sustainability

MDPI

Type of the Paper (Article)

Optimal Selection of Short- and Long-Term Mitigation Strategies for Buildings within Communities under Flooding Hazard

Himadri Sen Gupta[1], Omar M. Nofal[2], Andrés D. González[1], Charles D. Nicholson[1], John W. van de Lindt[2]

[1] School of Industrial and Systems Engineering, University of Oklahoma, Norman, Oklahoma 73019, USA
[2] Department of Civil and Environmental Engineering, Colorado State University, Fort Collins, Colorado 80523, USA
* Correspondence: andres.gonzalez@ou.edu

Abstract: Every year, flood hazards cause substantial economic losses worldwide with devastating impacts on buildings and physical infrastructure throughout communities. Techniques are available to mitigate flood damage and subsequent losses, but the ability to weigh such strategies with respect to their benefits from a community resilience perspective is limited in the literature. Investing in flood mitigation is critical for communities to protect the physical and socio-economic systems that depend on them. While there are multiple mitigation options to implement at the building-level, this paper focuses on determining the optimal flood mitigation strategy for buildings to minimize flood losses within a community. In this research, a mixed integer linear programming model is proposed to study the effects and trade-offs associated with pre-event short-term and long-term mitigation strategies to minimize the expected economic loss associated with flood hazards. The capabilities of the proposed model are illustrated for Lumberton, North Carolina, a small, socially diverse inland community on the Lumber River. The mathematically optimal building-level flood mitigation plan is provided based on the available budget level, which can significantly minimize the total expected direct economic loss of the community. The results reveal important correlations among investment quantity, building-level short- and long-term mitigation measures, flood depths of various locations, and buildings' structure. Besides, this study shows the trade-in between short- and long-term mitigation measures based on available budget level by providing decision support to the building owners regarding mitigation measures for their buildings.

Keywords: Community Resilience, Optimization Framework, Lumberton, Flooding, Economic Loss

Citation: Lastname, F.; Lastname, F.; Lastname, F. Title. *Sustainability* **2021**, *13*, x. https://doi.org/10.3390/xxxxx

Academic Editor: Firstname Lastname

Received: date
Accepted: date
Published: date

1. Introduction

Community resilience is defined as a community's ability to withstand disruptions and rapidly recover functionality following a hazard such as a flood [1]. When a natural hazard strikes a community, there is a wide range of potential consequences, and a community may suffer significant losses as a result of damage to the built environment, with the effects cascading into the economy and social institutions. Although it is better to avoid building in flood-prone areas to reduce those risks [2,3], this is not always a viable option due to other factors such as community cohesion and social norms. Climate change and socio-economic growth exacerbate the consequences of natural hazards such as floods as a result of sea-level rise and changes in intensity and frequency of storms [2]. Therefore, communities need more robust solutions to reduce economic and social losses. Researchers from different disciplines, including social science, economics, civil engineering, and industrial engineering, are working to identify effective methods to enhance community resilience. Social scientists are trying to improve community resilience by considering social responsibility [3]. Moreover, diverse studies analyzed a wide range of effects of natural hazards, including social, psychological, socio-economic, socio-demographic, and political impacts [4]**.** Additionally, engineering studies focused on building resilient communities by improving infrastructure systems [5]. Other advanced methods to enhance community resilience have also been developed [6].

In recent years, research in community resilience has significantly increased [7] where researchers are using computational tools such as probabilistic modeling in uncertain environments, rating models for community resilience assessment, optimization-based modeling for resilient community design, game theory, agent-based, and probabilistic dynamical modeling [8]. Lio et al. [9] used optimization techniques to study the resilience of transportation networks in the face of natural and man-made hazards, and they sought to determine how to employ multi-objective optimization after weighting each objective function. After that, Nozhati et al. [10] employed dynamic programming with reinforcement learning approaches, followed by multi-objective optimization to increase resilience. This method was used to reduce the number of days it takes a community to restore electricity to a given level of functionality and to increase the number of individuals who have power throughout a series of repairs. Furthermore, when a community is affected by a water-induced natural catastrophe like floods, the buildings and infrastructure are severely affected since they are destroyed and rendered useless. For addressing this issue, Sen et al. [11,12] developed a model using the Bayesian Belief Network (BBN) to increase flood resilience for residential buildings within a community in India. Also, Gudipati and Cha [13] used artificial neural networks to create community-level optimization of functionally interdependent structures, and they worked with office and hospital buildings to execute seismic hazard mitigation. However, in their analysis, the selection of building-level mitigation measures was not studied, which is also vital to minimize the loss of a community.

Furthermore, the preparedness of a community to withstand and recover from a natural hazard depends on the type of event. For example, we must examine the modification of the roof structure for the tornado hazard and the basement structure modification for flooding, thus, the appropriate mitigation analysis methods for each one of these hazards is unique. This study mainly focuses on flood hazards to identify the most critical components that have the most substantial effect on flood losses. There are different approaches that account for flood damage/losses for buildings and infrastructure, including deterministic approaches that use stage-damage functions [14–17] and probabilistic approaches that use fragility functions [18–20]. Marvi [21] reviewed the developed flood vulnerability functions and identified that the flood-related data scarcity and the inability to propagate uncertainty in the flood damage models are the main challenges to develop a robust flood vulnerability model. Recently, component-based flood fragility functions were introduced to propagate uncertainty in flood damage models and inform building probabilistic safety margins [14,22,23]. For community-level flood damage and loss analysis, Nofal and van de Lindt developed a portfolio of 15 building archetypes to model flood vulnerability for the different building typologies within the community [24]. This approach depends on dividing the building into components and investigates the flood susceptibility of each component using a Monte Carlo simulation framework to propagate uncertainty in the flood depth and flood duration resistance along with the replacement cost of each component. Afterward, a set of damage states (DSs) was developed to characterize the building performance during flooding. The exceedance probability of each DS was calculated based on the failure of the components contributing to each DS. Such an approach provided a systematic mechanism to model different types of mitigation measures at the building- and community-level [14,19,23].

Based on the damage states (DSs) of a building, we can analyze the direct economic loss of a building due to building damage by any natural hazard. To minimize economic loss, a community must invest in its infrastructure, but if the investment exceeds the monetary loss, it has historically not been considered viable; hence, a trade-off between investment and economic loss is critical. It is noted here that accounting for non-monetary benefits is critical in resilience studies and is not addressed herein but will be included in forthcoming work by the authors. Ideally, investments should not exceed their planned budgets nor result in a financial loss [25]. There are many studies in the literature that use a variety of methods and strategies to determine the ideal balance between investment and economic loss. Najarian and Lim [26] proposed a mathematical model for natural and human-made disasters to optimize resilience with budgetary constraints in terms of developing a budget allocation approach to any infrastructure component. To improve community resilience and reduce the overall cost associated with the restoration process, a multi-objective optimization framework with numerous constraints was presented by Almoghathawi et al. [27]. Recently, Wen [28] presented her multi-objective tornado mitigation model, where she sought to minimize the total economic loss and population dislocation due to the impact of a tornado and then applied their model to Joplin, Missouri. Then, Adluri [29] also created an optimization model to decrease overall direct economic loss due to building damage in a multi-hazard scenario and applied their model in Seaside, Oregon. Previously, Zhang and Nicholson [24] formulated an optimization model for retrofitting buildings with different mitigation strategies while minimizing the total economic loss of a community for a natural disaster and implemented the earthquake model in Centerville, a virtual community designed to test resilience models. Also, Wiebe and Cox [30] analyzed the direct economic loss of the community of Oregon by applying fragility curves for the Tsunami hazard though they did not consider the indirect tangible losses of that community. Onan et al. [31] also worked on the bi-objective model for minimizing the economic loss for a natural hazard along with another objective function of reduction of hazardous waste exposure to transportation risk. Though few researchers [25,28,29] presented their natural hazard mitigation optimization models for minimizing the direct economic loss of a community, they mainly focused on mitigation strategies based on altering existing building structure and design, which may not always be ideal or applicable when also considering community-level changing mitigation strategies and adaptation, as more temporal building-level mitigation strategies would provide more flexibility and adaptability.

In this research, we used mixed-integer linear programming techniques to minimize the community-level economic losses due to building damage by flood hazards. Decision-makers can benefit from optimization techniques while deciding on the optimal option that can achieve community resilience. The main focus of this study was minimizing building damage caused by flood hazards. Previously, Nofal et al. [32] worked on the analysis of strategies for making the individual building more resilient, but they did not suggest any separate mitigation strategy for each building or building archetype. It is critical to choose the proper mitigation techniques for decreasing flood damage while determining which mitigation approach is suitable for specific infrastructure.

Furthermore, the study separated mitigation actions into two categories, including short-term and long-term mitigation methods. Depending on the kind of their structure, the model will assist building owners in deciding whether to take short- or long-term mitigating measures. However, this research contributes to the formulated optimization model, which can help the building owner in their decision-making processing regarding mitigating their building from flooding hazards. The proposed model can inform the decision-maker regarding the optimal mitigation strategy for each building in a community. The flood risk and mitigation model, as well as the optimization model, are discussed in Section two of the article. In section three, the proposed model is applied to Lumberton, North Carolina, and key findings are described. Section four contains concluding thoughts and recommendations for further study.

2. Research Methodology

A novel optimization model was developed to minimize the total direct economic loss due to building damage in a community with an optimal building-level mitigation plan. The proposed model considers several mitigation strategies as an input to choose the mitigation plan that minimizes the total losses with an associated investment within a given budget. Figure (1) shows a schematic representation of the required models and inputs for this optimization model. This approach uses a high-resolution flood loss analysis that combines detailed information about the flood hazard and the impacted community to identify the exposed buildings. The flood hazard intensity at each building location was calculated to be used in a probabilistic fragility-based flood loss analysis at the building-level. An algorithm was then developed to use the hazard, exposure, and vulnerability information for each building to calculate the amount of flood losses. This algorithm was then modified to include the impact of different types of mitigation strategies on the amount of flood loss reduction at the building-level. Afterward, an optimization model was developed to optimally allocate these mitigation measures such that the total economic loss can be reduced. The model is designed to inform the decision-makers regarding resources and funds allocation for the possible mitigation enhancements/modifications to buildings. The main inputs of this optimization model are the mitigation interventions, their corresponding losses, and the total available budget of the decision-maker to retrofit buildings.

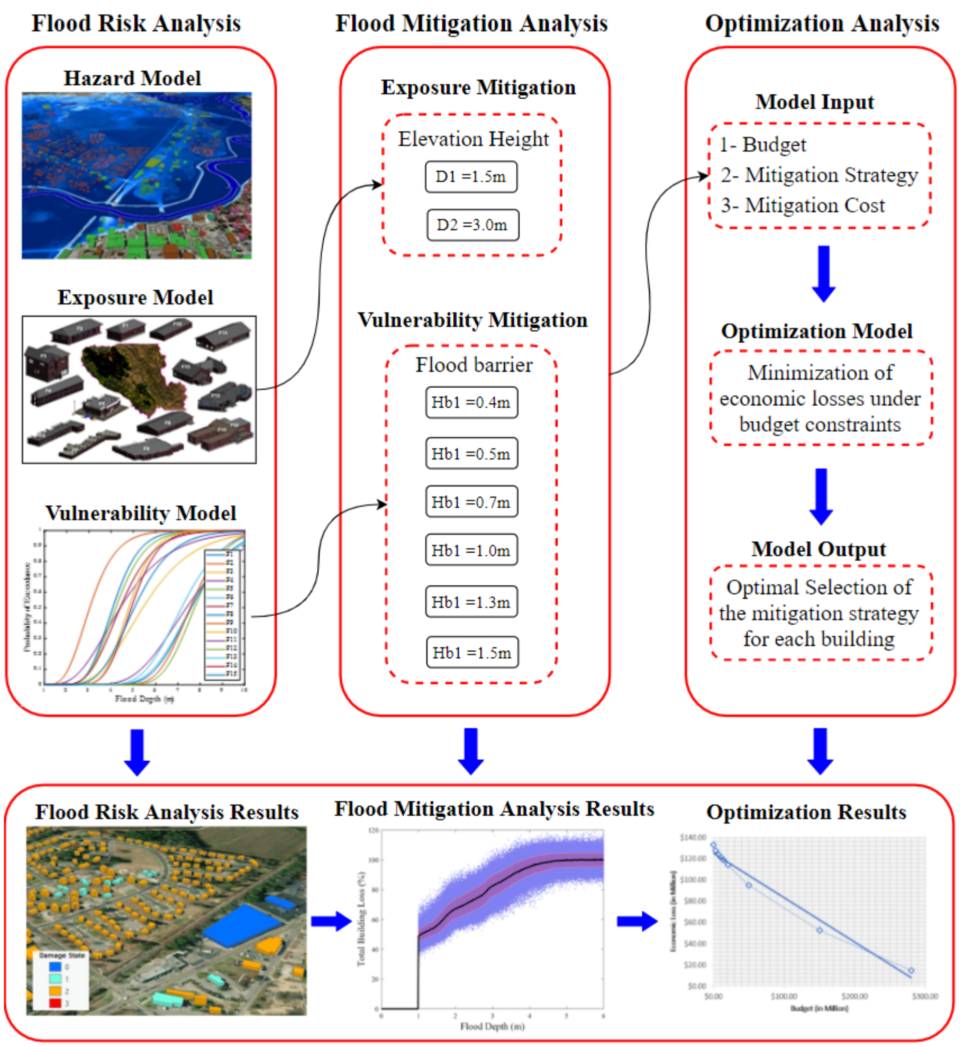


Figure 1: Schematic representation for the needed models and inputs for the optimization model

2.1. Flood Risk and Mitigation Model:

The flood risk components, including hazard, exposure, and vulnerability models, were developed using high-resolution models based on the concept developed herein [32]. The hazard model is based on a 2D hydrodynamic model that can capture the extent and intensity of flood inundation across the community. This hydrodynamic model uses HEC-RAS to solve the Saint Venunt shallow water equation, which has been calibrated and validated in this study [19] The community model was developed using a portfolio of 15 building archetypes that can populate the building stock within the community [14]. The flood hazard model in terms of a raster map of the flood hazard scenario of interest was overlaid on the GIS community model in terms of a shapefile of the buildings' location. This allowed extracting the flood hazard intensity at each exposed building to be used as input for the vulnerability analysis. Then, the concept of fragility analysis was used to model the flood vulnerability of buildings. A fragility function is a probabilistic vulnerability model that can inform the marginal safety of a system in terms of the exceedance probability of prescribed damage states. For this study, a component-based fragility function corresponding to each building archetype was used to account for building damage in terms of the exceedance probability of a set of five damage states (DSs). Figure (2a and 2b) shows component and total building fragility functions for an example building archetype for one-story residential buildings on a slab-on-grade foundation. Similar fragility functions for a portfolio of 15 building archetypes were developed by Nofal and van de Lindt [14]. Since there are no fragility functions in the literature to be used for verification and validation, these fragility functions were converted into loss functions and validated with the HAZUS-stage-damage functions, which show excellent match up to flood depth 3.0m. This validation process was applied to all the 15 building archetypes, which are fully presented herein. Table 1 provides a brief description of these DSs along with their damage scale, loss ratio (percent loss from the building replacement value), and the anticipated building functionality, and more details about each DS can be found herein [13]. Also, it should be noted that the loss ratios corresponding to each DS are based on the average calculated loss for a portfolio of 15 building archetypes developed in this publication [14]. However, the exact loss values corresponding to each DS associated with each building archetype were used to conduct the global loss analysis in this study.

A fragility-based flood loss analysis was conducted using Eq. (1), which multiplies the probability of being in each DS by the replacement cost of each DS. The loss analysis for each building was calculated by determining the building archetype and then using the corresponding fragility functions. The calculated probabilities from these fragilities are then transformed into loss analysis based on Eq. (1). The analysis resolution used in this approach allowed the investigation of different types of mitigation strategies ranging from the component-level to building-level and community-level. These strategies include pre-event, short-term flood mitigation measures for buildings, such as using flood barriers with different elevations. Additionally, pre-event, long-term flood mitigation measures (e.g., increasing building elevation) are also modeled, such as increasing building elevation. A set of flood mitigation scenarios associated with each mitigation strategy is investigated, and the flood loss for each building corresponding to each mitigation scenario is then calculated to be used as an input for the optimization model.

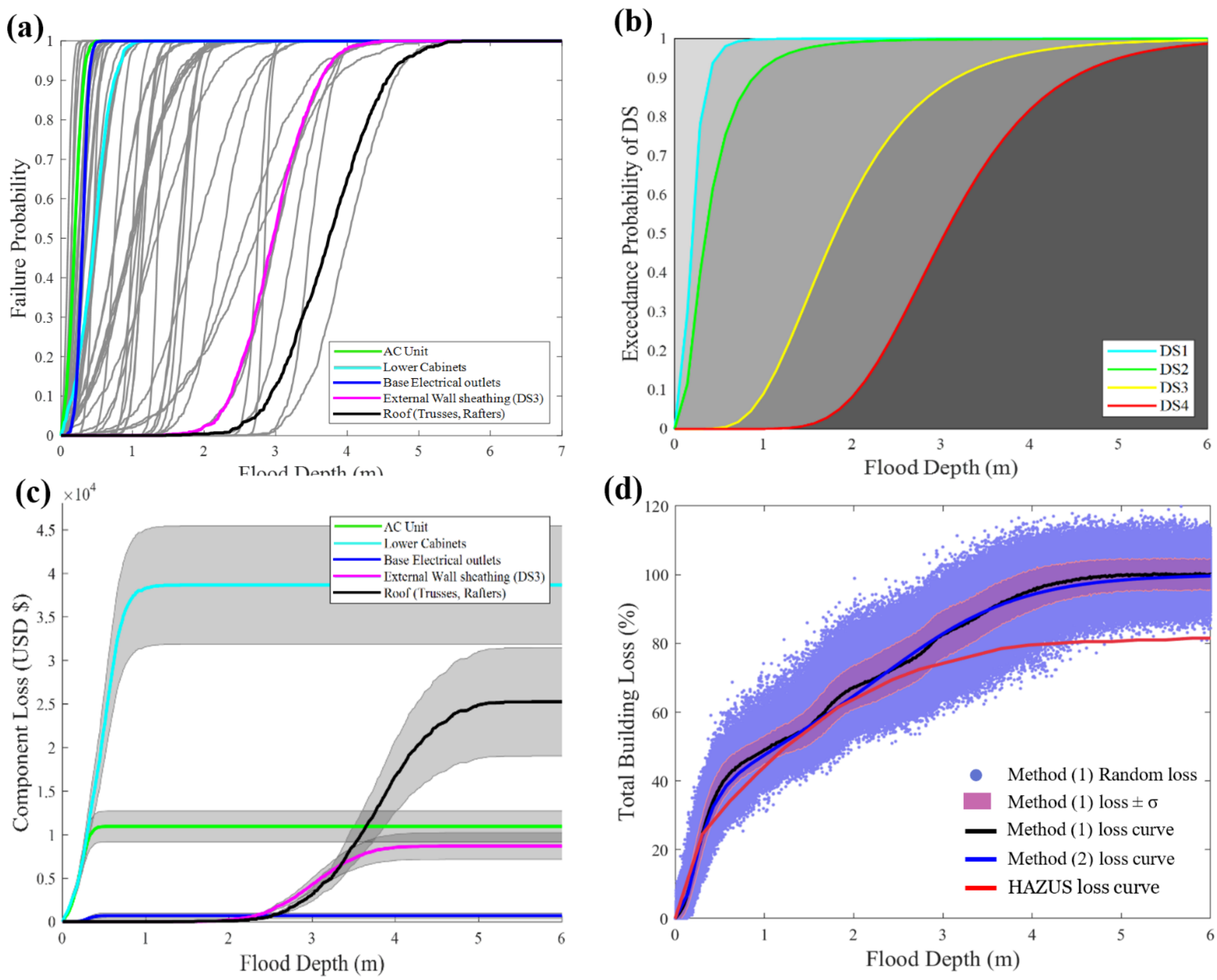


Figure 2: Total building and Component flood fragility and loss functions for one-story residential building on a slab-on-grade foundation.

$$L_f\ (IM = x) = \sum_{i=0}^{n} [\ P\ (DS_i|IM = x) - P(DS_{i+1}|IM = x)] * Lr_{ci} * V_t \tag{1}$$

where L_f $(IM = x)$ =is the total building fragility-based flood losses in monetary terms at intensity measure $IM = x$ (replacement or repair cost), $P(DS_i | IM = x)$ =is the exceedance probability of DS_i at $IM = x$, $P(DS_{i+1})$ =is the exceedance probability of DS_{i+1} at $IM = x$, Lr_{ci} =is the cumulative replacement cost ratio corresponding to DS_i, and V_t= is the total building cost (replacement cost).

Table 1: Building Damage State Description

Damage State Level	Functionality	Damage Scale	Loss Ratio
DS-0	Operational	Insignificant	0.00-0.03
DS-1	Limited Occupancy	Slight	0.03-0.15
DS-2	Restricted Occupancy	Moderate	0.15-0.50
DS-3	Restricted Use	Extensive	0.50-0.70
DS-4	Restricted Entry	Complete	0.70-1.00

2.2. Optimization Model:

Mathematical optimization is the science of finding the best solutions to mathematically described problems, which may be models of physical reality [33]. Optimization helps to identify the best feasible solution among several feasible or infeasible solutions. In this paper, a mathematical optimization model is developed to enhance the resilience of buildings by reducing the total direct economic loss from a flood hazard. The set Z denotes the set of all buildings in the community, and the set S denotes the set of all building archetypes. Each building $i \in Z$ is associated with precisely one archetype $j \in S$. The set K denotes all possible building mitigation intervention levels available across the community. The mitigation alternative $k = 0$ $k \in K$ implies that no retrofits have been implemented (i.e., the status quo). All buildings are assumed to be in this state prior to the modeling. Additionally, a set of valid strategy level changes from strategy level $k \in K$ to level $k' \in K$ is presented by L.

This optimization model can help inform building owners for decision-making regarding building retrofit to minimize their economic loss during flooding hazards. Mathematically, this decision is taken using two different decision variables in the optimization model. The first decision variable of this model is x_{ijk} that denotes the total number of buildings $i \in Z$, of archetype $j \in S$ for mitigation strategy level $k \in K$. The other decision variable $y_{ijkk'}$ denotes the total number of buildings $i \in Z$, of archetype $j \in S$, associated with retrofit strategy level $k \in K$ to level $k' \in K$. As a result, for each mitigation option, the model determines the number of buildings that would need to be modified for other mitigation measures. This model may be used to identify the best mitigation strategies for individual buildings, or it can be used when the decision-maker is considering a small number of buildings in a block and selecting single mitigation methods for each block.

2.2.1. Objective of the Optimization Model

In most cases, budget is an essential factor, and analysts restrict their mathematical model with budgetary constraints, which can significantly affect the subsequent decisions regarding retrofitting [34]. In this model, the mitigation budget is also considered a significant factor which is presented by B (the total amount of budget will be used for retrofitting purposes). It is crucial for the model to identify the b_{ijk} which is the initial number of buildings at a certain mitigation strategy level $k \in K$. To make an investment decision, we needed to know the cost of implementing any building mitigation measure. Thus, we need another parameter called strategy cost $c_{ijkk'}$ which mainly presents retrofitting costs corresponding to each strategy level associated with changing a building $i \in Z$, of archetype $j \in S$, from strategy level $k \in K$ to level $k' \in K$, given that $k \leq k'$. Again, in this model, economic loss is a vitally important factor that is directly related to one of the multiple objective functions. Economic loss is presented as l_{ijk} in this optimization mode which is the expected direct economic losses for building $i \in Z$, of archetype $j \in S$, which are at the mitigation strategy level $k \in K$.

After obtaining the value of the direct expected economic losses (l_{ijk}), multiplying with a total number of buildings $i \in Z$, of archetype $j \in S$, which are at strategy level $k \in K$, over all the buildings, all the archetypes and all strategy, we can easily find the total direct economic loss of the community. Moreover, the main objective is to minimize this amount of losses which is presented by equation (2).

$$min \sum_{i \in Z} \sum_{j \in S} \sum_{k \in K} l_{ijk}\, x_{ijk} \tag{2}$$

Though this model is currently focusing on the financial aspect of the community, the objective function can be extended to address any other social contexts like population dislocation [25,35]. In that case, in equation (2), we need to replace the expected economic loss with the expected population dislocation. If we create a set of objective functions, N, then a more generalized view of equation (2) can be presented by formulating equation (3) where ϕ_{ijk}^{n} where objective number $n \in N$.

$$min \sum_{i \in Z} \sum_{j \in S} \sum_{k \in K} \phi_{ijk}^{n}\, x_{ijk}\,, \qquad \forall\, n \in N \tag{3}$$

In equation (3), we can allocate any other social matrices we want to minimize with the same set of constraints in the optimization model. Nevertheless, in this research, we only focused on minimizing the total direct economic loss of the community due to building damage.

2.2.2. Constraints of the Optimization Model

The first constraint presented in equation (4) is a budgetary constraint, which is making sure that the costs associated with all suggested building-level mitigation strategies are within the available budget level. The total cost of mitigation can be calculated by multiplying the strategy cost $c_{ijkk'}$ with $y_{ijkk'}$, the total number of buildings $i \in Z$, of archetype $j \in S$, which are retrofitted from strategy level $k \in K$ to level $k' \in K$. This amount has to be less than or equal to the total available budget, B.

$$\sum_{i \in Z} \sum_{j \in S} \sum_{k \in K} \sum_{k' : (k',k) \in L} c_{ijkk'} * y_{ijkk'} \leq B \tag{4}$$

The second constraint of this optimization model is shown in equation (5) which ties the total number of buildings $i \in Z$, of archetype $j \in S$, which are at strategy level $k \in K$ with the total number of buildings $i \in Z$, of archetype $j \in S$, which are to be retrofitted from strategy level $k \in K$ to level $k \in k'$ logically. Furthermore, this equation ensures that only (k, k') interventions are allowed. The model will suggest any specific mitigation measures that can help to reduce the direct economic loss of the buildings. If any buildings of the community are already following one mitigation strategy, i.e., elevated building structure or having flood barrier, then the model will not suggest dismissing that by suggesting a "do nothing strategy". Another logical constraint of this model is that the total number of buildings $\boldsymbol{i} \in \boldsymbol{Z}$ of archetype $\boldsymbol{j} \in \boldsymbol{S}$ must be the same before and after any retrofitting efforts, as shown in equation (6) which is also known as flow balance constraint of the formulated optimization model. Equations (7) and (8) are presenting the domain of the decision variables and all the decision variables are non-negative integer variables.

$$x_{ijk} = \sum_{k':(k',k) \in L} y_{ijk'k} + b_{ijk} - \sum_{k':(k,k') \in L} y_{ijkk'} , \qquad \forall\, i \in Z, \forall\, j \in S, \forall\, k \in K \tag{5}$$

$$\sum_{k \in K} x_{ijk} = \sum_{k \in K} b_{ijk} , \qquad \forall\, i \in Z, \forall\, j \in S \tag{6}$$

$$x_{ijk} \in \mathbb{Z}^{\geq 0}, \qquad \forall\, i \in Z, \forall\, j \in S, \forall\, k \in K \tag{7}$$

$$y_{ijkk'} \in \mathbb{Z}^{\geq 0}, \qquad \forall\, i \in Z, \forall\, j \in S, \forall\, (k,k') \in L \tag{8}$$

3. Illustrative Example of Lumberton, NC

The approach described above is applied to Lumberton, NC, to illustrate the applicability of the developed methodology at the community-level. Lumberton is a small city within Robeson County in southern North Carolina with a population of 20,000 people who live on the banks of the Lumber River, as shown in Figure (2). The cascading flooding events following severe hurricanes made Lumberton an ideal location for investigating flood damage and identifying the applicability of the developed optimization model. Also, the availability of data about the buildings of North Carolina makes it a perfect example to apply the used high-resolution flood risk model. Therefore, many researchers have used Lumberton as a testbed for flood risk, mitigation, and recovery analysis [19,36–38]. There are 9,000 buildings within the physical boundary of Lumberton, but, in this study, the buildings around Lumberton that share the city facilities are included in the analysis as well. As a result, the number of buildings in the considered community is around 20,000, among which 2857 buildings were impacted by flooding.

The concept of a building portfolio was used to model the different building typologies within the community. A portfolio of 15 building archetypes developed by Nofal and van de Lindt [14] was mapped to each building. This was done using a mapping algorithm that uses detailed building information to map specific archetypes to each building. More information about the mapping process and the mapping algorithm can be found herein [19,32]. Figure (2b) shows the spatial location of each building within Lumberton, with the buildings color-coded based on their archetypes (e.g., occupancy). Table 2 provides a brief description of each one of these archetypes. The flooding event after Hurricane Matthew in 2016 was used as a flood hazard scenario to investigate the developed approach.

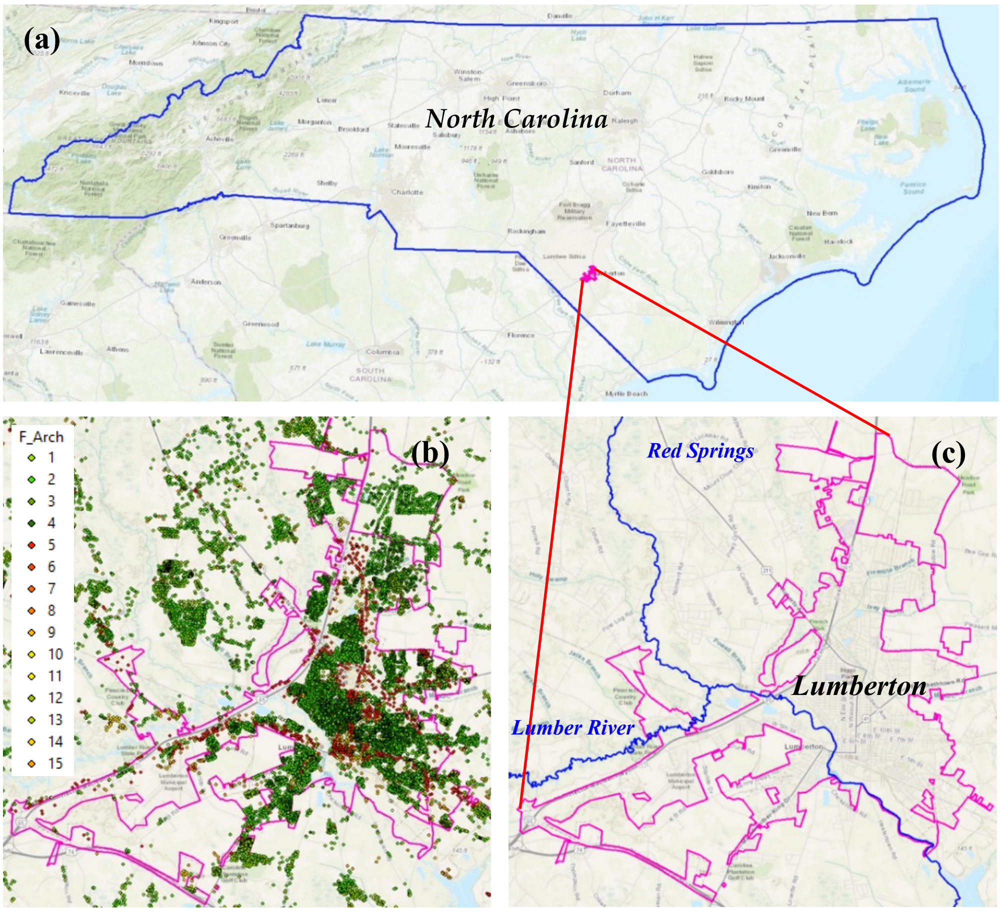


Figure 2: The spatial location of Lumberton city and its buildings with respect to the State of North Carolina: (a) The physical boundary of North Carolina State; (b) The spatial location of the buildings within Lumberton color-coded based on their archetypes; (c) The spatial location of Lumberton city with respect to the state of North Carolina.

3.1. Flood Hazard and Damage Analysis Results

A detailed hydrologic analysis was conducted using the rainfall, land use, and soil information to account for the water flow in the main streams that deliver the water to the study area. This water flow (flow hydrograph) was used as a boundary condition for a hydrodynamic analysis along with a LiDAR-based digital elevation map (DEM) of a resolution of 0.75m. HEC-RAS was used for the hydrodynamic analysis for the study area using the flow information at upstream. In this hydrodynamic model, the Saint-Venanunt shallow water equation is solved using finite volume by dividing the analysis domain (study area) into 50ftx50ft mesh sizes. The final analysis results are the flood hazard characteristics in terms of flood depth, flood velocity, and flood duration. Readers are referred to [19] for more details about the flood hazard analysis. Figure (3a) shows the simulated flood hazard map for the flooding event after Hurricane Matthew in 2016, which shows the flood inundation intensity and extent with respect to Lumberton, NC. The exposure analysis results revealed that there are 2857 buildings exposed to flooding.

Figure (3b) shows the spatial location of the flooded buildings color-coded based on their archetypes. Detailed information about the buildings within Lumberton, NC, was retrieved from the North Carolina OneMap which includes building occupancy, foundation type, number of stories, and building value. This data allowed us to do detailed loss analysis at the building-level and then aggregate them to be at the community-level. Table 2 provides information about the number of buildings exposed to flooding by archetype, along with their *replacement value* and the amount of flood losses. Table 3 shows the fragility analysis results in terms of the exceedance probability of each DS corresponding to five ranges from 0% up to 100% and the number of buildings within each of these ranges. So, the flood-exposed buildings within the community were categorized based on the exceedance probability of each DS. For example, there are 144 buildings with an exceedance probability of DS2 between 40% and 60%.

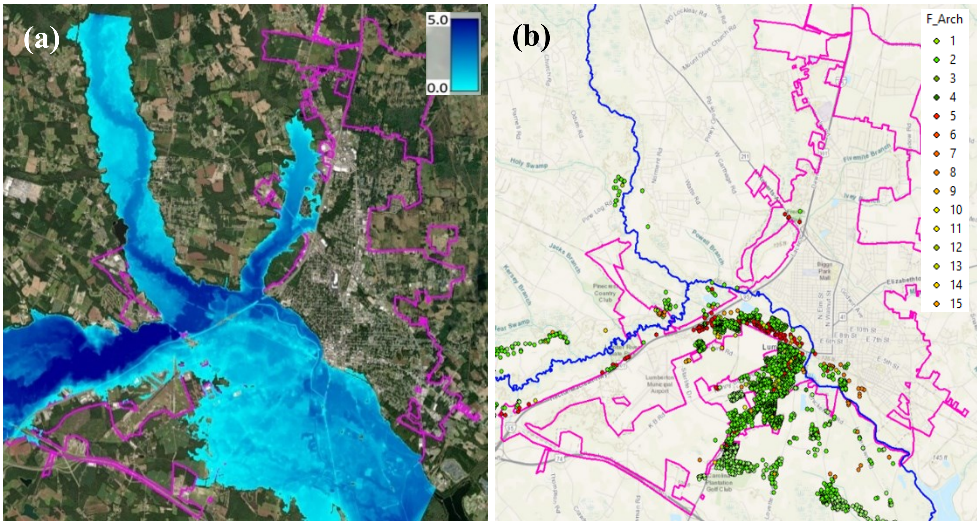


Figure 3: The simulated flood hazard for the flooding event in Lumberton, NC after Hurricane Matthew in 2016 and the exposed buildings: (a) Flood hazard map in terms of the flood extent and flood inundation measured from ground elevation (m); (b) The flood exposed buildings color-coded based on their archetypes.

Table 2: The number of exposed buildings by archetype along with their current replacement value and base flood loss

Archetype	Number of Buildings	Total Current Apprised Value	Total Base Flood Losses
F1: One-Story Single-Family Residential Building	665	$37,527,864	$10,097,519
F2: One-Story Multi-Family Residential Building	1741	$194,990,289	$80,651,358
F3: Two-Story Single-Family Residential Building The	7	$1,059,617	$316,074
F4: Two-Story Multi-Family Residential Building	96	$21,174,848	$5,548,556
F5: Small Grocery Store/Gas Station with a Convenience Store	157	$62,855,685	$7,921,982

F6: Multi-Unit Retail Building (Strip Mall)	1	$7,195,517	$0
F7: Small Multi-Unit Commercial Building	1	$256,600	$157,864
F8: Super Retail Center The	2	$408,318	$176,194
F9: Industrial Building	62	$124,562,628	$12,002,943
F10: One-Story School	8	$7,429,091	$2,495,461
F11: Two-Story School	3	$23,456,627	$3,621,603
F12: Hospital/Clinic The	0	$0	$0
F13: Community Center (Place of Worship)	44	$23,381,452	$6,720,040
F14: Office Building	17	$8,782,066	$2,565,452
F15: Warehouse (Small/Large Box)	53	$40,975,016	$860,940

Table 3: fragility analysis results in terms of the exceedance probability

Exceedance Probability of a DS (Fragility)	Number of buildings (Total=2858)				
	DS0	DS1	DS2	DS3	DS4
0% < P_DS < 20%	2201	396	567	2071	2822
20% < P_DS < 40%	5	72	115	355	25
40% < P_DS < 60%	7	72	144	293	7
60% < P_DS < 80%	30	108	290	121	3
80% < P_DS < 100%	614	2209	1741	17	0

3.2. *Comparative Analysis of Short- and long-term Mitigation Strategies*

The initial analysis results showed that Lumberton's total economic loss is predicted to be more than $133 million if the community does not invest in mitigation. However, the choice of various optimal implementation of mitigation techniques has a significant impact on reducing overall direct economic loss. This study performed three distinct methods of mitigation modes: (i) long-term methods, (ii) short-term methods, and (iii) a combination of both long- and short-term interventions. A long-term mitigation measure can be defined as a building retrofitting method that can protect a building from the subsequent few natural hazards and help reduce the loss in the long run. On the other hand, short-term mitigation measures have the ability to save a building from any natural hazard for once. Short-term mitigations can be easily applicable for most buildings, and the cost will be significantly cheaper than long-term mitigation measures. Nofal and van de Lindt [19,23]described various flood mitigation measures which can help to reduce the impact of flooding. According to their analysis, flood water pumping can be a suitable mitigation measure which can reduce the flood water from a building. Furthermore, they also mentioned flood barrier systems as an effective flood mitigation measure. Water pumping or flood barriers system can be two examples of short-term flood mitigation measures. On the contrary, building buyout or building elevation can be two examples of long-term mitigation measures where that will help the building owner to be safe and successive several natural disasters. Although building elevation is one of the costliest mitigation measures, it is still one of the most effective direct flood mitigation measures. Sometimes homeowners get federal funding for such mitigation measures to cover a percentage of the total cost.

Also, homeowners could get mitigation loans in front of more equity on their building value. For implementing the optimization model with various mitigation measures, we need to make sure to have the respective expected economic loss if any certain mitigation measure is chosen. Furthermore, we need to know the cost of adopting any specific mitigation measures for a building. Firstly, this study was done by employing mitigation techniques to eliminate flood threats, such as elevating structures to a specific height. Second, flood barriers of various sizes, ranging from 0.4 to 1.5 meters, were employed in the mitigation approach. Due to a scarcity of cost information for flood barriers of over 1.5 meters, a limit on the height of the flood barrier to 1.5 meters was put in place in this study. Finally, all of the strategies (long- and short-term) were combined in the model to provide a diverse set of results.

Building owners who want to retrofit their buildings with a specific mitigation measure must invest a particular amount of money based on their chosen mitigation method. This linked expense is referred to as strategy cost in this model and is funded from the model's budget. Based on the type of mitigation measures, we needed to calculate that. For instance, the cost of putting a flood barrier is dependent on the building area. On the other hand, the cost of elevating buildings depends on required materials, labor, and equipment. The user can specify any budget level for retrofitting the buildings while using the model, and the program will only offer mitigation methods based on the available budget. For example, if a user wants to spend $3.5 million retrofitting all the buildings of a community with long-term mitigation measures, the user may not be able to advise building elevations for all of the structures. As a result, the model will suggest "No Intervention" for the rest of the building where the model could not invest. The formulated model was tested with various budget levels to test the model's workability for different budget levels.

Long-term mitigation strategies include increasing building elevations from 5 ft (1.5 m) to 10 ft (3 m) to reduce the flood losses for each building. Table 4 summarizes the optimization model's findings in terms of a specific building and in terms of different mitigation strategies. The base flood loss analysis without any mitigation results in a direct economic loss of over $133 million. The optimization model was tested with an initial budget of 3.5 million dollars, and the model showed an economic loss reduction of more than 4 million dollars. On the other hand, for a budget of $280 million, 1738 buildings can be retrofitted to reduce the economic loss by more than $118 million. This is because long-term measures such as increasing building elevation have a significantly high retrofit cost, but such mitigation intervention can decrease the overall building damage in the long-term. Furthermore, the implementation of long-term mitigation will help the building owners to save their buildings from any future flooding events by a one-time investment. So, by investing 280 million dollars, it will be possible to save $118 Million in each flooding event.

Table 4: Result Summary for Long-term Mitigation Strategy

	Number of buildings retrofitted				
Budget	No intervention	Elevate 5ft (1.5m)	Elevate 10ft (3m)	Total # of Retrofitted Buildings	Economic Loss
$0M	2,857	0	0	0	$133,135,992
$3.5M	2,836	17	4	21	$127,398,555
$7M	2,817	33	7	40	$124,164,674

$10.5M	2,786	57	14	71	$121,268,774
$14M	2,761	81	16	97	$118,517,884
$ 20M	2717	123	18	141	$114,017,769
$50M	2523	288	46	334	$94,973,886
$150M	1796	726	335	1061	$52,520,789
$280M	1119	1329	409	1738	$14,704,547

For long-term mitigation, the model sought to identify the optimal mitigation option for a specific building based on the cost of the mitigation strategy. Although 10 feet (3 meters) of elevation can make a structure safer than 5 feet (1.5 meters), the financial loss will be zero with 3 meters of elevation. However, some industrial buildings in Lumberton will not be able to achieve this building elevation since it would require substantial funds for mitigation. At various budget levels, Figure **4** depicts the selected buildings for long-term mitigation solutions for individual structures in Lumberton, NC, at various budget levels. The figure shows that red and dark pink dots increase when a larger budget is used, implying that more community structures would be mitigated/retrofitted. The model showed how resources were optimally allocated across buildings in terms of mitigation funds that can minimize the economic losses.

Flood barriers were also investigated and implemented in the optimization model in Lumberton as an example of a short-term mitigation strategy. Table 5 shows the investigated budget levels along with the number of flood barriers that are selected from 0.4 meters to 1.5 meters in height to mitigate flood impacts on buildings, as well as the resulting estimated direct economic loss. The main objective of the developed optimization model is to minimize the total economic loss within a given budget level. The developed optimization model is designed to select buildings that can minimize the total economic loss. The analysis results showed that investing $50M in a long-term mitigation strategy can mitigate the flood impacts on 334 buildings. On the contrary, investing the same amount of mitigation funds ($50M) on short-term mitigation can increase the number of mitigated buildings to 832. This is because of the lower cost of short-term mitigation, which can only be implemented for buildings during a single flooding event. Using a flood barrier of 1.5 m is the costliest option among all the short-term strategies, and as the model gets more money to invest, it is giving more money to use the mitigation strategy. If flood barriers are used of more height, then they can get better results, but, in this case, due to the lack of pricing information for higher flood barriers, we need to stop at 1.5 m. The location of the buildings and the distribution of various short-term mitigation strategies are presented in **Figure 5** for different budget levels, respectively.

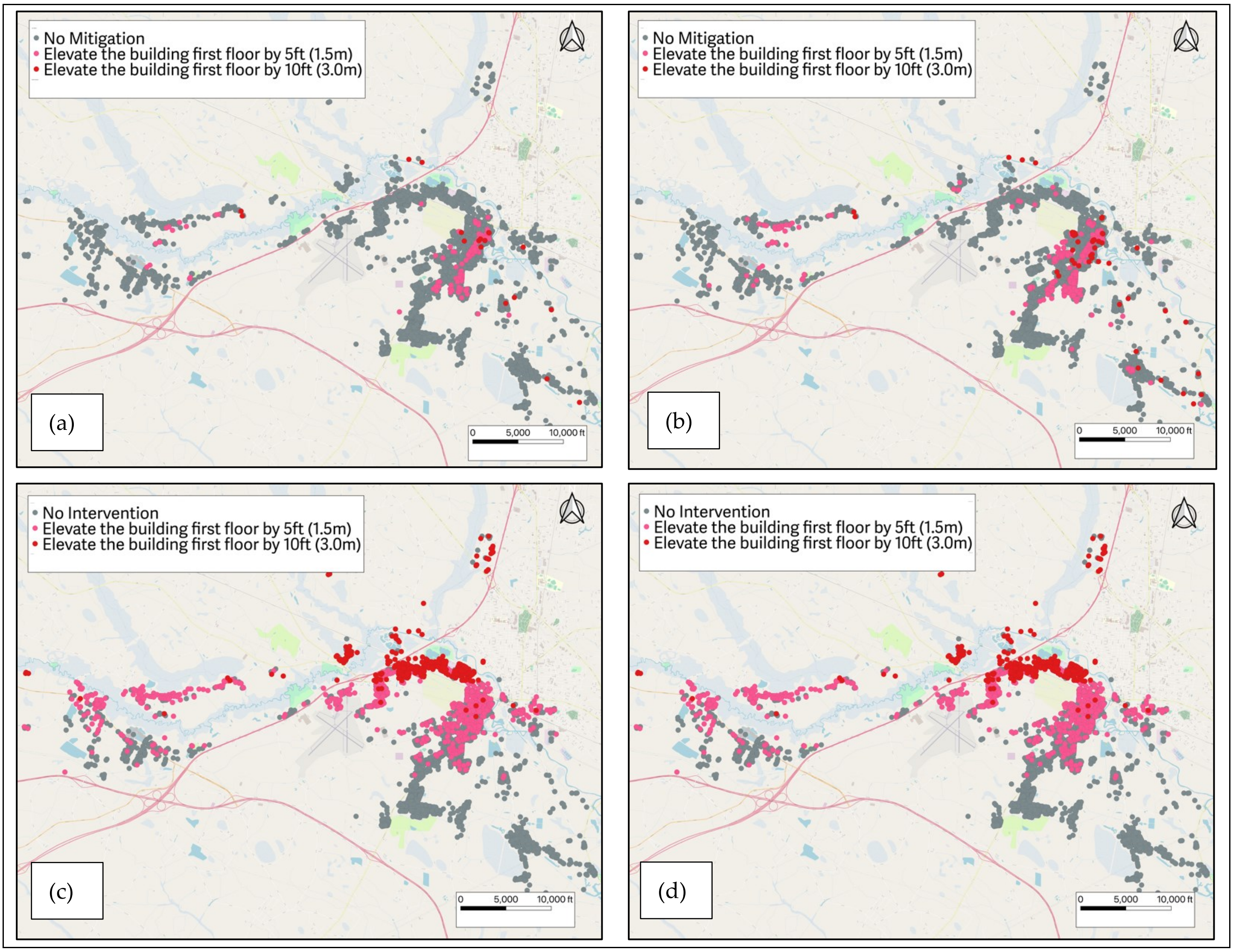


Figure 4: Location of buildings based on long-term strategy implementation while the total investment is $20 Million (a), $50 Million (b), $150 Million (c), and $280 Million (d)

Table 5: Result Summary for Short-term Mitigation Strategy

	Number of buildings surrounded by a barrier of height (Hb)								
Budget	No intervention	Hb= 0.4m	Hb= 0.5m	Hb= 0.7m	Hb= 1.0m	Hb= 1.3m	Hb= 1.5m	Total # of Retrofitted Buildings	Economic Loss
$0M	2857	0	0	0	0	0	0	0	$133,135,992
$3.5M	2826	0	0	5	4	7	15	31	$124,118,022
$7M	2766	1	0	9	16	26	39	91	$119,675,195

$10.5M	2706	1	0	12	29	47	62	151	$116,597,842
$14M	2637	1	0	14	37	74	94	220	$114,059,986
$20M	2513	2	1	16	47	116	162	344	$110,680,315
$50M	2026	33	8	70	146	264	311	832	$107,224,597
$150M	2026	33	8	70	146	264	311	832	$107,224,597
$280M	2026	33	8	70	146	264	311	832	$107,224,597

The analysis showed that the developed optimization model could be used efficiently for both short- and long-term mitigation options. Also, the developed optimization model has the essential features needed to recommend the optimal mitigation strategy for buildings in terms of short-term (flood barriers) and long-term (building elevation). Flood barriers may not be advantageous for some buildings after being used and need to be installed before each event and do not add to the building equity. On the other hand, increasing building elevation as a long-term plan is much better since they are permanent mitigation, and the value invested is added to the building equity. Though it is a costly alternative, it can help significantly reduce the amount of flood losses for the community.

At the highest budget level of $280 M, the model allows mitigating more than 2000 buildings. At the other budget level, the model suggests elevating the building by 5 ft because of two main reasons. Firstly, it is cheaper than elevating 10ft. Secondly, it allows reducing the economic loss significantly. However, building elevation is highly dependent on the area of each building. Typically, commercial buildings hold large areas, which makes the cost of building elevation very high for them. Figure 6 depicts the mitigation strategies in the Lumberton map based on the budget level while implementing both short- and long-term strategies together.

Table 6: Result Summary for Short and Long-Term Mitigation Strategy

		Number of Buildings Retrofitted									
		Using flood barrier									
Budget	No intervention	Hb= 0.4m	Hb= 0.5m	Hb= 0.7m	Hb= 1.0m	Hb= 1.3m	Hb= 1.5m	Elevate 5ft	Elevate 10ft	Total # of Retrofitted Buildings	Economic Loss
$0M	2,857	0	0	0	0	0	0	0	0	0	$133,135,992
$3.5M	2833	0	0	4	3	4	9	3	1	24	$ 123,380,846
$7M	2787	1	0	7	8	15	28	8	3	70	$ 118,059,178
$10.5M	2745	1	0	9	16	28	39	15	4	112	$ 114,175,819
$14M	2715	1	0	10	22	34	44	24	7	142	$ 110,893,178
$20M	2649	1	0	10	27	45	60	51	14	208	$ 105,849,491
$50M	2377	2	1	14	39	80	106	212	26	480	$ 84,368,342
$150M	1538	2	1	18	53	131	184	601	329	1319	$ 39,452,522
$280M	787	5	3	23	75	185	239	1091	446	2067	$ 4,539,084

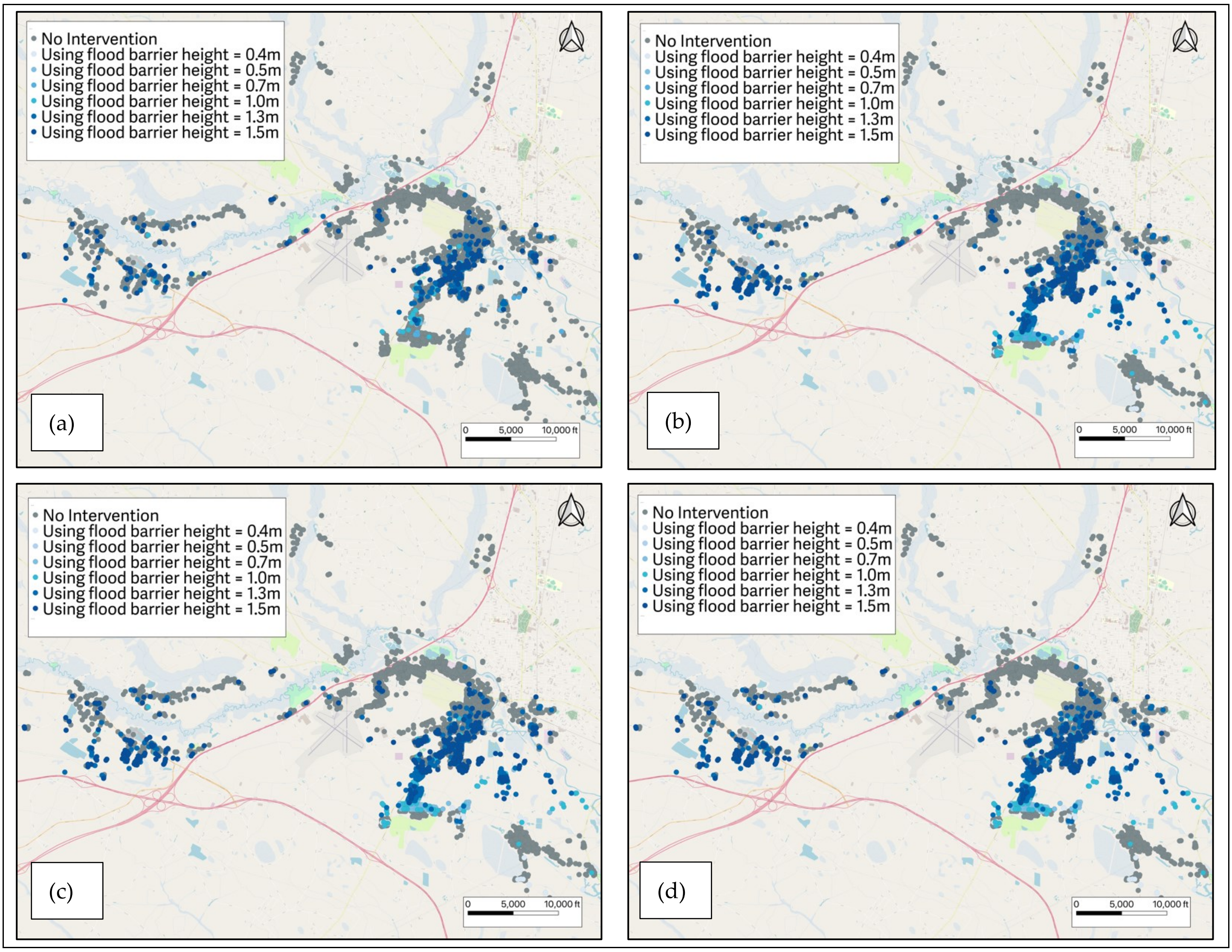


Figure 5: Location of buildings based on short-term strategy implementation while the total investment is $20 Million (a), $50 Million (b), $150 Million (c), and $280 Million (d)

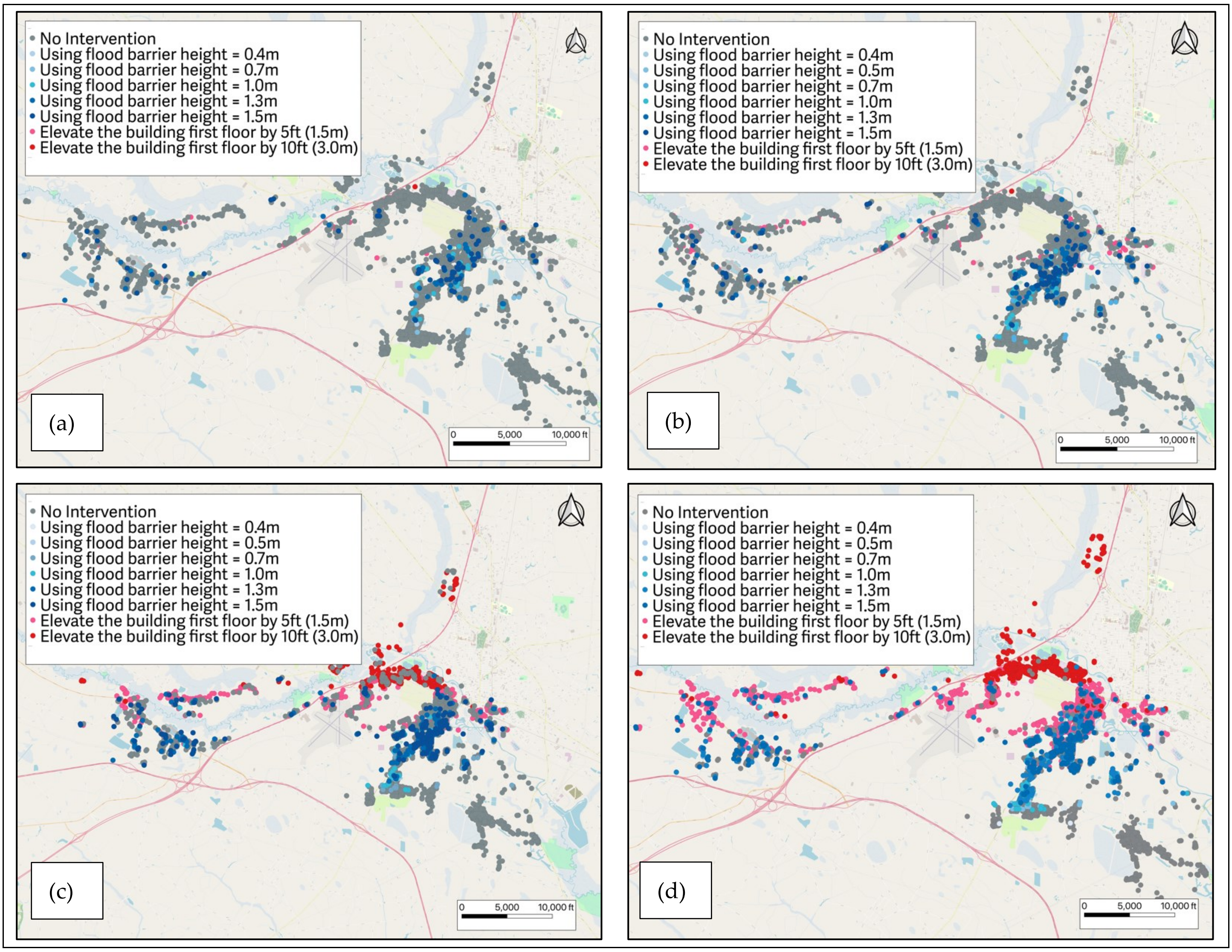
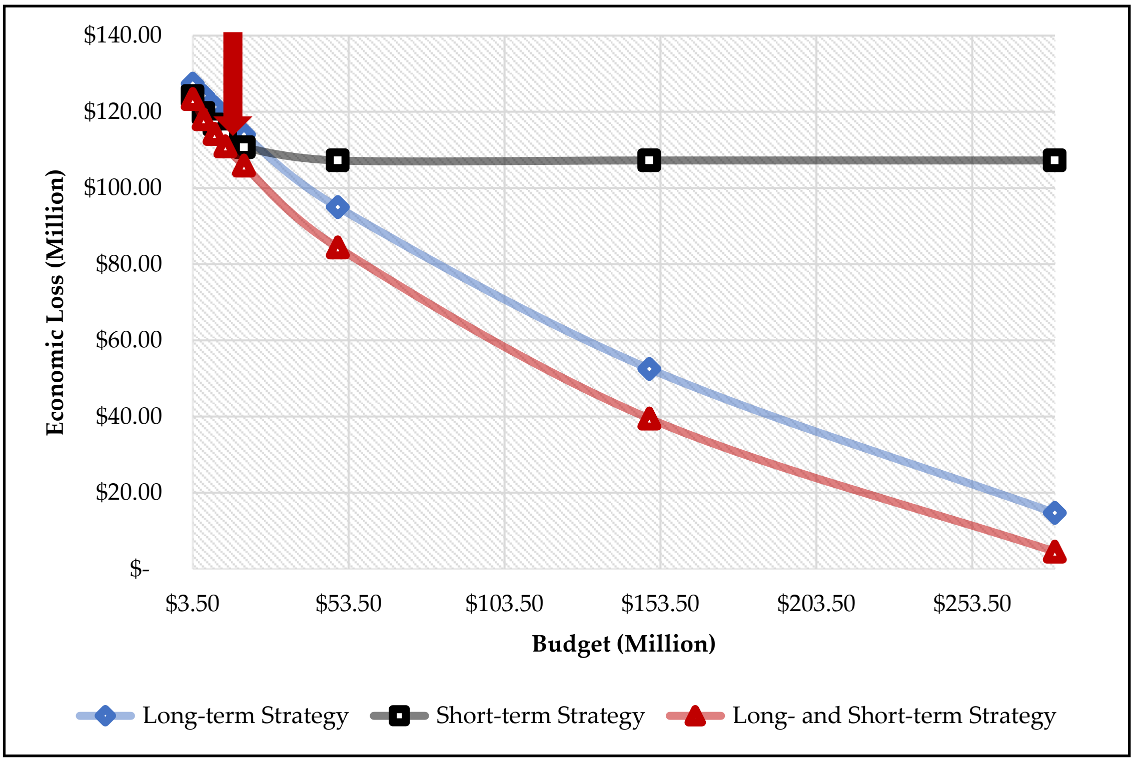
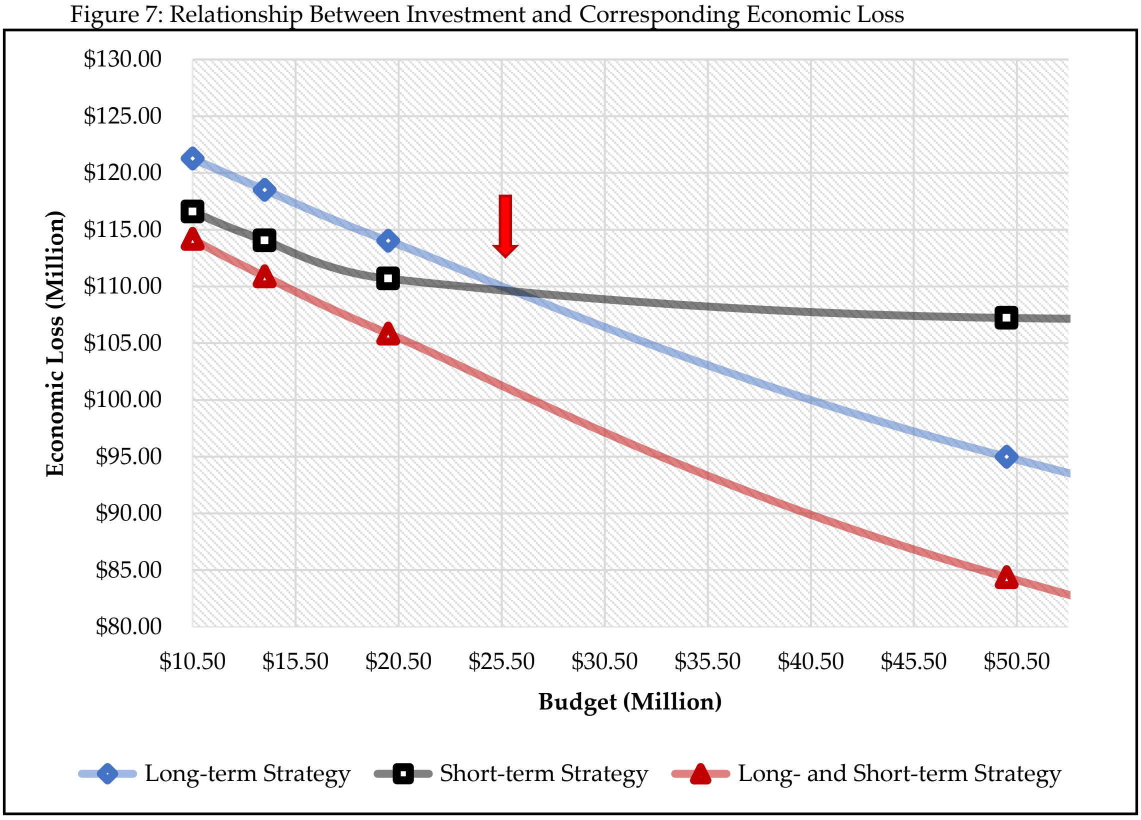


Figure 6: Location of buildings based on short and long-term strategy implementation while the total investment is $20 Million (a), $50 Million (b), $150 Million (c), and $280 Million (d)



513

Figure 7: Relationship Between Investment and Corresponding Economic Loss 514



515

Figure 8: Relationship Between Investment and Corresponding Economic Loss (Close-up View)

Figure 7 and Figure 8 (close-up view) show the total direct economic loss and the invested budget, which show the decreasing rate of economic loss corresponding to the amount of invested mitigation funds. These graphs depict how the economic loss decreases as the budget level increases for different strategies. When long-term mitigation is used, the model seeks to identify a mitigation option for a specific building based on the strategy cost of that mitigation approach. It is noticed that till a specific budget (nearly $25 Million), short-term mitigation measures can help the community reduce the amount of direct economic losses due to building damage, but after that, long-term strategies showed much better performance after that. Since short-term strategies are not much costly as long-term ones, the model suggests short-term mitigation measures for lower budget levels. Buildings with a 10 ft (3m) elevation have higher mitigation plan costs than those with a 5 ft height. However, 10 feet (3m) of elevation can make a structure safer than 5 feet (1.5m), and in some circumstances, the financial loss will be nil if the owner chooses 10 feet (3m) of elevation. However, some industrial buildings in Lumberton will not be able to achieve this building elevation since it would require them to invest substantially more money.

4. Conclusions

Previous researchers worked on various building-level mitigation measures analysis for different natural hazards, but this research mainly focuses on finding optimal mitigation strategies for buildings threatened by flooding. The contribution of this research is to develop this optimization model, which can determine optimal building-level mitigation measures for each and every building in a community to minimize the total direct expected economic loss due to building damage. The model detailed in this paper is formulated in such a way that it can be used in any community subjected to flood hazards. Although the optimization model provides decisions at the building-level, the model can also be employed when stakeholders at the community-level seek to look at a block of buildings as a whole.

The optimization model was applied to Lumberton, North Carolina, which is subjected to recurrent flooding, and was used to test the performance of the model. Two different types of mitigation techniques were investigated in this case study. Firstly, building elevation was investigated using two elevation values of 1.5 and 3 meters as a long-term mitigation measure, and secondly, flood barriers, as a short-term mitigation measure, were then investigated. It was demonstrated that long-term mitigation measures could help the community reduce the expected economic loss significantly. On the other hand, short-term mitigation measures for some buildings will not help reduce their loss due to the high flood depth in that region. According to this study, it is preferable to implement long-term building mitigation measures if the budget allows due to the high flood depth in most of the areas. Furthermore, this long-term mitigation will protect a structure from several natural hazards. The optimization approach can be expanded to use other mitigation techniques to efficiently reduce the total direct economic loss at the building- and community-level. It is noted here that one of the study's limitations is that the optimization model only has one objective, which is minimizing the expected economic loss, despite the fact that it may be expanded to include several objectives.

The current model does not consider community-level decisions prior to determining building-level mitigation strategies for individual building owners. The developed model can be extended so that the model addresses community-level decisions along with building-level mitigation measures. Additionally, some machine learning algorithms can help to predict the mitigations for both community- and building-level.

Author Contributions: Conceptualization, Himadri Sen Gupta, Andrés González and Charles Nicholson; Data curation, Omar Nofal and John Van de Lindt; Formal analysis, Himadri Sen Gupta and Omar Nofal; Funding acquisition, Andrés González, Charles Nicholson and John Van de Lindt; Investigation, Himadri Sen Gupta, Andrés González, Charles Nicholson and John Van de Lindt; Methodology, Himadri Sen Gupta, Andrés González and Charles Nicholson; Resources, John Van de Lindt; Software, Himadri Sen Gupta and Omar Nofal; Supervision, Andrés González; Validation, Omar Nofal and John Van de Lindt; Writing – original draft, Himadri Sen Gupta; Writing – review & editing, Himadri Sen Gupta, Omar Nofal, Andrés González, Charles Nicholson and John Van de Lindt. All authors have read and agreed to the published version of the manuscript.

Funding: This research was partially funded by the National Institute of Standards and Technology (NIST) Center of Excellence for Risk-Based Community Resilience Planning through a cooperative agreement with Colorado State University [70NANB20H008 and 70NANB15H044]. Also, this research was partially funded by the National Science Foundation (NSF) through award 2052930.

Acknowledgments: The contents expressed in this paper are the views of the authors and do not necessarily represent the opinions or views of the National Institute of Standards and Technology (NIST) or the National Science Foundation (NSF).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Walters, P. The Problem of Community Resilience in Two Flooded Cities: Dhaka 1998 and Brisbane 2011. *Habitat International* **2015**, *50*, 51–56, doi:10.1016/j.habitatint.2015.08.004.
2. Hemmati, M.; Ellingwood, B.R.; Mahmoud, H.N. The Role of Urban Growth in Resilience of Communities Under Flood Risk. *Earth's Future* **2020**, *8*, 1–14, doi:10.1029/2019EF001382.
3. Mullins, A.; Soetanto, R. Enhancing Community Resilience to Flooding through Social Responsibility. *International Journal of Safety and Security Engineering* **2011**, *1*, 115–125, doi:10.2495/SAFE-V1-N2-115-125.
4. Lindell, M.K.; Prater, C.S. Assessing Community Impacts of Natural Disasters. *Natural Hazards Review* **2003**, *4*, 176–185, doi:10.1061/(ASCE)1527-6988(2003)4:4(176).
5. Elms, D.; McCahon, I.; Dewhirst, R. Improving Infrastructure Resilience. *Civil Engineering and Environmental Systems* **2019**, *36*, 83–99, doi:10.1080/10286608.2019.1615479.
6. González, A.D.; Dueñas-Osorio, L.; Medaglia, A.L.; Sánchez-Silva, Mauricio. Resource Allocation for Infrastructure Networks within the Context of Disaster Management. In Proceedings of the International Conference on Structural Safety and Reliability (ICOSSAR); New York, USA, June 2013; pp. 1–8.
7. Koliou, M.; van de Lindt, J.W.; McAllister, T.P.; Ellingwood, B.R.; Dillard, M.; Cutler, H. State of the Research in Community Resilience: Progress and Challenges. *Sustainable and Resilient Infrastructure* **2020**, *5*, 131–151, doi:10.1080/23789689.2017.1418547.
8. Melendez, A.; Caballero-Russi, D.; Gutierrez Soto, M.; Giraldo, L.F. Computational Models of Community Resilience. *Natural Hazards* 2022, *111*, 1121–1152.

9. Liao, T.Y.; Hu, T.Y.; Ko, Y.N. A Resilience Optimization Model for Transportation Networks under Disasters. *Natural Hazards* **2018**, *93*, 469–489, doi:10.1007/s11069-018-3310-3.
10. Nozhati, S.; Sarkale, Y.; Ellingwood, B.; K.P. Chong, E.; Mahmoud, H. Near-Optimal Planning Using Approximate Dynamic Programming to Enhance Post-Hazard Community Resilience Management. *Reliability Engineering and System Safety* **2019**, *181*, 116–126, doi:10.1016/j.ress.2018.09.011.
11. Sen, M.K.; Dutta, S.; Kabir, G. Flood Resilience of Housing Infrastructure Modeling and Quantification Using a Bayesian Belief Network. *Sustainability* **2021**, *13*, 1026, doi:https://doi.org/10.3390/su13031026.
12. Sen, M.K.; Dutta, S.; Kabir, G. Modelling and Quantification of Time-Varying Flood Resilience for Housing Infrastructure Using Dynamic Bayesian Network. *Journal of Cleaner Production* **2022**, *361*, 132266, doi:10.1016/j.jclepro.2022.132266.
13. Gudipati, V.K.; Cha, E.J. A Resilience-Based Framework for Design Optimization of Interdependent Buildings. *13th International Conference on Applications of Statistics and Probability in Civil Engineering, ICASP 2019* **2019**, 1–8.
14. Nofal, O.M.; van de Lindt, J.W. Minimal Building Flood Fragility and Loss Function Portfolio for Resilience Analysis at the Community Level. *Water (Switzerland)* **2020**, *12*, doi:10.3390/w12082277.
15. Pistrika, A.; Tsakiris, G.; Nalbantis, I.; Tsakiris, G.; Nalbantis, I. Flood Depth-Damage Functions for Built Environment. *Environ. Process* **2014**, *1*, 553–572, doi:10.1007/s40710-014-0038-2.
16. Noor, S.; Romali, M.@; Sulaiman, S.A.K.; Yusop, Z.; Ismail, Z. Flood Damage Assessment: A Review of Flood Stage–Damage Function Curve. *ISFRAM 2014* **2015**, 147–159, doi:10.1007/978-981-287-365-1_13.
17. Scawthorn, C.; Asce, F.; Flores, P.; Blais, ; Neil; Seligson, H.; Tate, E.; Chang, S.; Mifflin, ; Edward; Thomas, W.; Murphy, J.; et al. HAZUS-MH Flood Loss Estimation Methodology. II. Damage and Loss Assessment. *Natural Hazards Review* **2006**, *7*, 72–81, doi:10.1061/(ASCE)1527-6988(2006)7:2(72).
18. de Risi, R.; Jalayer, F.; de Paola, F.; Iervolino, I.; Giugni, M.; Topa, M.E.; Mbuya, E.; Kyessi, A.; Manfredi, G.; Gasparini, P. Flood Risk Assessment for Informal Settlements. *Natural Hazards* **2013**, *69*, 1003–1032, doi:10.1007/S11069-013-0749-0.
19. Nofal, O.M.; van de Lindt, J.W. High-Resolution Approach to Quantify the Impact of Building-Level Flood Risk Mitigation and Adaptation Measures on Flood Losses at the Community-Level. *International Journal of Disaster Risk Reduction* 2020, *51*.
20. Shane Crawford, P.; Mitrani-Reiser, J.; Sutley, E.J.; Do, T.Q.; Tomiczek, T.; Nofal, O.M.; Weigand, J.M.; Watson, M.; van de Lindt, J.W.; Graettinger, A.J. Measurement Approach to Develop Flood-Based Damage Fragilities for Residential Buildings Following Repeat Inundation Events. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering* **2022**, *8*, doi:10.1061/ajrua6.0001219.
21. Marvi, M.T. A Review of Flood Damage Analysis for a Building Structure and Contents. *Natural Hazards* **2020**, 1–29, doi:https://doi.org/10.1007/s11069-020-03941-w.
22. Figueiredo, R.; Romão, X.; Paupério, E. Component-Based Flood Vulnerability Modelling for Cultural Heritage Buildings. *undefined* **2021**, *61*, doi:10.1016/J.IJDRR.2021.102323.
23. Nofal, O.M.; van de Lindt, J.W. High-Resolution Flood Risk Approach to Quantify the Impact of Policy Change on Flood Losses at Community-Level. *International Journal of Disaster Risk Reduction* **2021**, *62*, 102429, doi:10.1016/j.ijdrr.2021.102429.
24. Nofal, O.M. High-Resolution Multi-Hazard Approach to Quantify Hurricane-Induced Risk for Coastal and Inland Communities, Colorado State University, 2021.

25. Zhang, W.; Nicholson, C. A Multi-Objective Optimization Model for Retrofit Strategies to Mitigate Direct Economic Loss and Population Dislocation. *Sustainable and Resilient Infrastructure* **2016**, *1*, 123–136, doi:10.1080/23789689.2016.1254995.
26. Najarian, M.; Lim, G.J. Optimizing Infrastructure Resilience under Budgetary Constraint. *Reliability Engineering and System Safety* **2020**, *198*, 106801, doi:10.1016/j.ress.2020.106801.
27. Almoghathawi, Y.; González, A.D.; Barker, K. Exploring Recovery Strategies for Optimal Interdependent Infrastructure Network Resilience. *Networks and Spatial Economics* **2021**, doi:10.1007/s11067-020-09515-4.
28. Wen, Y. *DEVELOPMENT OF MULTI-OBJECTIVE OPTIMIZATION MODEL OF COMMUNITY RESILIENCE ON MITIGATION PLANNING*; 2021;
29. Adluri, T. Multi-Objective Optimization of Building Mitigation Strategies to Address Multiple Hazards. **2021**.
30. Wiebe, D.M.; Cox, D.T. Application of Fragility Curves to Estimate Building Damage and Economic Loss at a Community Scale: A Case Study of Seaside, Oregon. *Natural Hazards* **2014**, *71*, 2043–2061, doi:10.1007/s11069-013-0995-1.
31. Onan, K.; Ülengin, F.; Sennaroılu, B. An Evolutionary Multi-Objective Optimization Approach to Disaster Waste Management: A Case Study of Istanbul, Turkey. *Expert Systems with Applications* **2015**, *42*, 8850–8857, doi:10.1016/j.eswa.2015.07.039.
32. Nofal, O.M.; van de Lindt, J.W.; Cutler, H.; Shields, M.; Crofton, K. Modeling the Impact of Building-Level Flood Mitigation Measures Made Possible by Early Flood Warnings on Community-Level Flood Loss Reduction. *Buildings* **2021**, *11*, doi:10.3390/buildings11100475.
33. Snyman, J.A.; Wilke, D.N. *Practical Mathematical Optimization*; 2005; ISBN 9783319775852.
34. Mejjaouli, S.; Alzahrani, M. Decision-Making Model for Optimum Energy Retrofitting Strategies in Residential Buildings. *Sustainable Production and Consumption* **2020**, doi:10.1016/j.spc.2020.07.008.
35. Calle, P.M.; Norman, C. *A COMPARATIVE ANALYSIS OF POPULATION DISLOCATION MODELS FOR MULTI-OBJECTIVE COMMUNITY RESILIENCE OPTIMIZATION*; 2019;
36. Deniz, D.; Sutley, E.J.; Lindt, J.W. van de; Peacock, W.G.; Rosenheim, N.; Gu, D.; Mitrani-Reiser, J.; Dillard, M.; Koliou, M.; Hamideh, S. Flood Performance and Dislocation Assessment for Lumberton Homes after Hurricane Matthew. **2019**, doi:10.2/JQUERY.MIN.JS.
37. ID. 41 - Modeling Business Recovery after Natural Disasters: The Case Study of Lumberton, NC Following Hurricane Matthew - ICONHIC 2019 Available online: https://iconhic.com/2019/2019/11/id-41-modeling-business-recovery-after-natural-disasters-the-case-study-of-lumberton-nc-following-hurricane-matthew/ (accessed on 16 November 2021).
38. Khajehei, S. Recovery Challenges of Public Housing Residents after Disasters: Lumberton, North Carolina after Hurricane Matthew. *Graduate Theses and Dissertations* **2019**.