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Building-level adaptation analysis under uncertain sea-level rise

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ABSTRACT

Recent studies show climate-induced sea-level rise (SLR) will accelerate storm surge impacts in many coastal areas around the world. The decision-making of building-level adaptation strategies is a challenging task due to uncertain climate impacts. This study evaluates building-level adaptation strategies through a dynamic programming-based cost-benefit analysis approach to incorporate the latest information of SLR in adaptation decision-making. The adaptation outcomes are estimated by applying a Monte-Carlo method with stochastic flood damage of buildings under four SLR projections. Based on a case study in Bay County, Florida (USA), results indicate that single-family and multi-family buildings are the most vulnerable buildings in Bay County. Mobile homes have a lower flood risk, while they are more sensitive to SLR. The long-term flood damage shows SLR could exponentially increase the average annual flood damage in the community from \$17.7 million to \$204 million. Investing in adaptive measures can substantially mitigate building-level flood risk, where the adapted average annual damage ranges from \$9.57 million to \$38.2 million in the county. The proposed adaptation method could facilitate more effective risk communications between the public and private sectors and improvise community adaptation planning under uncertain SLR.

1. Introduction

Although storm surges have created considerable social and economic impacts to coastal urban areas around the world, recent climate projections indicate that surging waves and high tides could cause substantial damages to coastal communities under uncertain sea-level rise (SLR) (Rahmstorf et al., 2007; Sriver et al., 2012; Strauss et al., 2015). Uncertainties of future SLR mainly comes from an incomplete understanding of global mean SLR processes, such as ice sheet mass loss, and uncertain parameters from probability distributions used to characterize the extreme sea-level events (Rasmussen et al., 2020). Investing in flood adaptation measures could significantly reduce flood damages to buildings and infrastructures in coastal communities. Nevertheless, the benefits of adaptation highly depend on the projection of extreme sea-level heights. Accordingly, to improve adaptation decision-making, adaptation decision analysis needs to incorporate the combined effects of storm surges and SLR over the long-term period of adaptation analysis (IPCC, 2014). In this study, we extend previous efforts of flood adaptation to evaluate building-level adaptation benefits, community damages, and cost-effective adaptive measures under stochastic storm surges and uncertain SLR projections.

Due to the increased risk of natural hazards in cities, adaptation strategies under uncertain climate change require public authorities to apply risk-based approaches, which includes likelihoods, consequences, and cost-benefits of adaptation options in flood

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risk management (Lawrence et al., 2018; Willows et al., 2003). Kirshen et al. (2008), for example, applied a Monte Carlo approach to evaluate the cumulative cost of flooding under two SLR and four adaptation scenarios in Metro Boston, USA. They found that when current and future developments were all protected with building retrofitting, the cumulative damage and adaptation cost in 100 years would be both lower than the retreat or floodproofing of new developments. Nevertheless, environmentally benign adaptation with natural defenses and floodproofing was more attractive in suburban areas due to a higher net economic value. Since adaptation benefits are usually expressed as potential damage reduction by a specific adaptation option, Yohe et al. (2011) further emphasize the criticality of specifying a baseline in evaluating adaptation options. Relying on the same model framework, they estimated the value of adaptation to SLR against two baselines, where the first one has the availability of actuarially fair insurance as a policy response to the increasing flood damage while the other one does not have this option. Their study shows that the provision of an actuarially fair insurance program would be an essential component of the efficient adaptation baseline. Neumann et al. (2015) developed the National Coastal Property Model (NCPM) by integrating a tropical cyclone model, a property value exposure model, and an economic cost and damage model to measure flood damage of buildings and the effectiveness of adaptation strategies under multiple SLR scenarios. Their results showed the importance of considering the combined effects of SLR and storm surges in analyzing climate change risk to coastal buildings. Lorie et al. (2020) further applied the updated version of the NCPM to measure the aggregate effects of economically sub-optimal adaptation decisions. They found sub-optimal adaptation decisions can result in inefficient adaptation and cost over a billion-dollar loss compared to optimal adaptation approaches in Tampa and Virginia Beach County.

The cost-benefit analysis (CBA) integrates engineering, economic, and geophysical factors into flood risk analysis and thus provides a well-established foundation to evaluate adaptation decisions from an economic perspective (Tiggeloven et al., 2020). Oddo et al. (2017), for example, applied a classic CBA model to measure adaptation decisions with multi-objective risk mitigation under uncertain SLR using a Monte-Carlo approach. To incorporate SLR information in adaptation decision-making, Lickley et al. (2014) applied a dynamic programming method to evaluate adaptation decisions of seawall construction, where the cumulative seawall height was estimated by minimizing the net present value of the expected future flood damage through the backward induction. In CBA, the benefits of adaptation are usually measured by aggregating the reduced expected flood damage (EAD) within a given time period. To evaluate the costs and efficacy of adaptive measures, Lasage et al. (2014) evaluated the effectiveness of major building-level adaptive measures, and Aerts (2018) comprehensively reviewed the costs of major private and public adaptive measures for flood mitigation.

Most existing studies on the economic aspects of adaptation either compare aggregated costs and benefits in an area or evaluate the economic efficacy of a specific adaptive measure. For example, Klima et al. (2011) investigated building flood risk of storm surges in Miami-Dade County, FL relying on FEMA's HAZUS-MH model. Their results illustrated aggregated building damages and adaptation benefits on the census tract level. Kirshen et al. (2020) compared multiple adaptation options and found that storm surge barriers were more effective in managing flood risk in Boston, and meanwhile produced moderate impacts to harbor users. Nevertheless, large-scale barriers are less flexible to accommodate uncertainties of climate change over time and have low cost-effectiveness compared to natural-based adaptation options.

Building-level adaptation CBA could promote risk communications between the public and private sectors in community risk education, therefore, deserves more attention in coastal risk analysis. de Ruig et al., 2019 applied CBA to measure the benefits of adaptive measures in coastal areas in Los Angeles. Zarekarizi et al. (2020) evaluated house elevation strategy by incorporating deep uncertainties of flood hazard risks. Different elevation strategies for building structures are evaluated by considering four sources of uncertainty, including the stochastic flood hazard, discount rates on future flood damages, the flood height versus damage model of buildings, and the building's life-time.

The impacts of storm surge emerge from the interaction between physical hazards and the exposure of the built environment (Academies, 2018; McNamara & Keeler, 2013). Therefore, to improve public awareness of climatic risk and adaptation benefits, a risk-based approach examining community vulnerability and adaptation benefits would facilitate risk communications between public and private sectors in flood hazard management. This paper provides further insights on adaptation decision-making under uncertain SLR by proposing a CBA framework based on dynamic programming. Based on a case study in Bay County, Florida, building flood damages are evaluated through stochastic storm surges under four SLR projections. Compared to previous studies, our simulation model could evaluate large-scale vulnerable buildings in coastal communities and improve risk communications for local adaptation planning. To begin with, this study first presents the methods to estimate the flood risk, adaptive measures, as well as the CBA model. Second, we introduce the case study area. Afterward, the model results are evaluated based on Monte Carlo simulations. Finally, we discuss the main findings and limitations of this research.

2. Methods

This study integrates a CBA adaptation method, the randomness of storm surges, and the uncertainty of SLR projections to evaluate community flood risk and adaptation benefits. Due to the dynamic and uncertain climate conditions, the flood risk of buildings could vary significantly. Consequently, there are tradeoffs between competing objectives in flood risk adaptation. For example, although private-adaptive measures can significantly mitigate building flood damages, the discounted annual adaptation costs could be higher than the discounted annual damage reduction due to the low frequency of severe natural hazards. Therefore, understanding the uncertainty of flood damage in communities could guide the development of local adaptation planning. To evaluate the robustness of adaptation decisions, this study applies a Monte-Carlo-based approach to simulate the randomness of future storm surges and adaptation decisions in the evaluation of community adaptation outcomes. The long-term impacts of coastal storm surges reflect flood risks of buildings, and therefore, could identify vulnerable communities and corresponding adaptation benefits under uncertain SLR.

2.1. Flood risk estimation

The impacts of SLR and storm surge varies between geographical regions. We use the generalized extreme value (GEV) distribution to describe the exceedance of storm surges (Lopez-Cantu et al., 2020). The cumulative distribution function of storm surge is applied in this study to randomly generate storm surge in each year of simulation:

$$F(x; u, \sigma, \xi) = \exp\left\{ - \left[1 + \xi \left(\frac{x - u}{\sigma} \right)^{-\frac{1}{\xi}} \right] \right\} \tag{1}$$

In Eq. (1), $F(x; u, \sigma, \xi)$ is the cumulative probability of a storm surge height, x is the storm surge height,u, σ, ξ represent the location, scale, and shape parameters of the distribution, respectively. In our study, the location parameter refers to the threshold of a storm surge in meters. The scale and shape parameters are determined by the changes of storm surge categories. We applied five categories of inundation maps from the Sea, Lake and Overland Surges from Hurricanes (SLOSH) model in the US to fit the storm surge height distribution function (Zachry et al., 2015). The simulated inundation data has a resolution of 15 m.

There are two types of GEV distributions, namely stationary GEV and nonstationary GEV distributions. A stationary GEV distribution function assumes that the distribution remains constant with temperature and other variables, while a nonstationary GEV distribution function allows location, scale, and shape parameters to change over time. Lee et al. (2017) considered four types of GEV distributions in the projection of storm surges: the stationary distribution with constant parameters, the nonstationary distribution with location parameters only, the nonstationary distribution with location and scale parameters, and a full nonstationary distribution with constant location, scale and shape parameters. In our simulation, we only considered the nonstationary distribution with location parameters only, where the increase of flood frequency in this study relies only on the changes in water level. The distribution after the increase of SLR could be estimated through $\mu_{future} = u + \mu_{SLR}$ (Vitousek et al., 2017). We applied the annual SLR projection based on the USACE (2019):

$$\mu_{SLR} = a + bt + ct^2 \tag{2}$$

where a, b, and c represent parameters of the second order thermosteric expansion process. The t represents the simulation year and b is a constant based on the local sea-level. In our study, the parameter b is derived based on SLR scenarios. Four SLR scenarios, which are low (scenario 1), intermediate low (scenario 2), intermediate high (scenario 3), and high SLR (scenario 4), are considered in the analysis according to IPCC (2014). In the model simulation, the storm surge heights are generated randomly in each year of simulation, and results are aggregated based on the Monte Carlo simulation.

The estimation of flood loss is measured based on the flood depth-damage table from HAZUS-MH 4.2 model (Scawthorn et al., 2006). This study estimates flooding damage based on the building value and flood height (Karamouz et al., 2016). The flood risks are estimated based on the expected annual damage (EAD) for each building. Since the flood damage functions depend on the building value, the EAD depends on the current building value and could be calculated as

$$EAD = \int_{i=0} D(p_i) dp_i = \frac{1}{2} \sum_{i=1}^{n} (p_i - p_{i+1})(D(p_i) + D(p_{i+1})) \tag{3}$$

where $D(p_i)$ is the flood damage occurs at storm surge event with probability p_i, dp_i is the probability density of the hurricane event i. In our calculation, we applied the numerical integration method to calculate flood damage across all probabilities (Han et al., 2020; Olsen et al., 2015), where EAD could be further calculated based on n storm surge events.

Table 1
Estimated costs and standard deviation of adaptive measures per square feet.

Adaptation height (ft)	Single-family	Mobile home	Multi-family	Non-residential				
	Mean ($)	Standard deviation	Mean ($)	Standard deviation	Mean ($)	Standard deviation	Mean ($)	Standard deviation
Building elevation								
+2 ft	25.96	5.64	31.67	6.88	32.29	7.01	48.45	10.52
+4 ft	27.59	5.96	33.85	7.31	34.13	7.37	51.21	11.06
+6 ft	28.95	6.23	35.65	7.67	35.65	7.67	53.50	11.51
+8 ft	30.49	6.53	37.68	8.07	37.40	8.01	56.12	12.02
Wet-proofing								
+2 ft	1.57	0.31	1.76	0.35	1.65	0.33	1.95	0.39
+4 ft	2.91	0.57	3.28	0.65	3.06	0.61	3.65	0.72
Dry-proofing								
+2 ft	4.93	0.62	6.55	0.82	5.62	0.70	8.41	1.05
+4 ft	6.06	0.77	8.02	1.02	6.85	0.87	10.30	1.31

2.2. Building-level adaptive measures

This study applied a dynamic programming-based CBA to evaluate risk mitigation under four SLR projections. Three major adaptive measures for buildings are considered in the analysis, namely building elevation, wet-proofing, and dry-proofing. Based on FEMA's retrofitting manual, floodproofing measures are usually effective when flood height is lower than 1 m, and building elevation is usually considered when the elevating height is lower than 9ft (FEMA, 2017). Therefore, for wet-proofing and dry-proofing measures, we evaluated adaptive measures at 2ft and 4ft. For building elevation, we evaluated elevation height at 2ft, 4ft, 6ft, and 8ft. We estimated the mean unit costs of these adaptive measures at different levels based on existing studies (Aerts et al., 2018; Aerts, 2018; de Ruig et al., 2019; Eastern Research Group, 2013). We also incorporated uncertainties of adaptive measure costs by assuming a 0.5 coefficient of variation in the simulation (Wang & Small, 2014).

Table 1 shows the estimated mean unit cost and standard deviation for different adaptive measures. For adaptation efficacy, we apply the estimated damage curves by Lasage et al. (2014) to estimate adapted damage of flooding for each type of adaptive measure. We assume all adaptive measures in this study are well-maintained and effective during the simulation period. In the analysis, a 2% of total adaptation cost was assumed for annual maintenance cost for flood proofing measures, and a 4% of annual maintenance cost was applied for building elevation (Aerts, 2018).

2.3. Cost-benefit analysis (CBA)

The analysis of adaptation choices is based on minimizing the cost and benefit of adaptive measures. There are multiple ways to frame the costs and benefits of adaptation strategies over time. The easiest evaluation method is to assume that mean water levels stay constant over time so that only today's flood risk is relevant to the decision to invest in adaptive measures. This approach is intuitive but cannot capture the dynamic climate impacts in adaptation decision-making. A better approach is to incorporate the latest SLR information in the analysis of adaptive measures at the time of decision-making. However, this approach needs to calculate the increasing risk of buildings at each time point of decision-making, which requires a high computational burden for large-scale analysis. Given the availability of long-term projections of SLR from historical records and service lifetime of buildings, adaptation decisions can be evaluated at discrete time periods (Lickley et al., 2014). The dynamic programming could save computational resources in the iteration, so we applied the dynamic programming method to minimize the total costs of a building given the analysis period.

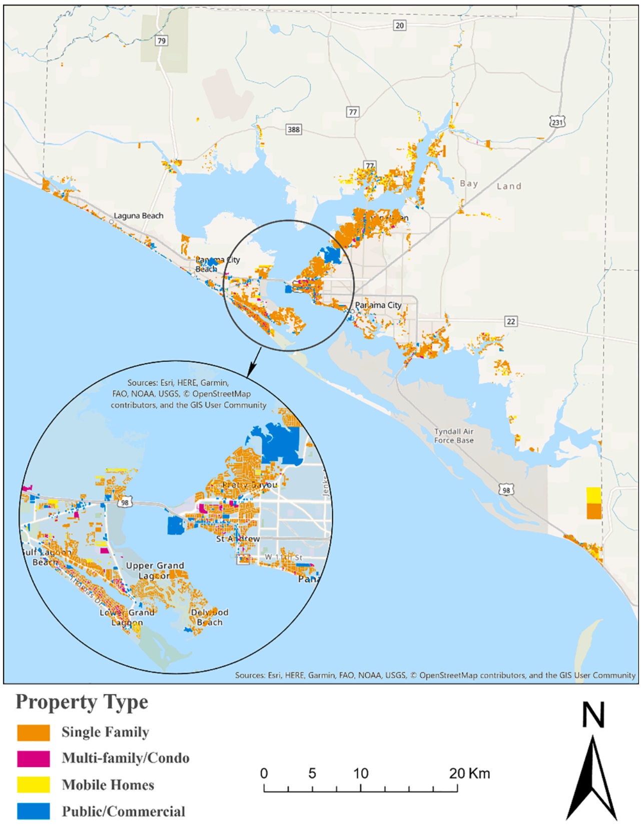

Fig. 1. Building information in Bay County, FL.

$$V_T = \min_{A_t}\left(\sum_{t=k}^{T}\frac{1}{(1+r)^{t-k}}C_t(S_t,A_t) + \frac{1}{(1+r)^{t+\Delta t-k}}V_{t+\Delta t}(S_t,A_t)\right) \quad (4)$$

$$C_t(S_t,A_t) = EAD_{A_t} + C_{A_t} \quad (5)$$

In equation (4), V_T represents the minimized total cost at time T. $C_t(S_t, A_t)$ is defined as total costs of a building in time t given a building state S_t and adaptive action A_t. $C_t(S_t, A_t)$ includes the cost of adaptive measures and flood risk of buildings at time t. $V_{t+\Delta t}(S_t, A_t)$ represents the costs in a previous time $t+\Delta t$ with building state S_t and adaption action A_t, r is the annual discounting factor, which is chosen as 0.04 (Zarekarizi et al., 2020). $C_t(S_t, A_t)$ can be calculated using equation (5), which includes flood risk and total adaptation costs (C_{A_t}) at time t. Since adaptive measures aim to protect buildings over a long time period, we choose analysis period T = 100 years (2014). Over the 100 years simulation, buildings in low-lying areas have the risk to be inundated under a high SLR. We assume when the height of the mean sea-level is above the height of a low-lying building, the building is deemed to be lost and the corresponding building value is \$0. Since the adaptation cost is always higher than the benefit, adaptation will not be considered after a building is lost.

3. Case study area

To illustrate the methodology proposed above, we choose Bay County in Florida as the case study area for the evaluation of adaptation decisions. Bay County is one of the most vulnerable areas in the U.S. Gulf Coast region. It experienced widespread damage from Hurricane Michael in 2018 (Zhai & Peng, 2020). We collect four kinds of geographical datasets from the US census and Florida Geographical Digital Library (FGDL) in this study: the US Census and spatial data of Bay County, The cadastral parcel data, 5-meter DEM data, numerical inundation simulation results from the NOAA's SLOSH model (Glahn et al., 2009).

We choose all buildings within the 100-year floodplain and classified four types of buildings, including single-family houses, multi-family houses, mobile homes, and public/commercial properties. Fig. 1 shows the selected buildings in the case study area. A total of 26,471 buildings are identified in the study area. Table 2 shows the number and percentage of buildings in each type. In general, the single-family and mobile homes take the majority of all buildings, only a few multi-family buildings are included in this study, while public/commercial buildings are mainly located near the coastline of the county. Fig. 2 shows the fitted cumulative distribution of storm surge elevation in Bay County. We use the simulated storm surge data from the SLOSH model to fit the GEV distribution function of storm surge height in feet, where the fitted model parameters are $u = 0.5884$, $\sigma = 0.4536$, $\xi = 0.6296$, respectively (Han et al., 2020).Fig. 3.

4. Results

4.1. The proposed adaptive measures

Due to the low-frequency nature of storm surge damage, the adequacy and efficacy of adaptive measures need to be evaluated under stochastic storm surge damages in a long-term period. We project the long-term flood damage for 100 years with a base year of 2017 based on stochastic storm surge events. 5000 model replications for each SLR scenario is determined in the convergence calculation (Tonn & Guikema, 2018). To reduce computational burden, we also determine the $\Delta t = 50\text{years}$ in Equation (4) based on results of the first 100 model replications.

We first show adaptation outcomes under the low SLR scenario. Fig. 4 shows spatial patterns of adaptive measures, life-cycle adaptation cost, average adaptation damages, and reduced damages in Bay County. We show the spatial pattern of adaptive measures with the highest likelihood to be implemented in the low SLR scenario based on Monte Carlo results. In general, buildings near the coast have a high flood risk. Therefore, buildings near the coast are more likely to be protected with building elevation or dry-proofing, while only a small percentage of buildings will implement wet-proofing due to its lower benefit-cost ratio. This finding is consistent with statistics from FEMA's Hazard Mitigation Assistant Program Dataset (FEMA, 2020). In the low SLR scenario, our results show 4276 buildings could be elevated, 1318 buildings would be protected with wet-proofing, and 6406 buildings would be implemented with dry-proofing. We further show the number of adaptive measures with the maximum likelihood to be implemented for other SLR scenarios in Table 3. With the increase of SLR, the number of building elevation ranges from 4272 to 4282, the number of wet-proofing ranges from 1227 to 1530, and the number of dry-proofing ranges from 6405 to 6761. It should be noted that some high-risk buildings near the coast would be lost after 2070 years due to SLR under scenario 3 and scenario 4. As a result, scenario 2 has the highest number of elevated buildings and implemented wet-proofing measures. The average annual adaptation costs of most buildings are lower than \$500. For some buildings with building elevation or high flood risk, their annual adaptation costs would be over \$1500. After adaptation, the average annual flood damage of buildings in high-risk areas is over \$800, meanwhile, the reduced damage would

Table 2
Total number of buildings for each type.

Building Type	Single Family	Multi-family/Condo	Mobile Homes	Public/Commercial
Count	23,089	708	2038	636
Percentage	87.22%	2.67%	7.7%	2.40%

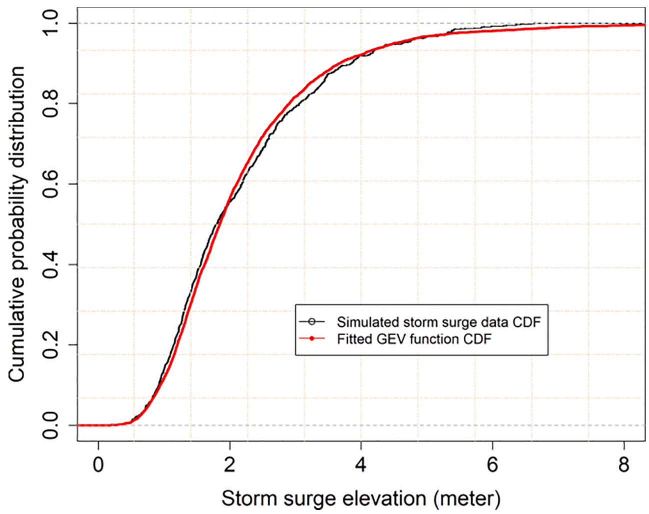

Fig. 2. The fitted cumulative distribution of storm surge height in Bay County.

be higher than $800 annually in those areas.

We further use Table 4 to show the average annual damage reduction, the average annual discounted adaptation cost, the average benefit-cost ratio, the average number of implemented adaptive measures, and the number of lost buildings under SLR for each kind of buildings calculated from stochastic simulation results. The optimized average annual adaptation cost for all kinds of buildings is significantly less than the mitigated average annual flood damage. It can be seen that public/commercial buildings have the highest average flood damage reduction, ranging from $1813 to $2089. Single-family properties and multi-family properties have the average annual flood damage reduction between $626 and $1743, while mobile homes have the lowest risk reduction on average, ranging from $220 to $705. Compared with the benefit-cost ratios, Public/Commercial buildings have the highest benefit-cost ratios, ranging between 4.35 and 4.66. The benefit-cost ratio for mobile homes has a sharp increase under the increase of SLR rate. Single-family buildings take the vast majority of buildings with adaptive measures. Mobile homes, although have smaller benefit-cost ratios due to lower home values, still have the second largest number of buildings with adaptive measures. Over 80% of Multi-family/Condo buildings and about 50% of Public/Commercial buildings will implement with adaptive measures. Under the high SLR, about 1375 single-family properties and 402 mobile homes will be totally inundated. The variation of adaptation decisions depends on the benefit of adaptation at the time point of decision-making. It can be seen that the number of buildings with adaptive measures in scenario 4 is over 2000 compared to that in scenario 1. Fig. 4 also shows distributions of average benefit-cost ratios for all buildings under the four SLR scenarios. These distributions all have fat-tails. With the increase of SLR, the distribution will have a fatter tail, which means an increased average benefit-cost ratio.

4.2. Long-term building damage under SLR scenarios

We evaluated building damages by assuming that damaged buildings will be timely repaired or rebuilt after flooding. This assumption allows us to evaluate the long-term trends of flood damage in the county with adaptation decisions. We aggregated the average total flood damage in the county on the temporal scale.

Fig. 5 shows the average total building flood damage and uncertainties with and without adaptation in each SLR scenario. At the beginning of the simulation, the total community damage ranges from $17.7 million to $32 million when without considering adaptation, and from $9.57 million to $21.8 million when considering adaptation. Compare with different SLR scenario, the low SLR scenario after 100 years only results in a slightly increased total building damage. As the increase SLR rates, building damages will increase exponentially after 2070. In the case without adaptation, total average community flood damage ranges from $43.2 million in the low SLR scenario to $204 million in the high SLR scenario at the end of the simulation. In the low SLR scenario, the total annual damage of buildings with adaptation behavior ranges from $18.1 million to $38.2 million at the end of the simulation. However, the flood damage uncertainties in the county increase significantly in the intermediate high and high SLR scenarios, ranging from $39.2 million to $110 million at the end of the simulation. This indicates that coastal communities are expected to have a higher risk of damage when SLR rate is high even with the mitigating effects of adaptive measures.

We further show the average annual flood damage under each SLR scenario in Table 5. For Single-Family buildings, the average annual flood damage in the high SLR scenario could be doubled compared to the low SLR scenario if adaptation is not considered, ranging from $1650.01 to $3216.60. The average annual damage of mobile homes ranges from $684.11 to $1725.39 when the SLR rate changes from low to high. Similarly, the average annual damages range from $1488.25 to $2209.97 for multi-family/condo and from $5695.20 to $7047.65 for public/commercial buildings between the low and high SLR scenarios. The flood damages of mobile homes change more significantly under the increase of SLR rates. This indicates that mobile homes near the coast are very sensitive to SLR.

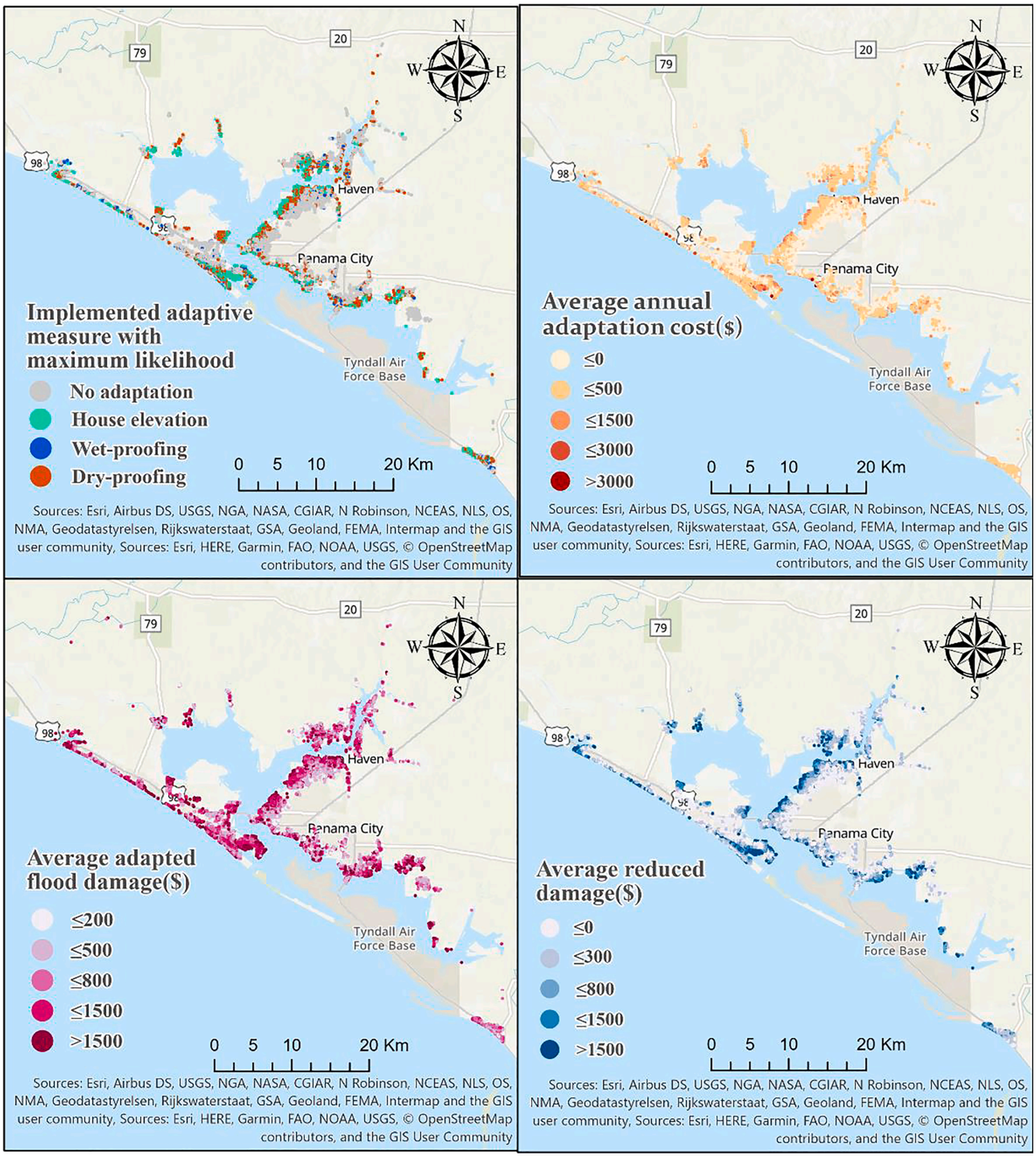

Fig. 3. Average adaptation outcomes under the low SLR scenario.

Nevertheless, when considering adaptive measures, flood risk of mobile homes could be significantly mitigated.

To examine the average damage of each type of building under different SLR scenarios, we further classified the average annual building damage into low, moderate, high, and very high categories based on quantile damage values in the base year. In Fig. 6, most highly damaged buildings come from single-family and mobile homes. These buildings are extremely vulnerable to flooding, which also refer to as buildings with repetitive flood risk (de Koning & Filatova, 2020). If considering private adaptive measures, more buildings will be classified into the moderate damage category. However, the number of buildings with high damage also increases notably when adaptation is considered. This phenomenon is from the fact that a large number of single-family houses from the very high damage category will move to the high damage category when adaptation is considered. This result also illustrates that a CBA based risk mitigation decision could not fully mitigate flood damage of buildings.

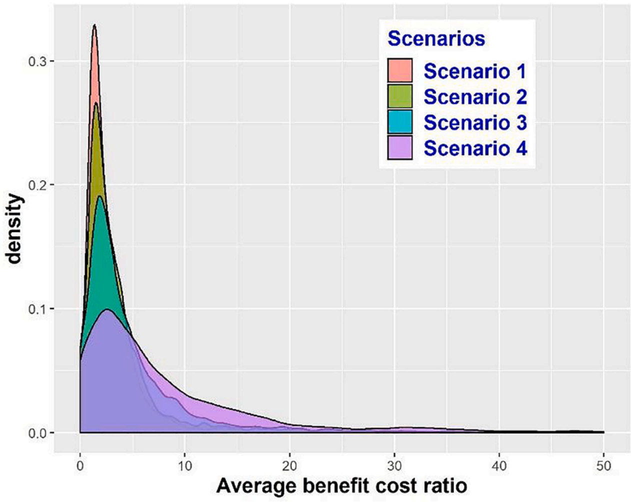

Fig. 4. Density distributions of the average benefit-cost ratio.

Table 3
The number of adaptive measures with maximum likelihoods to be implemented in the simulation.

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Building elevation	4276	4281	4275	4272
Wet-proofing	1318	1530	1227	1385
Dry-proofing	6405	6453	6539	6761

Table 4
Number of high-risk buildings before and after adaptation with corresponding annual costs and benefits.

Scenario/House type		Average annual flood damage reduction ($)	Average annual flood adaptation cost ($)	Average annual benefit-cost ratio	Average number of implemented adaptive measures	Number of lost buildings
Low SLR	Single-Family	722.65	128.01	2.35	15,080	0
	Multi-family/ Condo	626.02	93.02	2.58	578	0
	Mobile Homes	220.64	45.53	1.92	1182	0
	Public/ Commercial	1813.13	206.45	4.35	311	0
Intermediate low SLR	Single-Family	780.86	185.18	2.59	15,837	2
	Multi-family/ Condo	660.66	107.19	2.67	612	0
	Mobile Homes	245.95	73.46	2.22	1255	87
	Public/ Commercial	1935.92	387.26	4.66	334	0
Intermediate high SLR	Single-Family	1078.12	178.60	3.51	16,421	101
	Multi-family/ Condo	795.63	105.08	3.26	624	2
	Mobile Homes	379.44	71.18	3.42	1294	303
	Public/ Commercial	1941.81	359.83	4.65	360	5
High SLR	Single-Family	1743.09	171.92	5.98	17,049	1375
	Multi-family/ Condo	1077.37	103.08	4.68	636	22
	Mobile Homes	705.41	68.88	6.74	1338	402
	Public/ Commercial	2089.23	338.14	4.66	384	27

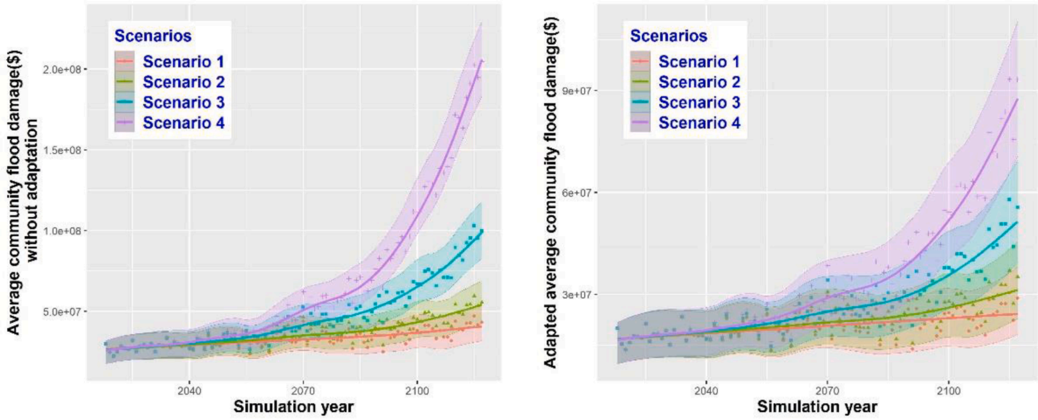

Fig. 5. The total building flood damage with and without considering adaptation.

Table 5
Average annual flood damage under uncertain SLR.

Scenarios	Adaptation	Single Family	Multi-family/Condo	Mobile Homes	Public/Commercial
Low SLR	No adaptation ($)	1650.01	1488.25	684.11	5695.20
	Adaptation ($)	927.36	862.23	463.47	3882.06
Intermediate low SLR	No adaptation ($)	1758.96	1535.10	754.31	5869.41
	Adaptation ($)	978.10	874.45	508.36	3933.49
Intermediate high SLR	No adaptation ($)	2246.31	1771.09	1064.41	6259.76
	Adaptation ($)	1168.18	975.46	684.96	4317.95
High SLR	No adaptation ($)	3216.60	2209.97	1725.39	7047.65
	Adaptation ($)	1473.50	1132.60	1019.97	4958.42

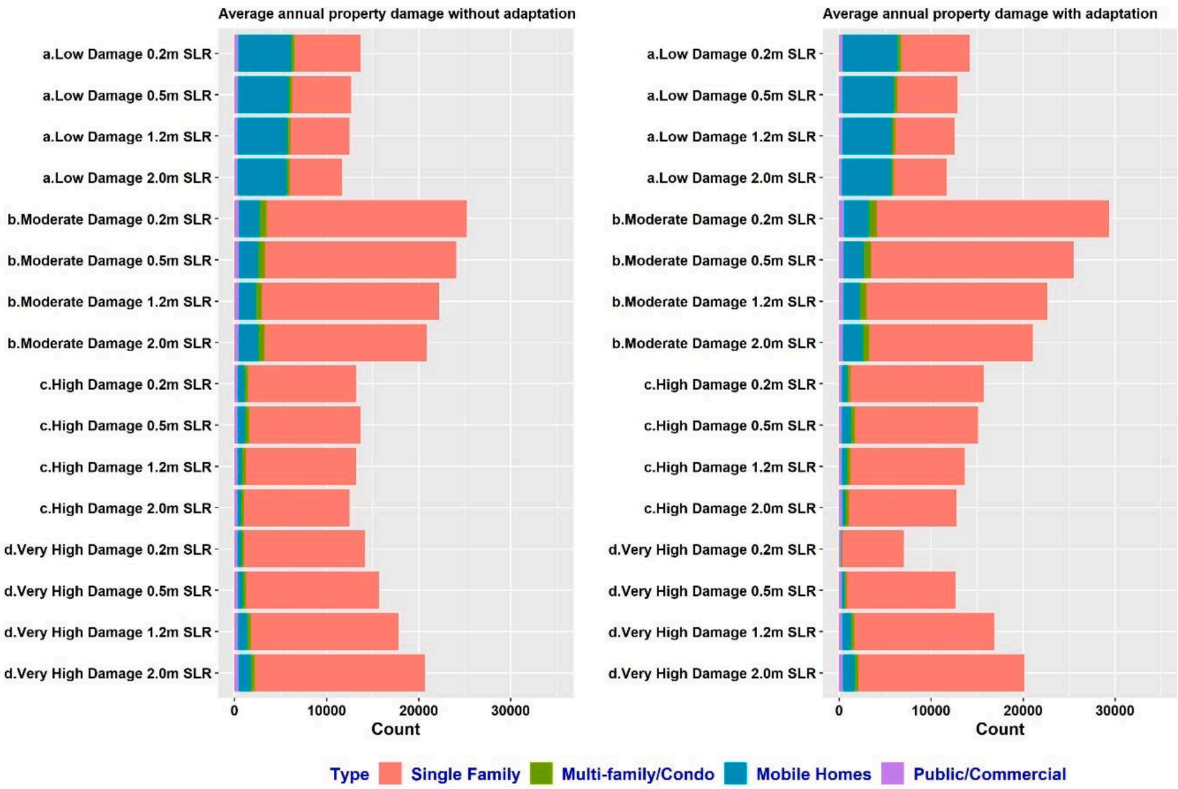

Fig. 6. The number of damaged buildings with and without adaptive measure.

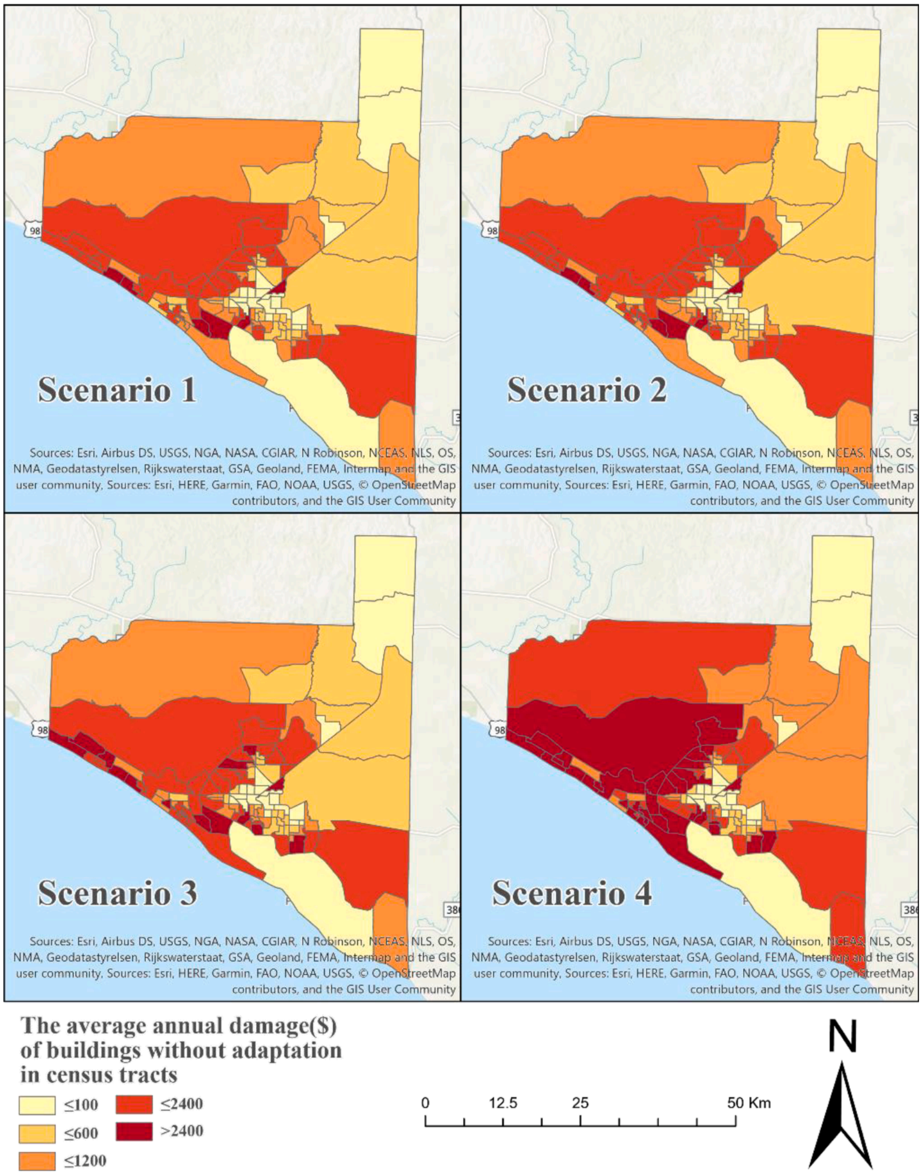

Fig. 7. The average annual flood damage without adaptation across census blocks under SLR.

4.3. Community adaptation benefits

Fig. 7 shows the average annual flood damage of buildings without adaptation in census blocks under SLR scenarios. It can be seen that buildings in most coastal communities of Bay county have the average annual flood damage over $1200. Under the high SLR scenario, most of these communities have the average annual flood damage over $2400. After the adaptation, results in Fig. 8 show that some high-risk communities change to low-risk communities, with an average annual damage lower than $600. However, in the high SLR scenario, coastal communities in Bay county are still vulnerable to storm surge flooding even with adaptation, where the average annual damage is above $1200. To identify the benefits of adaptation at the community level, we examined the average benefit-cost ratios of adaptation at census block levels, as shown in Fig. 9. In general, communities located near the shoreline have higher benefit-cost ratios due to the high vulnerability of buildings to storm surge flooding and the SLR. In the low SLR scenario, communities along the shoreline have benefit-cost ratios range between 2 and 5, while in high SLR scenarios, these communities will have benefit-cost ratios greater than 5. Other communities, adjacent to communities near the shoreline, will also have high adaptation benefits under the high SLR scenario. Our results in Figs. 7, 8 and, 9 indicate that a CBA based adaptation decision-making framework would produce cost-effective adaptation strategies in local flood risk management. Nevertheless, for vulnerable communities, the average annual flood damages with adaptation could be still high under high SLR scenarios.

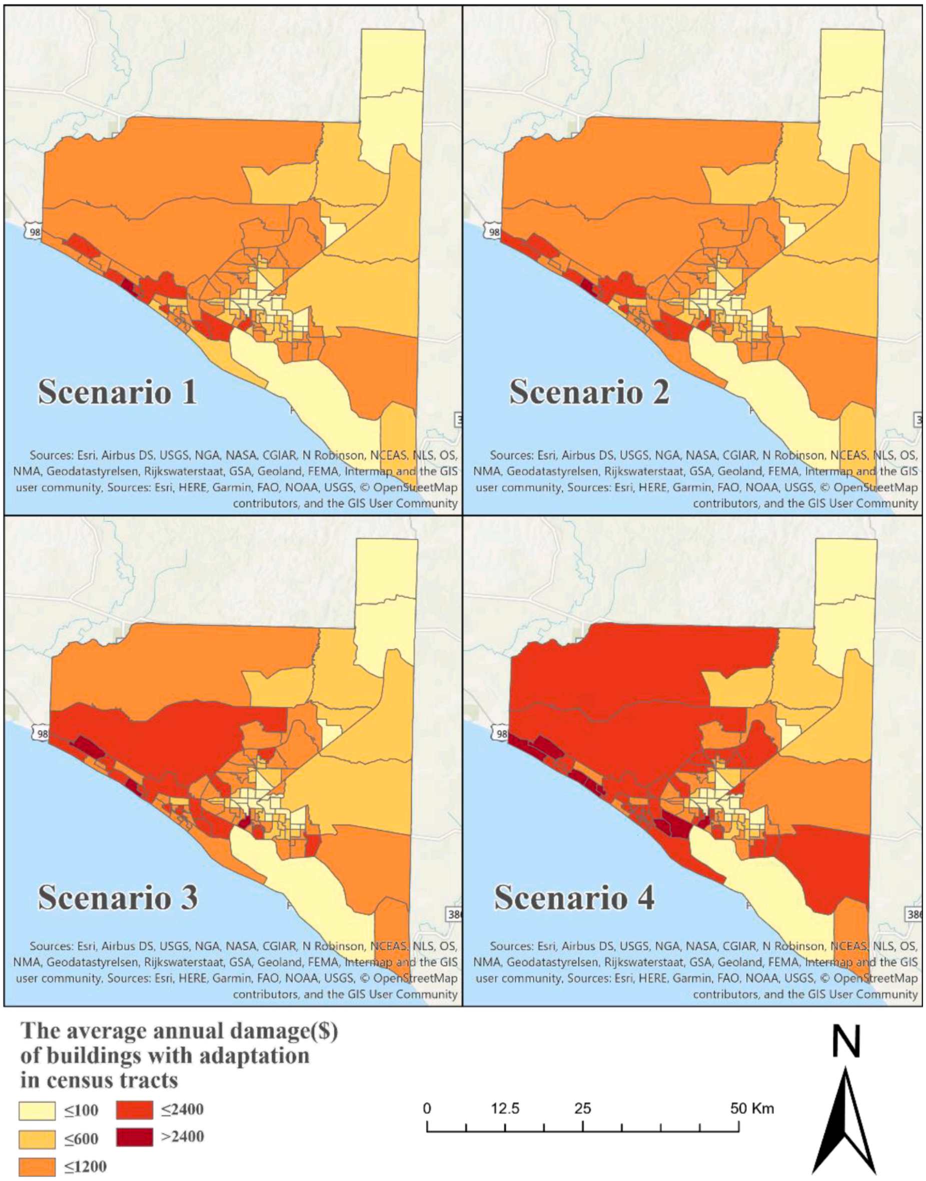

Fig. 8. The average annual flood damage with adaptation across census blocks under SLR.

5. Discussion and conclusions

This study presents a dynamic cost-benefit analysis framework to evaluate adaptation decisions under SLR and evaluate adaptation outcomes through the Monte Carlo simulation. We have integrated the randomness of storm surge events, a dynamic programming-based adaptation cost-benefit analysis, and the SLR projection scenarios to estimate the long-term flood damage to vulnerable coastal communities. Our modeling approach considers decision outcomes under natural system changes in the life-cycle of adaptation analysis. Results illustrate the long-term benefits of flood adaptation, as well as uncertainties of flood damage in Bay County, Florida. The developed simulation approach in this research can serve as a decision support tool to facilitate adaptation planning to the rising coastal risk.

This study finds that most single-family buildings close to the beach are vulnerable to storm surge damages. Public and commercial buildings, Multi-family buildings, and condominiums are also vulnerable to coastal hazards in the area. Mobile homes are more sensitive to SLR compared to other buildings. Most buildings near the coast could reduce their damage from storm surges by investing in risk mitigation measures. However, it is important to be aware that a CBA-based adaptation decision plan cannot fully mitigate damage from uncertain climate conditions. Due to the high uncertainty of climate change impacts on mean sea-level, a CBA-based approach with historical SLR information may underestimate future flood risk to buildings (Pozzi et al., 2017). The increasing

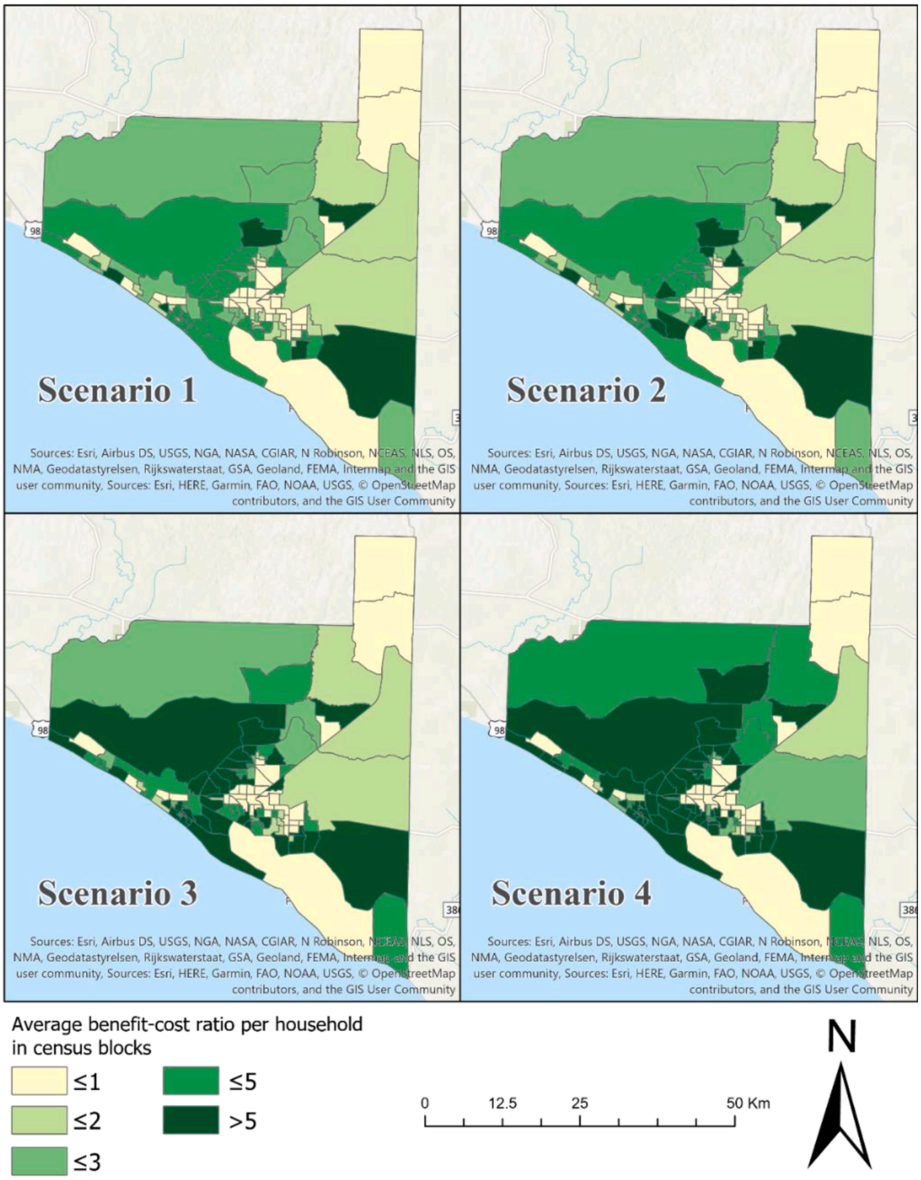

Fig. 9. The average benefit-cost ratios of adaptation across census blocks under SLR.

uncertainty of flood damage over time also indicates the future high flood risk of Bay County. Adaptation planning needs to incorporate more effective risk communication between public and private sectors through including uncertainties in climate risk analyses and corresponding adaptation strategies to handle all possible consequences. Based on our results, the relatively high and high SLR scenarios would substantially increase community risk, local planners are recommended to incorporate up-to-date scientific knowledge of SLR over time in the design of building codes for effective adaptation planning. The proposed methodology in this research provides a model framework to incorporate uncertainties in climate risk analysis to improvise adaptation planning.

Although our model could be applied to examine the hazardous effects of hurricane storm surge under SLR. There are some limitations to this study. First, this study evaluates future building damage of storm surge based on a GEV distribution function with only location parameter changes based on SLR. However, climate change could also impact the scale and shape parameters in the full nonstationary distribution functions. Future studies may incorporate nonstationary GEV distribution models to further evaluate storm surge impacts in coastal communities (Lee et al., 2017). Second, the proposed approaches could simulate individual building risk and adaptation benefits under stochastic storm surges and SLR. Although we made simplification on selecting the number of buildings and parameters of the CBA, it still requires high computational power. Our model results were obtained after 90 hours of simulation. Future research can rely on high-performance cloud computing facilities to incorporate more adaptation decision scenarios in the evaluation. Third, the CBA framework in this study evaluates adaptation decisions from an economic perspective. Nevertheless, it is also important to include social vulnerability in adaptation decision-making (Huynh & Stringer, 2018). Future studies may evaluate adaptation outcomes within a coupled human-environment system to illustrate the social vulnerability of storm surges in coastal flood risk mitigation. Nevertheless, our approach presents a comprehensive framework for evaluating the long-term community risks and damages under SLR. The methodology of this study could facilitate more effective risk communications between community members, public and private sectors and help improvise community adaptation planning in the future.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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