); [Wittocx et al., 2022](#ref-wittocx2022)). Few studies, however, have applied such assessments in the context of natural hazards in general and floods in particular. Adhikari et al. ([2020](#ref-adhikari2020)) assessed the life-cycle carbon footprint of residential buildings exposed to tornadoes and found that selecting more tornado resistant components tended to be optimal for structures in terms of both life cycle costs and carbon footprint. Simonen et al. ([2018](#ref-simonen2018)) assessed the embodied carbon of various structural and non-structural building components using an economic input-output model to estimate the expected GHG emissions per dollar of damage to buildings impacted by earthquakes. They found that the most carbon intensive materials (e.g. gypsum and glass products) are among the most susceptible to seismic damage and therefore the GHG emissions associated with seismic events do not necessarily increase in proportion to their magnitude. Matthews et al. ([2016](#ref-matthews2016b)) used a Monte Carlo simulation to estimate life-cycle component-level flood damages and associated environmental impacts for two design alternatives for a case-study single-family residential structure located in a flood zone. This analysis showed that a more flood resistant design significantly reduced the total lifecycle environmental impact of the structure due to the need for fewer repairs. Hennequin et al. ([2019](#ref-hennequin2019a)) performed a similar assessment for a typical European single-family home and found that experiencing a flood can increase the life-cycle environmental impact of such a building by about 4-18%. These studies show that damages to structures caused by natural hazards can result in significant GHG emissions. However, because these studies focus largely on the effect of material choice and construction design or are not specific to flood damages, their generalizability to flood risk assessments in a potential project study area is limited.

EFTEC et al. ([2010](#ref-eftec2010)) assessed various policy strategies for FRM in the UK and estimated that emissions from the construction of flood mitigation projects would be offset by a reduction in emissions resulting from flood damages. However, the focus of this study was primarily on the carbon footprint of flood mitigation project construction, and their assessment of emissions from flood damages was limited to the use of a very high-level damage cost multiplier which does not consider the full life cycle of damaged components. Petit-Boix et al. ([2017](#ref-petit-boix2017a)) used historic insurance and flood mitigation investment data to compare the environmental impacts of flood mitigation efforts to the environmental impacts of flood damages and found a net environmental benefit for mitigation efforts. This study used emissions factors and input-output analysis to estimate the environmental impacts based on economic data rather than through a robust assessment of the environmental impacts to specific building components, and the results of this study are not generalizable to estimating potential benefits from future FRM projects. Matthews et al. ([2021](#ref-matthews2021)) presented a methodology for estimating the GHG emissions associated with flood damages to buildings and produced depth-emissions functions for structural components in one- and two-story single-family structures. In this study, the authors also demonstrated the use of their component-level damage functions in a building-level analysis, however producing building-level depth-emissions functions which could be used for future assessments of flood risk was outside the scope of this study. Also, while this study includes a range of estimates for the life-cycle carbon footprint of each component, the damage functions are deterministic with respect to the quantity of each component damaged at a given flood depth, limiting the ability to consider uncertainty in damage estimates when applying these functions.

To mitigate the risk posed by future floods under climate change, it is necessary to comprehensively account for all sources of GHG emissions as well as to develop effective and sustainable FRM solutions. In the existing literature, there is a lack of research investigating the extent to which floods and their effects may contribute to greenhouse gas emissions or the extent to which FRM projects may reduce the GHG emissions caused by flood events. There is also a lack of research incorporating uncertainty into flood risk assessment methodologies. In this paper, we attempt to address this research gap by developing a probabilistic model to quantify the GHG emissions associated with flood damages to individual components in residential structures affected by floods. We apply this model in a series of Monte Carlo simulations to assess the building-scale GHG emissions of flood damages across a variety of building construction types and produce building-scale depth-emissions curves which can be used to assess the GHG emissions of flood events affecting multiple structures. Finally, we apply these building-level curves to a real-world flood risk analysis to quantify the GHG emissions associated with a 100-year flood event in two study regions in the Mississippi River Valley. The results of this work will help planners better assess the environmental impacts of future flood events and the potential benefits of future FRM projects. Incorporating these impacts into cost-benefit analyses may justify additional investment into flood mitigation efforts and may also promote the development of more sustainable FRM practices.

# 2. Methods

We used documented expert judgement and information from residential building codes to develop synthetic damage functions for components of one- and two-story single family residential structures. We analyzed 50 real-world residential floorplans to document variability in component quantities in each structure type. We performed a Monte Carlo Simulation (MCS) to model the component-level damage, replacement cost, and associated GHG emissions across a range of flood depths. The results of the MCS were aggregated to produce damage functions for each structure type which estimate the total emissions produced from repairing damage to a structure exposed to a flood of a given depth. Finally, these damage functions were applied to a real-world flood risk case study in two locations in the Mississippi River Valley to assess how including these emissions in the assessment affects the magnitude and distribution of flood risk.

## 2.1 Component Failure Model

The first step in our analysis was to develop a component failure model which can be used to estimate the expected quantity of each component in a structure to be replaced as due to exposure to a flood of a given magnitude. To do this, we first developed a list of components adapted from the list in GEC ([2006](#ref-gec2006)) which includes 20 structural items for residential buildings. We expanded upon this list by separating certain components into distinct items when differences in materials could result in distinct unit cost or carbon footprint estimates (e.g. Subfloor vs. Finished Floor) or where it was possible based on information in the report or using our own engineering judgment to separate components to develop more specific fragility functions (e.g. bottom wall outlets vs. light switches). Ultimately our list includes 38 components for single-story structures, and 56 components for two-story structures, as some items may be found on both the first and second floor. We did not include foundations or structural framing materials in our component list as we assumed these would not require replacement due to exposure to flood depth in most cases.

To model the failure of each component in response to floods, we follow the methodology outlined in Nofal et al. ([2020](#ref-nofal2020a)) to develop fragility functions for each component. A fragility function is a mathematical model that shows the probability that a component will exceed a limit state due to exposure to a stressor of a given magnitude, or intensity measure ([Equation 1](#eq-fragility))([Saouma and Hariri-Ardebili, 2021, p. 610](#ref-saouma2021)). In the present study, the fragility function for each component shows the probability that the given component will fail and require replacement due to exposure to a flood of a given depth, and we use the triangular cumulative distribution function to represent this probability.

The triangular distribution is commonly used for risk modeling as it requires minimal information, taking just three parameters: the minimum, maximum, and mode (most likely value) of the model variable (in this case flood depth), and has been shown to be a suitable replacement for the more robust beta distribution ([Johnson, 1997](#ref-johnson1997)). Using this distribution function, we assume that the given component will never fail when the flood depth is below the minimum value and that the component will always fail when the flood is at or above the maximum value. The probability that the given component will fail when the flood depth is between the minimum and maximum values is shown in [Equation 2](#eq-triangcdf).

where is the depth of flooding relative to the structure’s first floor elevation, and , , and are the minimum, maximum, and mode, respectively. The GEC report includes a narrative of the assumptions made by the expert panel in developing their damage functions for each structural component which describes how damage will occur to each component under various flood depths ([GEC, 2006, pp. A5–A6](#ref-gec2006)). We determined the appropriate parameter values for each component based on our interpretation of these narratives. For example, regarding flood damage to doors, the panel said:

“Most doors in residential structures are hollow and are warped and destroyed between 0.0 and 1.0 foot of floodwater. Some higher quality doors can be refinished up to 1.0 foot of floodwater. Doors in commercial structures are usually of solid sturdy wood and are sealed at the top and bottom, helping to prohibit water damage. These doors would only require refinishing at 0.5 foot of floodwater. Some would require replacement at 1.5 feet of floodwater. All doors are totaled at 4.0 feet of floodwater. Hollow metal door frames are never a total loss.” ([GEC, 2006](#ref-gec2006))

Based on this description, we developed separate fragility functions for interior and exterior doors, assuming exterior doors are higher quality. For interior doors, we set the minimum, maximum, and most likely failure depths to 0, 0.5, and 2 feet, respectively, and for exterior doors we set these values to 1, 2, and 4 feet, respectively. For some components, the expert panel assumes complete loss as soon as water touches them. In these cases, we parameterize the fragility function based on the range of possible heights for the component within the structure. For example, we assume wall outlets will be located between 12 and 24 inches above the floor with 12 inches being the most likely ([The Home Depot, 2023](#ref-thehomedepot2023)). The fragility curves for interior doors, exterior doors, and wall outlets are shown in [Figure 1](#fig-dmgfns), and the fragility function parameters for all components are shown in [Table 1](#tbl-unit).

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| Figure 1: Plot of fragility curves developed for interior doors, exterior doors, and wall outlets. |

We were unable to define fragility functions for some of the components in our list, namely sheetrock/drywall, wall insulation, exterior wall sheathing, roof sheathing, and facade. These components cannot be represented as discrete items that fail entirely at a given flood depth. Rather, the quantity of these components to be replaced depends on the proportion of the total quantity inundated. Following Matthews et al. ([2021](#ref-matthews2021)), which also relied on the GEC ([2006](#ref-gec2006)) component list in their analysis, we assume that the quantity of sheathing material to be replaced will be equal to the inundated quantity. We also used this damage function for the facade, however, we assume that facades of brick veneer or vinyl or polypropylene siding would not require replacement due to flooding. Rather than develop separate damage functions for each material option in this step, we simply assume that the replacement cost and associated GHG emissions for these material choices are zero in the analysis described in [Section 2.2](#sec-cost-ghg). For sheetrock/drywall and wall insulation, we assume that any material inundated will be replaced, however, based on the narrative in GEC ([2006](#ref-gec2006)) we assume that the entire component will be replaced when the flood depth reaches half-way up the wall.

## 2.2 Component Cost and Greenhouse Gas Emission Analysis

**Weiwei, for some items I was not able to collect multiple cost estimates. Right now, the model assumes no variability in the replacement cost for these items. I am wondering if it would make sense for these items to assume this price represents the median replacement costs, and set the minimum and maximum values to be +/-10% (or some other percentage). I could implement this change in under ten minutes.**

Once we developed the model to estimate the failure of each structural component, the next step was to assess the impact associated with these failures. For each component, we collected unit replacement costs and life cycle GHG emissions estimates, considering multiple material options where possible. We used Building Construction Cost Data from RS Means ([Doheny, 2021a](#ref-doheny2021)) to estimate the replacement cost for each component. We gathered life cycle GHG estimates primarily from the National Institute of Standards and Technology (NIST) Building for Environmental and Economic Sustainability (BEES) LCA database ([NIST, 2023](#ref-nist2023)) and from the Ecoinvent database version 3.9.1 ([ecoinvent, 2023](#ref-ecoinvent2023); [Wernet et al., 2016](#ref-wernet2016)) when estimate were not available from BEES. We relied on estimates from the literature for the GHG emissions associated with countertops ([Adhikari et al., 2022](#ref-adhikari2022); [Silva et al., 2021](#ref-silva2021)) and water heaters ([Raluy and Dias, 2020](#ref-raluy2020)) as we were not able to find the appropriate data from BEES or Ecoinvent. For the same reason, we calculated the GHG emissions associated with water heaters based on our unit price data using the U.S. EPA’s Environmentally Extended Input-Output (USEEIO) model v.2.1 ([Ingwersen et al., 2022](#ref-ingwersen2022)) and the useeior package ([Li et al., 2022](#ref-li2022)) for the R statistical programming language ([R Core Team, 2023](#ref-rcoreteam2023)), classifying water heaters under the industry code for wiring device manufacturing. Unit replacement cost and GHG estimates for each component are shown in [Table 1](#tbl-unit).

We used the TRACI 2.1 impact methodology to calculate the global warming potential of the GHG emissions in terms of kgCO2 equivalents. We then multiplied this value by the social cost of GHG emissions, estimated by the U.S. Environmental Protection Agency[[2]](#footnote-2) to be $190 per 1000kg, to estimate the impact of the GHG emission in monetary terms allowing us to compare them to the replacement cost estimates and develop emission-based damage functions which can be incorporated into monetary cost-benefit analyses typical for FRM projects.

**TODO: add fragility parameters to table, show cost and co2 estimates as min, max, mode as discussed with Weiwei.**

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| Table 1: Mean and standard deviations of unit costs and GHG emissions for structure components   | Component | Unit | Unit Cost Mean (SD) | Unit CO2eq Mean (SD) | | --- | --- | --- | --- | | Underfloor Insulation | sqft | $2.35 ($0.95) | 0.51 (0.26) | | Underfloor Ductwork | ft | $26.97 ($8.4) | 2.93 (3.07) | | Heating/Cooling Unit or HVAC | ea | $3629.6 ($3668.18) | 2408 (2130.23) | | Wood Subfloor | sqft | $1.37 ($0.14) | 4.49 (5.73) | | Finished Floor Underlayment | sqft | $2.23 ($0.92) | 0.29 (0.2) | | Finished Floor | sqft | $7.65 ($4.72) | 1.33 (1.34) | | Bottom Cabinets | ea | $5505 ($3938.26) | 715.5 (400.14) | | Top Cabinets | ea | $5505 ($3938.26) | 715.5 (400.14) | | Bathroom Bottom Cabinets | ea | $529.5 ($59.13) | 143.1 (67.46) | | Bathroom Top Cabinets | ea | $226.38 ($37.78) | 143.1 (67.46) | | Counter Tops | ea | $698.62 ($473.7) | 286.5 (139.73) | | Water Heater | ea | $2068.88 ($992.55) | 55.73 (0) | | Wall Paint - Interior | sqft | $0.35 ($0) | 0.15 (0.06) | | Wall Paint - Exterior | sqft | $1.2 ($0) | 0.15 (0.06) | | Exterior Doors | ea | $740.25 ($451.43) | 221 (1.41) | | Interior Doors | ea | $165.83 ($92.2) | 123.6 (16.97) | | Baseboard | ft | $4.3 ($1.43) | 0.31 (0.01) | | Refrigerator | ea | $1135.83 ($676.25) | 291 (0) | | Dishwasher | ea | $1168 ($301.17) | 146 (0) | | Microwave | ea | $418 ($236.17) | 58.9 (0) | | Clothes Washer | ea | $1198 ($441.23) | 382 (0) | | Clothes Dryer | ea | $1140.67 ($167.53) | 210 (0) | | Oven/stove | ea | $1355.88 ($705.71) | 180 (0) | | Range hood | ea | $739 ($602.45) | 63.8 (0) | | Bottom Outlets | ea | $58.62 ($8.31) | 22.8 (0) | | Top Outlets | ea | $58.62 ($8.31) | 22.8 (0) | | Light Switches | ea | $42.65 ($5.37) | 22.8 (0) | | Electrical Panel | ea | $1471.67 ($539.66) | 0 (0) | | Windows | ea | $422.25 ($278.59) | 391.72 (205.2) | | Ceiling Paint | sqft | $0.35 ($0) | 0.15 (0.06) | | Ceiling | sqft | $0.79 ($0.15) | 0.38 (0.08) | | Ceiling Insulation | sqft | $2.62 ($0.86) | 0.5 (0.26) | | Roof Cover Underlayment | sqft | $0.2 ($0.09) | 0 (0) | | Roof Cover | sqft | $4.05 ($2.23) | 0 (0) | | Roof Cover and underlayment combined | sqft | $0 ($0) | 1.17 (0.61) | | Sheetrock/drywall | sqft | $0.78 ($0.09) | 0.38 (0.08) | | Wall Insulation | sqft | $1.25 ($0.62) | 0.29 (0.19) | | Roof Sheathing | sqft | $1.3 ($0.24) | 0.33 (0.02) | | Facade | sqft | $7.84 ($5.98) | 1.47 (1.06) | | Exterior Wall Sheathing | sqft | $1.41 ($0.26) | 0.33 (0.02) | |

### 2.2.1 Environmental Input Output Analysis

**Weiwei, I have the data to add this into the model, and I think I could have these additional results incorporated within 1 day of work. Do you think this is worthwhile to include to make our analysis more robust?**

To cross-validate and verify the results of our GHG analysis, we also calculated the GHG emissions associated with each component through an economic input-output analysis. Unlike previous studies which have performed this type of analysis using building-level damage costs, we associate each individual component with a certain industry code and calculate the carbon footprint associated with replacing one unit of the given item based on the unit cost data collected in the previous step. We used the U.S. EPA’s Environmentally Extended Input-Output (USEEIO) model v.2.1 ([Ingwersen et al., 2022](#ref-ingwersen2022)) and the useeior package ([Li et al., 2022](#ref-li2022)) for the R statistical programming language ([R Core Team, 2023](#ref-rcoreteam2023)) to run this analysis for each component. Average unit GHG emissions for each component are shown in [Table 2](#tbl-useeio).

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| Table 2: Mean unit costs and GHG emissions for structure components from USEEIO analysis   | Component | Functional Unit | Mean Unit Cost | Unit CO2eq Mean (kg) | | --- | --- | --- | --- | | Baseboard | ft |  | 1.467588e+00 | | Bathroom Bottom Cabinets | ea |  | 1.726308e+02 | | Bathroom Top Cabinets | ea |  | 6.766489e+01 | | Bottom Cabinets | ea |  | 1.694465e+03 | | Bottom Outlets | ea |  | 7.214359e-01 | | Ceiling | ft2 |  | 1.703077e+00 | | Ceiling Insulation | ft2 |  | 1.166130e+00 | | Ceiling Paint | ft2 |  | 6.128732e-02 | | Clothes Dryer | ea |  | 2.569563e+02 | | Clothes Washer | ea |  | 2.401682e+02 | | Counter Tops | ea |  | 1.092623e+03 | | Dishwasher | ea |  | 1.974233e+02 | | Electrical Panel | ea |  | 1.018881e+02 | | Exterior Doors | ea |  | 3.632757e+02 | | Exterior Wall Sheathing | ft2 |  | 8.471584e-01 | | Finished Floor | ft2 |  | 3.430746e+00 | | Finished Floor Underlayment | ft2 |  | 7.108371e-01 | | Heating/Cooling Unit or HVAC | ea |  | 1.663561e+03 | | Interior Doors | ea |  | 2.676921e+01 | | Light Switches | ea |  | 5.022655e-01 | | Microwave | ea |  | 8.468850e+01 | | Oven/stove | ea |  | 3.144893e+02 | | Range hood | ea |  | 7.648133e+01 | | Refrigerator | ea |  | 3.438463e+02 | | Roof Cover | ft2 |  | 2.996925e+00 | | Roof Cover Underlayment | ft2 |  | 1.063069e-01 | | Roof Sheathing | ft2 |  | 8.471584e-01 | | Sheetrock/drywall | ft2 |  | 1.703077e+00 | | Top Cabinets | ea |  | 1.590409e+03 | | Top Outlets | ea |  | 7.214359e-01 | | Underfloor Ductwork | ft |  | 2.093383e+00 | | Underfloor Insulation | ft2 |  | 1.160865e+00 | | Wall Insulation | ft2 |  | 5.603167e-01 | | Wall Paint - Exterior | ft2 |  | 1.350740e-01 | | Wall Paint - Interior | ft2 |  | 6.128732e-02 | | Water Heater | ea |  | 3.022251e+02 | | Windows | ea |  | 2.268886e+02 | | Wiring | 4m |  | 2.937526e-01 | | Wood Subfloor | ft2 |  | 8.471584e-01 | |

## 2.3 Building-Level Damage Analysis

The purpose of the building-level damage analysis is to develop damage functions that can be used in FRM projects to estimate the impacts caused by exposure of individual structures to a flood of a given depth. Building-level damage functions typically represent the total cost of damages to a structure at a given flood depth as a percentage of the structure’s total replacement value ([U.S. Water Resources Council, 1983](#ref-u.s.waterresourcescouncil1983)). Damage functions developed in existing studies do not account for variability in building size or design as a source of uncertainty in their damage estimates ([GEC, 2006](#ref-gec2006); [Hennequin et al., 2019](#ref-hennequin2019a); [Matthews et al., 2021](#ref-matthews2021); [Nofal et al., 2020](#ref-nofal2020a)). To address this limitation, we analyzed 50 real-world floor plans from ([Architectural Designs, 2023](#ref-architecturaldesigns2023)) and calculated material quantity estimates for all components for each floor plan. We calculated the total replacement cost for each floorplan using [Equation 3](#eq-sqft) derived from RSMeans Square Foot Costs Data ([Doheny, 2021b](#ref-doheny2021a)).

where is the total area of the building in square feet, is the number of floors, and is the number of bathrooms. Calculating the total replacement cost enables us to report our damage estimates as a percentage of this value. We analyzed 38 one-story floor plans and 12 two-story plans.

To develop structure-level damage curves, we performed a Monte Carlo analysis to estimate component-level damages for each floor plan across a range of flood depths. To do this, we generated a vector of flood depths ranging from -4 to 32 feet incrementing by 0.1 feet. Flood depths are relative to the structure’s first-floor elevation, therefore negative values are included to account for components located below the first floor level. For each flood depth in this vector, we performed 25 component-level simulations for each component in all 50 floor plans in which we estimated the expected quantity of each component to be replaced due to flood damage at the given flood depth.

For sheetrock/drywall, wall insulation, exterior wall sheathing, and roof sheathing, we calculated the replacement quantity in each simulation according to their unique damage functions as described in [Section 2.1](#sec-fragility). For the remaining components, we calculated their replacement quantity in each simulation by performing Bernoulli trials where is the total quantity of the given component. A Bernoulli trial is a discrete experiment testing whether or not a certain outcome occurs given a certain probability of occurence ([Papoulis, 1994, pp. 43–47](#ref-papoulis1994)). The outcome in questions for each Bernoulli trial is the failure of the given component, and its probability of occurrence is given by the fragility function for the given component at the given flood depth. We used the random.binomial method in the NumPy Python library ([Harris et al., 2020](#ref-harris2020)) to perform the Bernoulli trials. For components with a total quantity greater than one, this method allows us to consider them as independent items that may fail independently at a given flood depth (e.g. if a floor plan has 5 interior doors, it is possible that only three would need to be replaced after a flood with a depth of one foot).

Once we have calculated the replacement quantity for each component in the simulation, we multiply this value by the component’s unit replacement cost and unit carbon footprint. To incorporate uncertainty in these estimates, we randomly generate the unit costs and carbon footprints based on cost and carbon footprint data described in [Section 2.2](#sec-cost-ghg). We modelled the distribution of these values using a triangular distribution, assuming the most-likely value to be the mean of our collected data and assuming the minimum and maximum values to be the same as the minimum and maximum of our collected data. We used the random.Generator.triangular method in the NumPy Python library ([Harris et al., 2020](#ref-harris2020)) to generate these values based on the specified triangular distribution. We calculate the social cost of GHG emissions in each simulation by multiplying the randomly generated carbon footprint value by the social cost of GHG emissions discussed in [Section 2.2](#sec-cost-ghg).

For each simulation, we sum the replacement cost, GHG emissions, and social cost of GHG emissions for all components to determine the total building-level impacts of the given flood. We then divide the total replacement cost and total GHG social cost by the total replacement cost calculated for the given floor plan to report these impacts in each simulation as a percentage of the building’s total replacement cost. This allows us to apply these damage functions to buildings of different sizes and constructions and produce damage estimates that are responsive to these variations. Finally, we aggregated the results of the Monte Carlo simulations at each flood depth to produce probabilistic building-level damage functions. We performed this aggregation separately for one- and two-story structures to maintain compatibility with existing damage function frameworks.

## 2.4 Spatial Analysis

The purpose of the spatial analysis is to estimate the GHG emissions associated with an actual flood event and to assess the extent to which including GHG emissions in a flood risk assessment affects the magnitude and distribution of risk. To do this, we applied the building-level damage functions to a real-world flood risk analysis in two study regions in the Mississippi River Valley. The first study region is centered around the segment of the Mississippi River stretching from Davenport to Burlington, IA, and the second study region is centered around the intersection of the Mississippi and Ohio Rivers. Study region one has a population of roughly 1.9 million, and the population of region two is roughly 987,000. The study regions and their respective stream networks are shown in [Figure 2](#fig-map).

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| Figure 2: Map showing the location of each study region and their respective stream networks. |

We used AutoRoute ([Follum and Vera, 2023](#ref-follum2023)) to generate 100-year flood depth rasters for both study regions. Autoroute is a grid-based model that calculates flood extents and depths from elevation, landcover, and stream discharge data. We used elevation data from the National Elevation Dataset ([U.S. Geological Survey, 2022](#ref-u.s.geologicalsurvey2022)), landcover data from the National Landcover Database ([Dewitz, 2023](#ref-dewitz2023)), and stream segments from the National Hydrography Dataset PlusV2 river network ([McKay et al., 2012](#ref-mckay2012)). Streamflow data for each stream segment were provided by the U.S. Army Corps of Engineers Coastal & Hydraulics Laboratory. For more information about how the streamflow data were generated, see ([**memarsadeghi2024?**](#ref-memarsadeghi2024)).

We used data from the National Structure Inventory (NSI) ([U.S. Army Corps of Engineers, 2022](#ref-u.s.armycorpsofengineers2022)) to identify residential structures in both study regions. The NSI is designed for use in assessing the consequences of natural hazards and includes information on nearly every structure in the United States such as location, elevation, occupancy and construction type, and replacement cost. We filtered the dataset to include only one- and two-story residential structures and overlaid the 100-year flood raster to determine the flood elevation at the location of each structure and calculated the flood depth relative to the structure’s first floor elevation.

Using the damage functions developed in [Section 2.3](#sec-bldg-dmg), we calculated the cost and GHG emissions from flood damage at each structure and aggregated the results to the census tract level as well as for each entire study region. For each study region we calculated the total GHG emissions caused by the 100-year flood in kg CO2 equivalents and the total social cost of these emissions. We compared the total social cost in each region to the total monetary value of flood damages to assess the extent to which including GHG emissions affects the magnitude of flood risk in the region. We also calculated the percent change in total risk in each census tract to assess whether including GHG emissions affects the distribution of flood risk.

# 3. Results and Discussion

## 3.1 Model Validation

To validate our model, we compared our buiding-level damage curves to the damage curves presented in GEC ([2006](#ref-gec2006)) for one- and two-story structures on slab foundations. For both structure types, our damage functions are nearly identical at flood depths below five feet. At higher flood depths, our damage functions begin to diverge from those in GEC ([2006](#ref-gec2006)), with our model estimating lower damages on average than those presented in the report. The difference between our damage estimates and those in the report are greatest for flood depths around 9 to 13 feet, with our estimates being about 10 percentage points lower than GEC ([2006](#ref-gec2006)). For one story structures, the report assumes damages will peak at a flood depth of about 12 feet, while damage estimates from our model continue to increase slightly up to depths of about 20 feet. GEC ([2006](#ref-gec2006)) assumes damages for two-story structures will peak at a depth of 13 feet. Our model predicts damages will continue to increase until a depth of about 25 feet, at which point our average estimate is again almost identical to the estimate from the report. Except for the estimates for two-story structures for depths between 9 and 11 feet, the damage estimates in GEC ([2006](#ref-gec2006)) were within two standard deviations of the mean damage estimate produced by our model as shown in [Figure 3](#fig-dmgcompare).

**Weiwei, should I speculate here about what may be causing our model to produce lower estimates? One that come to mind is that the representative structures they use for their estimates are larger than the average of the floor plans we use, though it isn’t immediately clear to me that this would cause us to have lower estimates as a percentage of total structure value. I also suspect they are calculating roof damage to be a larger percent of the total value than we are which would explain why the differences are greatest at the higher flood depths. Should I investigate this to find out?**

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| Figure 3: Comparison of study damage functions to G2CRM damage functions for single-family residential structures. |

## 3.2 Greenhouse Gas Analysis Results

The results of our GHG analysis show that, on average, at the highest flood depths flood damages can cause 37,000 kg CO2eq in emissions for one-story single-family residential structrures and 60,000 kg CO2eq for two-story structures. For both one- and two-story structures this estimate varies by about +/- 50%. [Figure 4](#fig-ghgcurve) shows the depth-emissions curves generated from our analysis. Much of this variation is due to the variation in building construction alternatives we considered in our Monte Carlo analysis.

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| Figure 4: Estimated greenhouse gas emissions resulting from flood damages to single-family residential structures. The dark line indicated the mean estimate from the simulations at each flood depth, and the shaded region shows the 95% confidence interval of the estiamte. |

To adjust for this variation and produce damage curves that are more useful to flood risk analyses, we calculated the social cost of the GHG emissions as described in [Section 2.2](#sec-cost-ghg) and reported emissions for each simulation in monetary terms as a percent of the building’s total replacement cost. These adjusted damage curves are shown in [Figure 5](#fig-ghgcostcurve) and show that for the average one-story residential structure, the social cost of flood-induced GHG emissions can reach around 3.5% of the structure’s total replacement value (+/- 0.9%). For two-story structures, this value is about 3.7% (+/- 0.9%) of the structure’s total replacement cost. These results show that accounting for GHG emissions caused by floods can significantly increase the benefit associated with flood prevention. It is unlikely that most structures would ever be exposed to a flood depth of 10 or more feet, however, even for floods reaching just above the first floor elevation the social cost of flood induced GHG emissions are more than 1% of the buildings total replacment value for both one- and two story structures.

After producing the damage curves shown in [Figure 5](#fig-ghgcostcurve), we observed that the shape of the curve was similar to the damage cost curves produced by our model shown in [Figure 3](#fig-dmgcompare). Based on this observation, we hypothesized that GHG emissions from flood damages may increase linearly with cost, and performed a linear regression to test this hypothesis. [Table 3](#tbl-regression) shows the results of this regression and [Figure 6](#fig-mcsscatter) shows the relationship between total damage cost and total GHG emissions for each iteration of our Monte Carlo analysis. The regression results indicate that for each additional dollar in flood damages the associated GHG emissions increase by 0.31 kg CO2eq or $0.059 in terms of their social cost. In other words, accounting for the social cost of greenhouse gas emissions would increase the total value of flood damages by nearly 6% using this emission factor. There is, however, signigicant heteroscedasticity in the bivariate relationship between damage costs and GHG emissions which can be seen in [Figure 6](#fig-mcsscatter). This may limit the validity of the emissions factor derived from this analysis, especialy for deeper floods. Future work should explore this relationship in more depth and refine the analysis to develop valid emissions factors that could be applied in flood risk analyses.

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| Figure 5: Social cost of GHG emissions resulting from flood damages as a percentage of total structure value. The dark line indicated the mean estimate from the simulations at each flood depth, and the shaded region shows the 95% confidence interval of the estiamte. |
| Figure 6: Scatterplot showing the relationship between damage costs and GHG emissions from MCS results |
| Table 3: Linear regression results of GHG emissions versus damage costs.   | **Coefficient** | **Estimate** | **p-value** | | --- | --- | --- | | (Intercept) | -785 | <0.001 | | damage\_cost | 0.36 | <0.001 | | R² | 0.894 |  | |

## 3.3 Spatial Analysis Results

We modelled the 100-year flood event in two study regions in the Mississippi River Valley and determined the depth of flooding at each residential structure in both regions. Using the damage functions developed in [Section 2.3](#sec-bldg-dmg) we estimated the total cost and GHG emissions resulting from damages caused by these floods. We estimated that the 100-year flood would cause $234.6 million in direct damages in the Burlington-Davenport region and $180.4 million in the Paducah-Cairo region. Our results show that including the social cost of GHG emissions caused by these damages would increase the total valuation of risk for the 100-year flood by 8.48% in the Burlington-Davenport region and 8.07% in the Paducah-Cairo region. These results are shown in [Table 4](#tbl-region-result).

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| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Table 4: Total damages and GHG emissions from the 100-year flood in each study region   | Region | Total Damage Cost | Total GHG Emissions (10^6 kg CO2eq) | Total GHG Social Cost | Cost Increase From GHG | | --- | --- | --- | --- | --- | | Burlington-Davenport |  |  |  |  | | Paducah-Cairo |  |  |  |  | |

We also assessed how accounting for the GHG emissions from the 100-year flood would affect the distribution of risk in each study region. [Figure 7](#fig-tract-result) shows the percent increase in the total estimated value of 100-year flood damages in after adding the social cost of GHG emissions to the cost of direct damages in each census tract of the study regions. The change in risk valuation was not uniform across the study regions. The percent increase in total risk ranged from 1.58% to 13.6% in the Burlington-Davenport region and ranged from 3.42% to 15.6% in the Paducah-Cairo region. These results could have significant implications for flood risk management. We showed that on average, accounting for GHG emissions could increase the valuation of flood risk and thereby the benefit of flood prevention by over 8%. However, by considering the distribution of both direct impacts and the resulting GHG emissions and developing project alternatives which prioritize flood prevention in areas with the greatest total risk, planners may be able to achieve even greater benefit assessments in their projects.

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| Figure 7: Percent change in total damages from the 100-year flood after including the social cost of GHG emissions. Tracts in gray did not experience any damages to residential structures from the 100-year flood. |

We also assessed how the risk attributed to GHG emissions was associated with social vulnerability at the tract level. [Figure 8](#fig-svi) shows the relationship between the Social Vulnerability Index score for each tract and the percent increase in total risk when accounting for GHG emissions. Our results show that census tracts in both study regions with higher levels of social vulnerability tend to see greater increases in their valuation of total flood risk when accounting for GHG emissions. The implication of this finding is that including GHG emissions and the distribution of risk in flood risk assessments may help planners to prioritize flood prevention in areas with populations more susceptible to flooding and thus help to address issues of equity which have largely been ignored in flood risk management ([Seigerman et al., 2023](#ref-seigerman2023)).

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| Figure 8: Relationship between tract-level social vulnerability index and percent change in total damage cost when considering GHG emissions. |

# 4. Conclusion

High level overview:

1. Developed emissions based damage functions for flood damages.
2. Regional analysis showed that accounting for GHG emissions can increase the valuation of flood risk by more than 8%.
3. Increase in risk valuation is greatest in areas of higher social vulnerability

Policy implications:

1. depth-emissions functions produced in this study followed a rigorous methodology and should be suitable for use in real world FRM projects
2. The increased valuation of flood risk will increase the benefit calculation for FRM projects and help to justify spending on projects that will protect against the impacts of climate change.
3. Applying depth-emissions function in conjunction with a distributional analysis of risk may help to improve equity outcomes in FRM projects. This is especially significant as equity can be difficult to quantify ([Seigerman et al., 2023](#ref-seigerman2023)) and existing regulatory frameworks may make it difficult to do so.

Limitations:

1. synthetic damage functions. damage estimates based on judgement rather than real-world data.

* no real solution for this as data is difficult and expensive to collect. As such data becomes available it can be used as a source of validations.

1. Only separated buildings into one and two-story. No additional classification. This is the standard practice and we followed the standard assumptions.

* future paper will further refine damage functions and assess value of using more specific categorization of damage functions (e.g. by sqft)

1. Results from the two study regions in this study may not be generalizable elsewhere.

* Future study will apply depth-emissions functions to coastal flood risk assessment We only included a single flood event, rather than range of return periods.
* Coastal study will simulate 50-year time span in Monte Carlo simulation to get annualized estimates of risk. Did not assess effects of any FRM implementation.
* Coastal study will include multiple FRM project alternatives to compare against a no-project case.

# 5. Acknowledgements

Natalie Memarsadeghi, Adam Sisco, Ahmad Tavakoly, CityPULSE Research Group, Nikhila Lampman

# 6. Funding

This research was supported in part by an appointment to the Department of Defense (DOD) Research Participation Program administered by the Oak Ridge Institute for Science and Education (ORISE) through an interagency agreement between the U.S. Department of Energy (DOE) and the DOD. ORISE is managed by ORAU under DOE contract number DE-SC0014664. All opinions expressed in this paper are the author`s and do not necessarily reflect the policies and views of DOD, DOE, or ORAU/ORISE.

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1. EM\_DAT disaster records related to natural and technological hazards meet at least one of the following inclusion criteria: 1) At least ten deaths (including dead and missing), 2) At least 100 affected (people affected, injured, or homeless), or 3) A call for international assistance of an emergency declaration. [↑](#footnote-ref-1)
2. The social cost of CO2 emissions estimate used in this study is for emissions produced in the year 2020 with a discount rate of 2%. [↑](#footnote-ref-2)