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Retreat from flood zones: Simulating land use changes in response to compound flood risk in coastal communities

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ABSTRACT

Coastal communities are increasingly vulnerable due to sea level rise and population growth. Managed retreat is commonly recognized as a strategy that yields multifaced benefits in community adaptation. However, limited studies have explored the cumulative effects of sea level rise, population migration, and managed retreat on the community resilience. This study presents a parcel-level land use change model to analysis land-based flood mitigation strategies in Galveston County, Texas. The developed model integrates a Gradient Boosting Decision Tree with a flood risk model and diverse datasets. Our model results reveal the spatial patterns of urban development in Galveston under different relocation policies and the compounding impacts of sea level rise and population growth. Our findings illustrate that elevating the first floors of buildings can significantly mitigate flood risks and associated relocation costs. The private adaptation measure, together with government-led buyout policies, could foster a shift toward more resilient urban development and yield a more affordable relocation strategy. Our findings emphasize the need for a multidisciplinary approach in building resilient coastal communities, particularly in the face of escalating climate risks in local communities.

1. Introduction

Coastal communities increasingly confront by the recurrent challenges of flooding hazards, exacerbated by the compound risks of coastal storm surges, intense precipitation from tropical cyclones, and the ongoing effects of sea level rise (de Koning & Filatova, 2020; de Ruiter et al., 2020; Haasnoot et al., 2020). These multifaceted effects of coastal hazards not only threaten the resilience of coastal communities but also endanger vital coastal habitats (Khan et al., 2014). Moreover, the continuing urban development in these areas adds complex challenges for urban policymakers to implement effective risk mitigation strategies to ensure long-term coastal sustainability. Although scientific understanding of climate change adaptation is evolving, addressing these challenges at local scale necessitates the integration of transdisciplinary knowledge for accurately quantifying the impacts of coastal extreme weather impacts and improving local land use planning (Anguelovski et al., 2016; Davlasheridze et al., 2019).

Land-based adaptation policies, such as managed retreat, property buyouts, as well as nature-based solutions, have become increasingly popular in mitigating escalating climate risks and maintaining the long-term sustainability (Hino et al., 2017; Keesstra et al., 2018; Yin et al., 2023). The managed retreat is a strategic approach to prevent future damages of natural disasters by moving people, assets, and infrastructures away from high-risk areas. The property buyout program, which aims to use public funds to relocate high-risk properties in floodplains, offers homeowners fair market value to relocate to safer areas (Greer et al., 2022). Unlike other flood risk mitigation projects, property buyouts usually transfer developed land into conservation land and are used for flood mitigation projects (Weber & Moore, 2019). Examples of property buyout programs include FEMA's Hazard Mitigation

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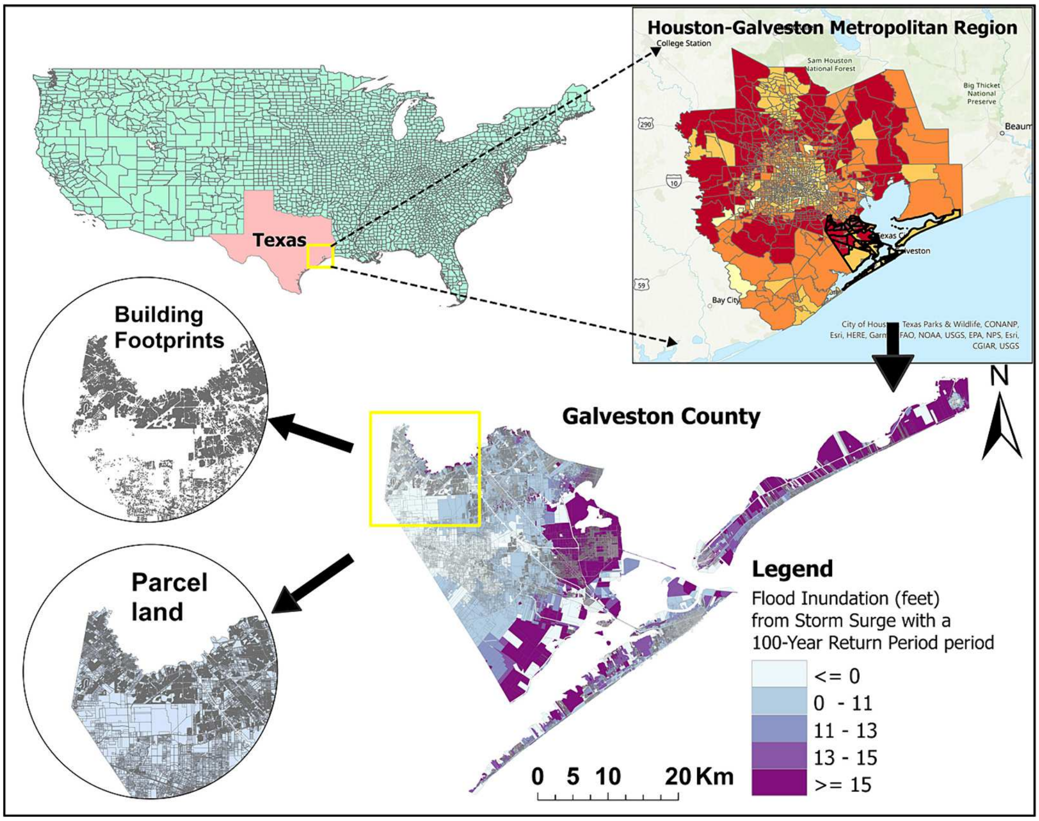

Fig. 1. The Houston-Galveston Region: Geographical Location in the U.S., and Detailed View of Galveston County's 100-Year Storm Surge Flood Inundation with Building Parcels and Footprints.

Grant Program, the Flood Mitigation Assistance Program, and the Building Resilient Infrastructure and Communities program. Nevertheless, existing studies show these property buyout programs are constrained by limited funding and could result in equity issue in buyouts (Peterson et al., 2020; Siders, 2019b).

Risk mitigation and urban development decisions of local governments are intertwined. Inappropriate risk mitigation decisions would result in unequal distributions of resources and increase social vulnerability to natural disasters (Muñoz & Tate, 2016). For example, neglecting to transform retired land in flood mitigation programs into beneficiary community assets can lead to unforeseeable ecological and social issues (Highfield et al., 2014). Nevertheless, acquiring properties located in floodplain areas and relocating vulnerable residents incurs substantial costs and adversely affects local tax revenues, utilities, and other municipal services (Siders & Gerber-Chavez, 2021). The financial paradox between investing in managed retreat for sustainability and facing reduced tax return due to exit of the relocated households from the city, compels most existing relocation programs focusing on a limited number of less expensive buildings(Siders, 2019a).

With the escalating impacts of climate change due to sea level rise and increasing population exposure, understanding the evolving risks and benefits of land-based adaptation in coastal communities becomes essential. This study focuses on enhancing managed retreat policy-making in coastal communities. By simulating parcel-level urban development and flood risk based on historical trends of relative sea level rise and population growth, our research is centered around two critical research questions: (1) How will community coastal flood risk evolve under sea level rise and population growth? (2) What are the effects of managed retreat policies on the resilience of coastal communities? Our modeling outcomes provide tools and methods to access the changing coastal flood risk faced by coastal communities and to support the development of effective land-based adaptation strategies for these areas.

2. Literature review

The vulnerability of communities to natural hazard is affected by both the changing frequency and intensity of these hazards, and by the varying exposed elements at risk to natural hazards (Papathoma-Köhle et al., 2007). Climate change strongly affects hazard characteristics and has been integrated into the assessment of natural hazard risk. For example, Ju et al. (2019) measured exposure of flooding in San Francisco under various climate change projections and highlighted the importance to cope with climate change uncertainties in adaptation planning. Nevertheless, considering urban development and adaptation policy, the projections of future climate risk also need to consider changes of exposed element-at-risk. Elements-at-risk usually refers to the people, property, systems, or other elements within an area that are potentially exposed to losses due to a natural hazard (van Westen et al., 2008). Land uses, population, and buildings are typical examples of elements-at-risk.

Land use/cover change (LUCC) modeling is a crucial approach for studying spatial-temporal land use changes and assessing urban development with environmental impacts (Tong & Feng, 2019). LUCC modeling could inform decision-making by comparing future urban land use patterns under different environmental scenarios and planning policies. Existing LUCC models commonly employ transition probabilities between land uses and neighborhood effects of land use changes to predict future land use patterns (Pan et al., 2021). For instance, Li et al. (2021) considered temporal effects of urban development to estimate future global urban growth under IPCC's projected climate scenarios. Using remote sensing observations, higher probabilities were assigned to new developed urban pixels in the neighborhood to influence changes from non-urban land to urban land of the central pixel. Wang et al.

Table 1
Data description.

Dataset	Description	Source	Nature
Cadastral Parcel data	Land parcels including land value, building value, area, and building height.	Galveston Central Appraisal District (https://galvestoncad.org/gis-data/)	Polygon Shapefiles for individual parcels
Building footprints	Building footprints of Galveston County	Microsoft Planetary Computer's dataset (https://planetarycomputer.microsoft.com/dataset/ms-buildings)	Polygon Shapefiles for individual buildings
Land use data	Land uses in 2011, 2015, and 2020 from NLCD land cover classification schemes	National Land Cover Database (NLCD) (https://www.usgs.gov/centers/eros/science/national-land-cover-database)	Raster imagery with 30-m resolution
Census data	Population demographical information in census tract	United States Census Bureau	Polygon Shapefiles in census tract
POI data	POI of schools, hospitals, parks, beaches, wetlands, and coast area	The archived OpenStreetMap data (https://download.geofabrik.de/)	Point Shapefiles
Population migration data	County level population migration between 2005 and 2021	United States Statistics of Income Division (SOI) of the Internal Revenue Service (IRS) (https://www.irs.gov/statistics/soi-tax-stats-migration-data)	Spreadsheets
Human mobility data	Daily population flows between census tracts	Multiscale Dynamic Human Mobility Flow Dataset in the U.S. during the COVID-19 Epidemic (Kang et al., 2020)	Spreadsheets
DEM data	Tidally adjusted raster digital elevation model	The National Oceanic and Atmospheric Administration (NOAA) (https://coast.noaa.gov/dataviewer/#/)	Raster imagery with 3 m resolution
Sea level data	Hourly relative sea level in millimeter from Galveston, Pier Tide Gauge Station between 1900 and 2020	University of Hawaii Sea Level Center (Caldwell et al., 2015)	Spreadsheets
Flood inundation data	Flood inundation maps from category 1 to category 5 hurricane storm surges	NOAA National Storm Surge Risk Maps (https://www.nhc.noaa.gov/nationalsurge/#data)	Raster imagery with 30-m resolution

(2022) considered the time-series influence of the spatial structure of the neighborhood effects to predict future urban development. Abolhasani et al. (2016) developed a parcel-based cellular automate model to simulate urban growth through estimating three neighborhood effect parameters, including compactness, compatibility, and dependency. Moeckel (2017) developed a dynamic land use and transportation model to represent location choices of households by considering utilities of housing and commuting costs. Recently, researchers have combined machine learning and neighborhood effects models to simulate future urban expansion. Zhuang et al. (2022) developed a LUCC model relied on both machine learning techniques and neighborhood effects to predict urban expansion through vectorized memory processing using Graphics Processing Units.

Given the catastrophic impacts of climate hazards, exacerbated by population growth, land-based risk reduction strategies have drawn increasing attention. Atoba et al. (2021) demonstrated the potential benefits of acquiring vacant land in Houston area before it is built up to mitigate sea-level rise impacts. They highlighted that acquiring vacant land can be a cost-effective way to reduce repetitive losses of coastal hazards, and meanwhile avoiding social and institutional problems associated with traditional buyout programs. To explore the economic feasibility of land-based risk mitigation policies, Rifat and Liu (2022) applied an artificial neural network and Markov-chain model to measure future urban growth patterns under different development strategies and sea-level rise impacts in southeast Florida. Their study illustrated that targeted land-use policies can curtail the economic costs associated with coastal hazards while enhancing the overall community resilience. Lin et al. (2022) employed land use simulation and maximum entropy method to identify future urban waterlogging-prone areas to heavy storms and to predict future land use patterns. Their results revealed the potential waterlogging risk from large impervious areas in cities. Liu et al. (2023) considered the derivative consequences of land use changes on future flood risk, integrating multiple model components into a model chain, which couples a land use simulation model with submodules to forecast future population and economic growths under various scenarios, including economic expansion, cropland protection and ecological preservation. Although existing studies have consistently observed the increasing impacts of natural hazards to urban communities, uncertainties associated with climate-related hazards and future development pose significant challenges to the efficacy of land-based adaptation strategies (IPCC, 2023). Hence, it is imperative to integrate knowledge across disciplines to strategically inform the potential impacts of these policies on community development under cumulative impacts of sea level rise and population migration.

3. Data and study area

The Houston-Galveston area is one of the most vulnerable regions in the Gulf of Mexico (Hamideh, 2020). It is a warm and low-lying region which experiences impacts of warm ocean every summer during hurricane season. Climate-induced Sea Level Rise (SLR) exacerbates the vulnerability of the low elevation land which is already prone to flooding. From 2000 to 2017, the Houston-Galveston area has more than three thousand federally funded residential buyouts, which is the largest number of property buy outs in the US (Loughran & Elliott, 2019). Understanding the effects of climate change and alternative risk management policies in this area could facilitate disaster management and risk mitigation policymaking for the extensive coastal communities in the US. Fig. 1 shows the location of Houston-Galveston region, which consist of 8 counties. In this study, we focus on urban development and relocation issue in Galveston County. Fig. 1 additionally illustrates the extent of flood inundation of exposed land parcels and building footprints during a 100-year storm surge event. Since the east and south parts of Galveston County are coastal areas with low elevation, the developed land parcels in these regions have much higher flooding risk compared to the northwest of the county.

Most of the land parcels in Galveston County are near the shoreline of the Gulf of Mexico. In this study, we collected data from multiple sources to estimate future community flood risk and land use patterns, as shown in Table 1. To build the land use simulation model, we use land use data, building footprints, parcel data, point of interest (POI) data, census level socio-demographic information and mobility data. Three levels of spatial data, namely land use, building footprints, and parcel data, were used to classify landscape features in the simulation. The parcel data was obtained from the official website of Galveston Central Appraisal District. Three periods of land use data, namely in 2011, 2015, and 2020, were acquired from the National Land Cover Data (NLCD). We also retrieved building footprints in Galveston County from Microsoft's Global Building Footprints database. We applied this data later to extract land use, building elevation, DEM, and flood inundation information to parcels and combined it with parcel data. Thereafter. The 2019 census block data was accessed from the US census bureau including households' socioeconomic attributes, composition, minority status, et al. POI datasets, including schools, hospitals, parks, beaches, and wetlands, were from OpenStreetMap. We also collected census tract level daily mobility flows in Houston-Galveston area to measure

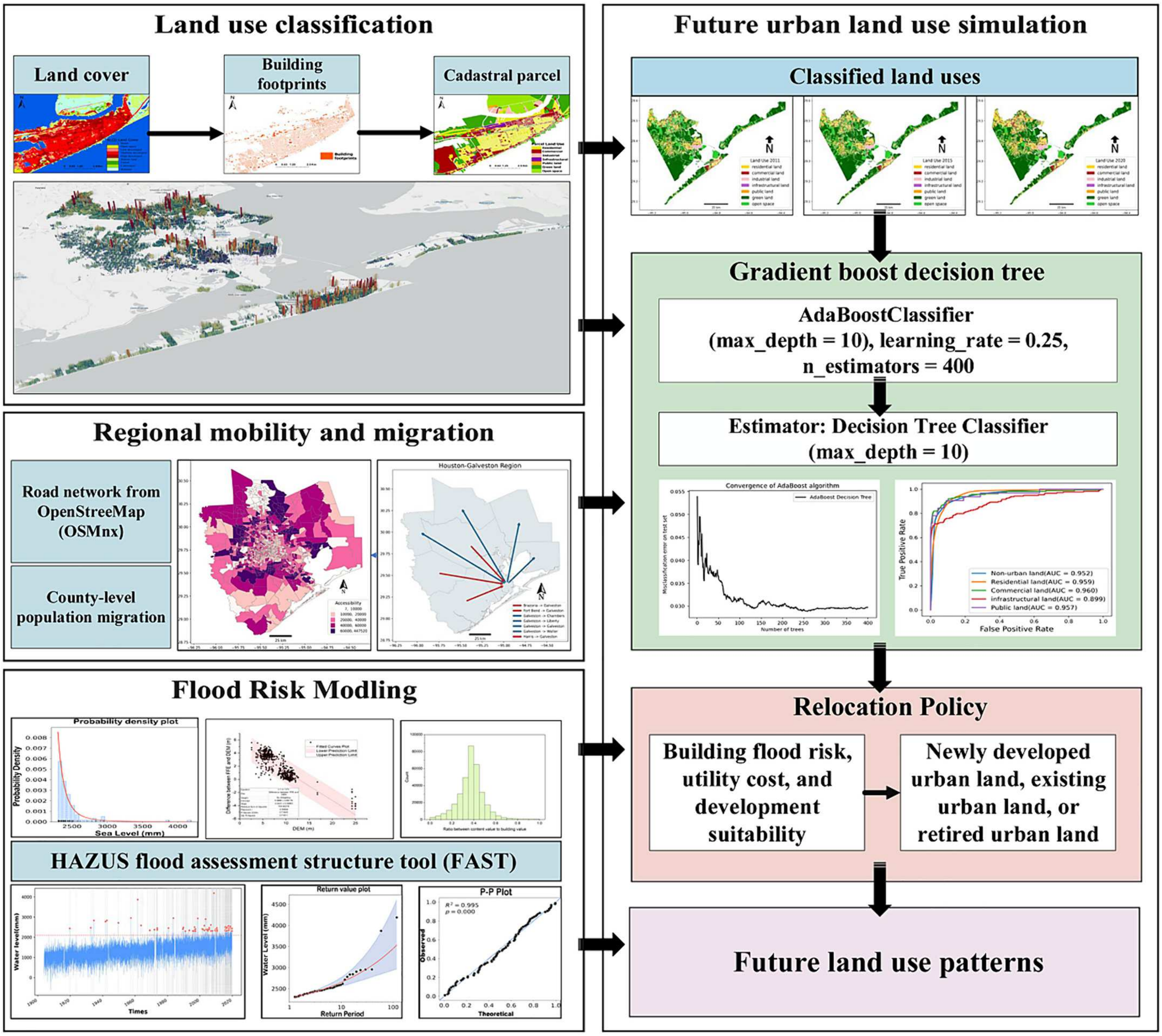

Fig. 2. An integrated framework of the parcel-level land use simulation model under coastal flood risk.

accessibility of communities. Since relocated households will mainly be redistributed within the Houston-Galveston region, we measured population migration between Galveston County and nearby counties in this area. Over one century hourly relative sea level data at Galveston was collected from University of Hawaii Sea Level Center (Caldwell et al., 2015). This dataset not only allows us to measure the distribution of extreme weather events, also enables us to project future trends of sea level rise in the area. For the analysis of extreme values, we employed the 'pyextremes' package in Python, which is specifically designed for extreme value analysis. To project future sea level rise trends, we implemented the Seasonal AutoRegressive Integrated Moving Average with eXogenous (SARIMAX) regressor model, available in the 'statsmodels' package in Python. Ground elevation data and five categories of simulated storm surges, ranging from category 1 to category 5 hurricane storm surges, were used to measure flood inundation and adjust the flood inundation mapping model.

4. Methods

Fig. 2 presents a comprehensive framework of the developed parcel-level land use model, designed to project future urban land use patterns in the context of coastal flood risks. Detailed figures within the model framework are provided in the Supplementary Information (SI). The right side of Fig. 2 shows three sub-modules of the model, which are land use classification, regional mobility and migration, and flood risk modeling. These sub-modules were then cohesively integrated into the land use simulation on the right side. On the right side of Fig. 2, a gradient boost decision tree (GBDT) model, trained using classified land use data from different periods, is employed to assess land use suitability and then applied to measure land use development under various relocation policies.

4.1. Land use classification

The land use classification module involves processing the raw datasets and merging raster level information to parcel features. We first conducted a spatial join of all raster value information to building footprints and then merged building footprints with parcel data to get cadastral parcels with building and land uses information in different years. There are several reasons that we started with building footprints and then joined attributes to cadastral parcels. First, although parcel data seamlessly covers the whole study area, building footprints are small patches and could capture raster information of a specific area more accurately. This information includes land use, building heights, and flood-related inundations, etc. Second, building footprints can uniquely represent individual buildings in the study area. As show on the upper left of Fig. 2, the processed building footprints could be visualized in a 3D environment with attributes (e.g. improved value) to enhance the visualization of buildings. Third, we need parcel data information to simulate future land use patterns. Although the cadastral parcel data downloaded from the Galveston County's GIS data portal was the raw parcel data with duplicated features, the dataset seamlessly covers the whole county with important land parcel information, such as building values, building code, built year, etc. We found 76,277 duplicated building parcels overlapped to each other in the raw parcel data and removed them. We employed land use data from the year 2011, 2015, and 2020 in conjunction with the building codes of parcel data and the Standard Type Land Code Table in Galveston County[1] to classify the NLCD land cover into 7 categories: residential land, commercial land, industrial land, infrastructural land, public land, green land, and open space. We cross validated the built year information of a parcel with our spatially joined land use in 2011, 2015, and 2020 to ascertain whether a land parcel has been developed in each of these specified periods. This process helped us reduce errors in land use classification. As a result, our final cadastral land parcel has 170,194 unique parcel features including land use attributes for three distinct time periods, which indicate the development status and timeline for each parcel land. For each developed parcel land, there is also an associated improvement value, and for undeveloped land, the improvement value is 0. The upper right of Fig. 2 shows the classified land uses in the three-time periods.

4.2. Regional mobility and migration modeling

We combined census tract level socioeconomic and mobility information to our parcel data. We retrieved population flow data in 2019 before the Covid-19 pandemic from Github (Kang et al., 2020) and utilized the weekly population flow data to measure accessibility and attractions of each census tract in the whole Houston-Galveston region (Higgins et al., 2022). The processed accessibility results are shown on the upper right corner of Fig. 1. Our processed land uses and accessibility results indicated that the development in the Galveston County is mainly driven by the attraction of Houston from the north. We measured population migration using historical yearly population and household migration data in Galveston County. This dataset was based on the reported taxpayers' geographic code changes from one year to the next from the Internal Revenue Service (IRS). We determined population flow directions from nearby counties to Galveston County in the Houston-Galveston area and later determined future population growth trends in Galveston County.

4.3. Flood risk modeling

Our flood risk model is based on the extreme value and time series analysis. We first analyzed the distributions of extreme storm surge events based on the historical hourly relative sea level dataset between 1990 and 2020 at the gauge station in Galveston County. The Peaks Over Threshold (POT) extreme values are extracted from the dataset. The process was accomplished by first generating a time series of exceedances by selecting values above a certain threshold and then delustering the exceedance time series by identifying clusters separated by a given time window and then selecting only the highest values within each cluster. A Generalized Pareto Distribution (GPD) distribution of storm surges was applied to model the extreme value behavior of sea level records. The density function of the GPD distribution is as follows:

$$F_{(\mu,\sigma,\xi)}(x) = 1 - \left(1 + \frac{\xi(x-\mu)}{\sigma}\right)^{-\frac{1}{\xi}}$$

In the given equation, ξ is the shape parameter, μ is the location parameter, and σ is the scale parameter. The fitted model yielded a location parameter 2300, shape parameter of 0.331, and a scale parameter of 116.14. The unit of analysis is in millimeter. The historical relative sea level data is nonstationary. We assume the nonstationary of the historical sea level mainly comes from temporal trends in the dataset. To examine our assumption, we first removed the temporal tends of sea level data and use the Augmented Dickey-Fuller (ADF) test to examine the stationary of the new data. We used the MSTL package to remove the temporal trends of sea level and the *adfuller* package to test if the new data is stationary. The ADF test for the new data has ADF statistic smaller than the 1 % critical level, which reject the null hypothesis and infer that the new time series is stationary. To project future extreme weather events, we also modeled the sea level rise trends and added it to our extreme value distributions in projecting future flood risk.

We modeled flood height and frequency distributions using historical sea level dataset and estimated flood height under each category of storm surge (Doss-Gollin & Keller, 2023). The flood inundation under each category was first estimated using a Bathtub method based on the difference between peak storm surge heights from the GEV model and the ground elevation. Afterward, we applied storm surge inundation maps from SLOSH model to adjust the estimated flood inundations of each parcel under each category (Han et al., 2022). We calculated the average difference between flood inundations from SLOSH model and estimated flood inundations from the Bathtub model for each parcel land and incorporate this information in estimating flood damage for any return periods and calculating flood risk. We also observed that the distance to rivers and coasts may affect flood inundations of buildings. We developed a linear model to measure effects of distance to rivers and coasts on flood inundation. Since sea level rise could gradually inundate low elevated areas, we estimate the changes of distance to rivers and coasts based on a linear relationship between DEM and distance to rivers and coasts. We measured changes of DEM due to sea level rise and translated this information to changes of distance to rivers and coasts in projecting future risk. The methods to describe this was incorporated into the SI.

We estimated the flood risk of properties relying on the HAZUS model. The HAZUS model was developed by the Federal Emergency Management Agency (FEMA) and the National Institute of Building Science (NIBS). HAZUS includes standard tools and data for estimating risk from earthquakes, floods, tsunamis, and hurricanes (Schneider & Schauer, 2006). Although the HAZUS model is a GIS-based modeling platform, the tool is distributed with a collection of simplified open-source codes (Moffatt & Laefer, 2010). In our study, we adopted the open-sourced flood assessment structure tool (FAST) from HAZUS to estimate physical damage and economic losses of properties from different categories of hurricane storm surge hazards, which can be accessed through *https://github.com/nhrap-hazus/FAST*. We applied HAZUS's FAST to estimate flood damages under different categories of storm surge inundations and calculated the expected annual damage as the flood risk. The FAST requires information regarding a property's building type, first-floor elevation (FFE), foundation, flood height, property value, and content value to estimate flood damages of buildings.

[1] The Standard Type Land Code Table in Galveston County was accessed: https://www.galvestontx.gov/DocumentCenter/View/8823/Land-Development-Regulations-PDF.

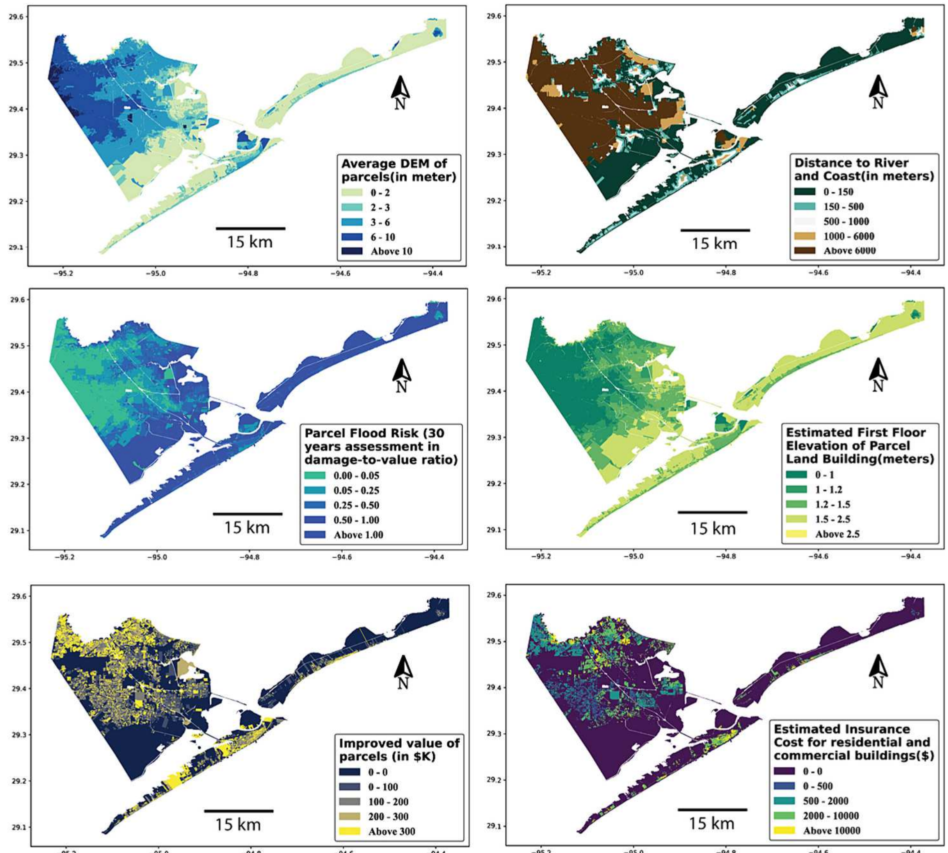

Fig. 3. Key Attributes in Model Simulation, including DEM, Water Body Proximity, Flood Risk, Building First Floor Elevations, Improved Value of Parcels, and Estimated Flood Insurance Costs.

We estimated the first-floor elevation of buildings in Galveston using a dataset of 3D measurements from selected residential buildings, provided by Diaz et al. (2022). A linear model was developed to relate ground elevation of these buildings to the difference between their first-floor elevation and ground elevation. This difference represents the extent of house elevation by homeowners as a measure to mitigate flood risk. To estimate the flood risk of buildings, we only measured land parcel with improved values in the county, which means flood risk will be 0 for vacant land and retired land. The content value of a property was also estimated based on improvement values of properties using FEMA's NFIP policy dataset (Han & Ye, 2022). In the flood risk component of Fig. 2 and the SI, we show the derived flood frequency distribution, the distributions of ratios between content values to building values, and the linear model between FFE and ground DEM of residential buildings in Galveston County. We applied these models to generate input parameters for the HAZUS-FAST. For each type of building, we measured flood risk by estimating the accumulated percentage of damage to its total value in a 30-year analysis. If the estimated risk is between 0 and 1, it means the total risk of a building in 30 years will be lower than the total value of the building. Otherwise, it will be higher than the total value of the building.

4.4. Machine learning model for land suitability analysis

We applied the gradient boost machine (GBM) in land use change suitability modeling with various variables. Land use suitability can be generally understood as a measure of the likelihood of a land parcel for a specific purpose. GBM is an ensemble learning technique that converts a group of weak machine learning predictors into strong learners (Tao & Cao, 2022). More specifically, the gradient boost decision tree (GBDT) model was used in the land use suitability modeling. In GBDT, each decision tree is fit on a modified version of the original dataset. In this study, we chose the AdaBoost algorithm from the Scikit-Learn library to build our model. The AdaBoost first trains a decision tree by treating each observation in the training sample with equal weight initially. After training the first decision tree, the weights of variables will be adjusted based on the previous decision tree. More specifically, the weights will increase for samples that are difficult to classify and decrease for samples that are easy to classify. The AdaBoost will also assign higher weights to trained classifiers with higher accuracy. Therefore, the final model is added up by a sequential of decision tree models.

Multiple spatial variables, including census tract level sociodemographic information and accessibility, POI data, DEM, slope, flood risk information, distances to roads and road densities, and percentage of developed land in the neighborhood, were used as inputs to train the gradient boost decision tree model. We listed details of these variables in the SI. As shown in Fig. 2, the model was further calibrated and validated for generating land use suitability maps. After we obtained the trained land use suitability model, we combined it with a set of criteria to simulate urban land use changes.

In simulating future urban land use changes, we first excluded wetland, parks, protected area, and all buyout land from the candidate list of new developed land. For potential new development land, we defined the land use transition rules as follows: we measured both the probabilities of neighborhood influence and urban land transition probability from the GBDT. If the maximum value of neighborhood influence probability $p_{N,k_1,i}$ for land use k_1 of parcel i and the highest transition probability $p_{GBM,k_2,i}$ of urban land use k_2 of parcel i from the GBDT model have the same building land use code, we choose the max between $p_{N,k,i}$ and $p_{GBM,k,i}$. Otherwise, we choose either the $p_{N,k_2,i}$ or $p_{GBM,k_1,i}$, which has the same land use with the building land use code. In very rare cases, where the land uses with the maximum transition

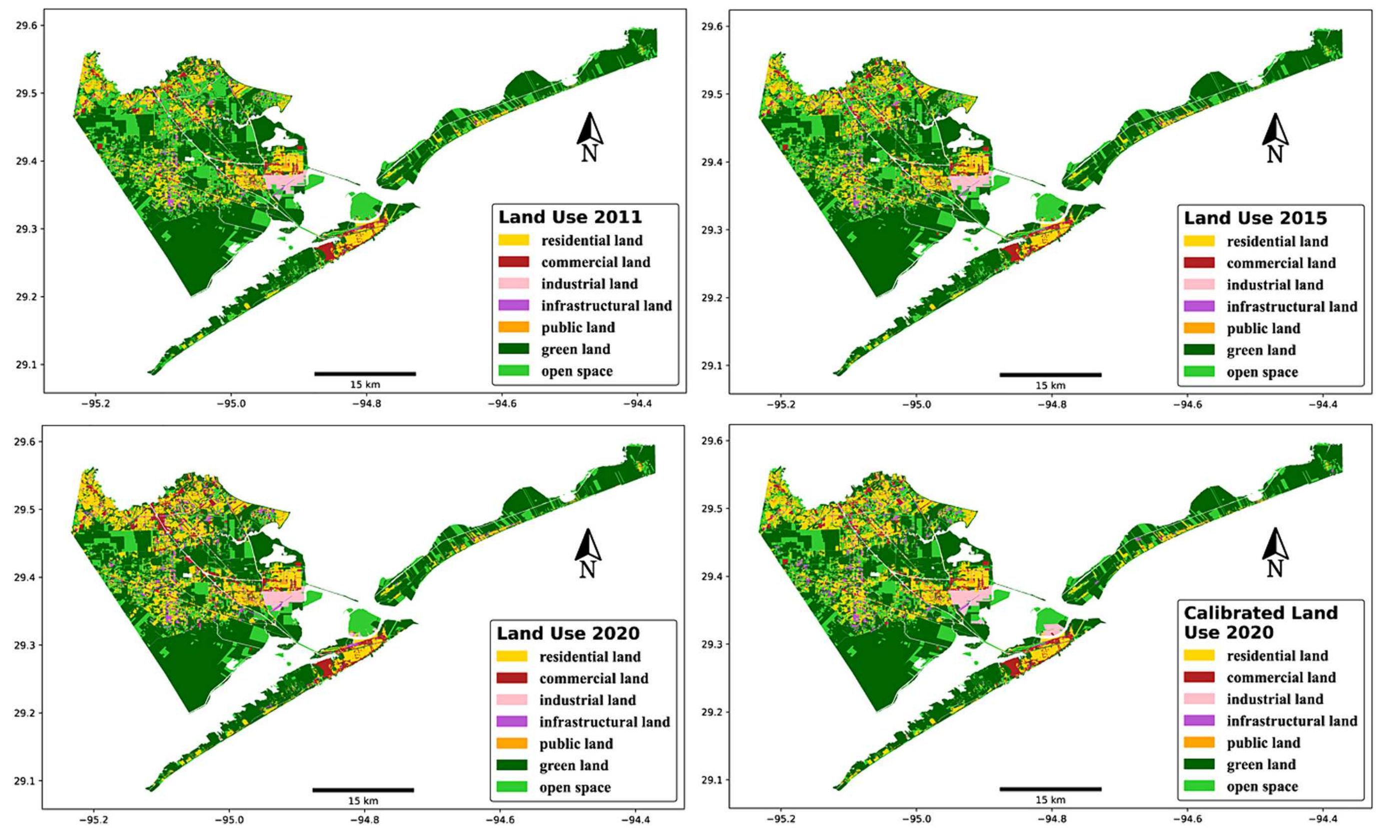

Fig. 4. Parcel land use data in 2011, 2015, and 2020 and validated land use in 2020.

probabilities in both the GBDT model and neighborhood influence are different from the building land use code, we choose the probability from the GBDT model. Relying on a linear relationship between the improvement value, land value, and areas of land parcels, we randomly generated an improvement value for new developed urban land.

4.5. Scenario design

We designed four relocation scenarios to simulate future land use changes in Galveston County by 2050, considering the impact of sea level rise. These scenarios incorporate future population changes, based on net migration data in the county, and sea level rise projections from historical data, serving as the boundary conditions for our model. Scenario 1 focuses on government buyouts of high-risk properties, where the existing flood risk exceeds their property values. New urban developments are simulated relying on land use transition rules. The amount of new urban developments is estimated based on population projections in the county. Additionally, the areas vacated by relocation will be added back to the new urban development demand in the next year, implying that property owners will move to new locations in the county. To preserve existing natural resources, land parcels with natural resources, such as beaches, wetlands, and parks, were not allowed to change to other land uses.

In Scenario 2, we assume the county officials of Galveston County will enforce a buyout policy targeting properties in high-risk flood zones. Targeted regions encompass land parcels in flood V zones and certain A zones within 2 km of the coast. Based on previous buyout requirements, only properties with a value of less than $275,000 will be included in the buyout plan (Siders & Gerber-Chavez, 2021). We assume building owners will evaluate their relocation decisions by comparing the total costs and benefits of the acquisition. If the total flood risk and cost of building, including flood insurance costs in 30 years, is higher than the total value of the building, the property owners will agree to relocate to new locations within the county. We estimated the annual insurance costs of households using FEMA's insurance rates table (Han et al., 2022). Different from Scenario 2, Scenario 3 adopts a forward-looking strategy, evaluating buildings in all flood A zones and the V zones. Building flood risk will be dynamically updated every 10 years, reflecting the latest sea level rise projection. The relocation decision will be the same as Scenario 2, however, relocated property owners do not relocate to low-risk areas within the county. This scenario aims to access potential population loss due to sea level rises. Since our population migration data indicates sudden population loss in the county due to coastal flood damages, we conducted 100 Monte Carlo simulations in Scenario 4 based on the GPD distribution to estimate the likelihood of properties experiencing repeated flooding. Properties with over a 50 % chance of recurring flood damage are marked for relocation or buyout. Like Scenarios 3, new developments are prohibited in the buyout regions in this scenario.

5. Results

We integrated the trained GBDT model in the developed parcel land use model. Fig. 3 illustrates the spatial distributions of key parcel attributes used in our land use change simulation. These variables include average ground elevation of parcels, distances to rivers and the coast, calculated parcel flood risk in damage to value ratios, estimated building first floor height, existing improved value of parcels, and estimated insurance costs for residential and commercial buildings. In general, Galveston County has lower elevations in the southeast areas, but areas on the south coast, east coast, and Galveston Island have more buildings. This result reflects the high exposure of buildings to flooding in Galveston County. The calculated first floor elevation suggests private adaptation by elevating their buildings above ground level to mitigate flood risk. Our results indicate that, on average, buildings situated in low-lying areas tend to have a higher elevation relative to those in areas

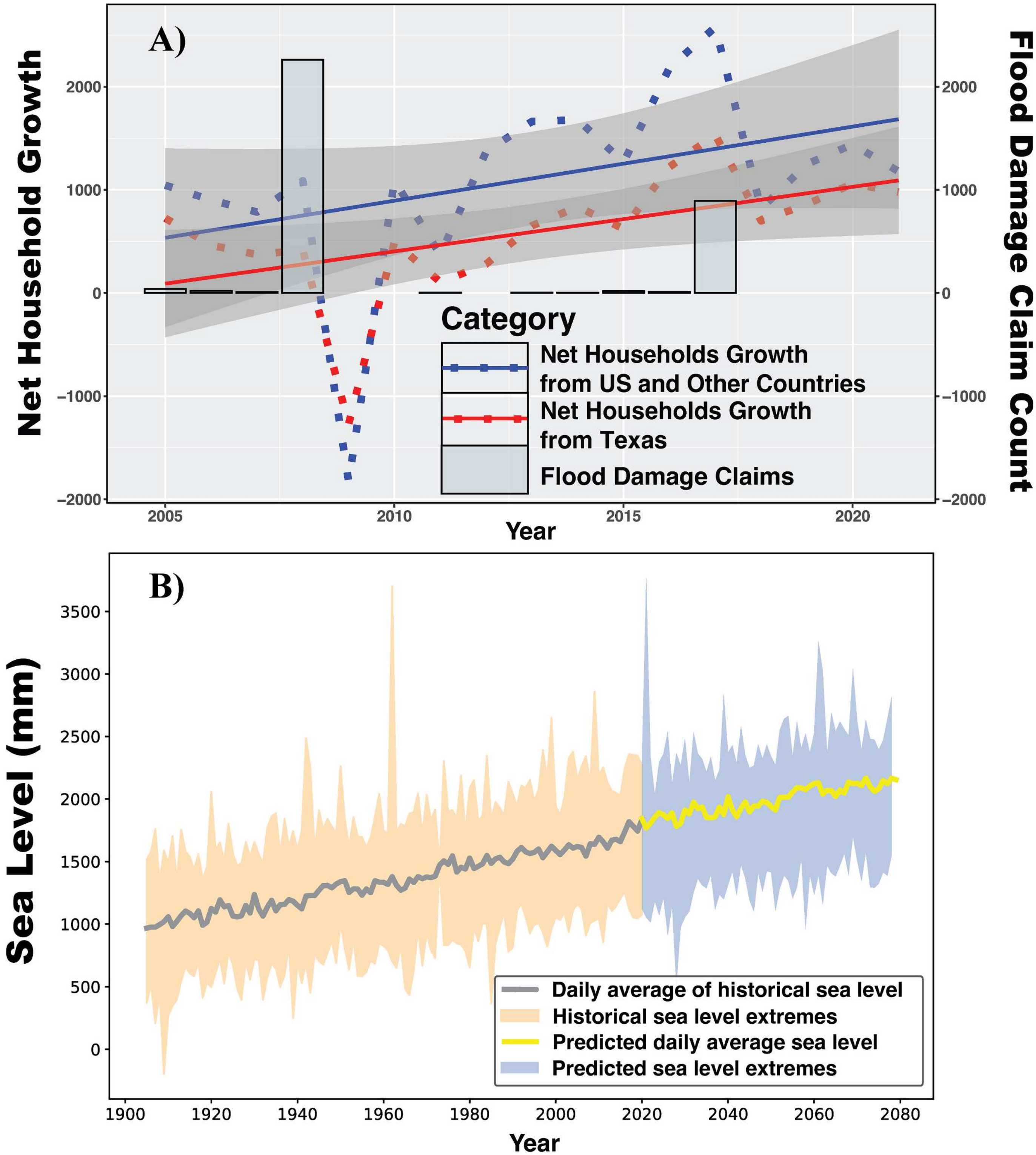

Fig. 5. A) Historical population trends and flood damage claims in Galveston County, Texas; B) Projected sea level changes based on historical data in Galveston, Texas.

with higher ground elevations.

We developed the calibration model using parcel land uses in 2011 and 2015, then we applied land use data and the calibrated land use suitability model in 2015 to validate model results in 2020. Fig. 4 shows land use of parcel data in 2011, 2015, and 2020, and validated model results in 2020. By comparing parcel to parcel land uses, the validated model accuracy is about 93.7 %, which is high enough for scenario-based land use simulation. Over the past 10 years, urban land use in Galveston County increased substantially in the north and northwest. Because of restrictions on building codes, new urban developments are limited near the south coast. Our simulated land uses in 2020 have a high consistency with parcel land uses of 2020, with small areas of differences in the County.

We integrated the developed land use suitability model above with

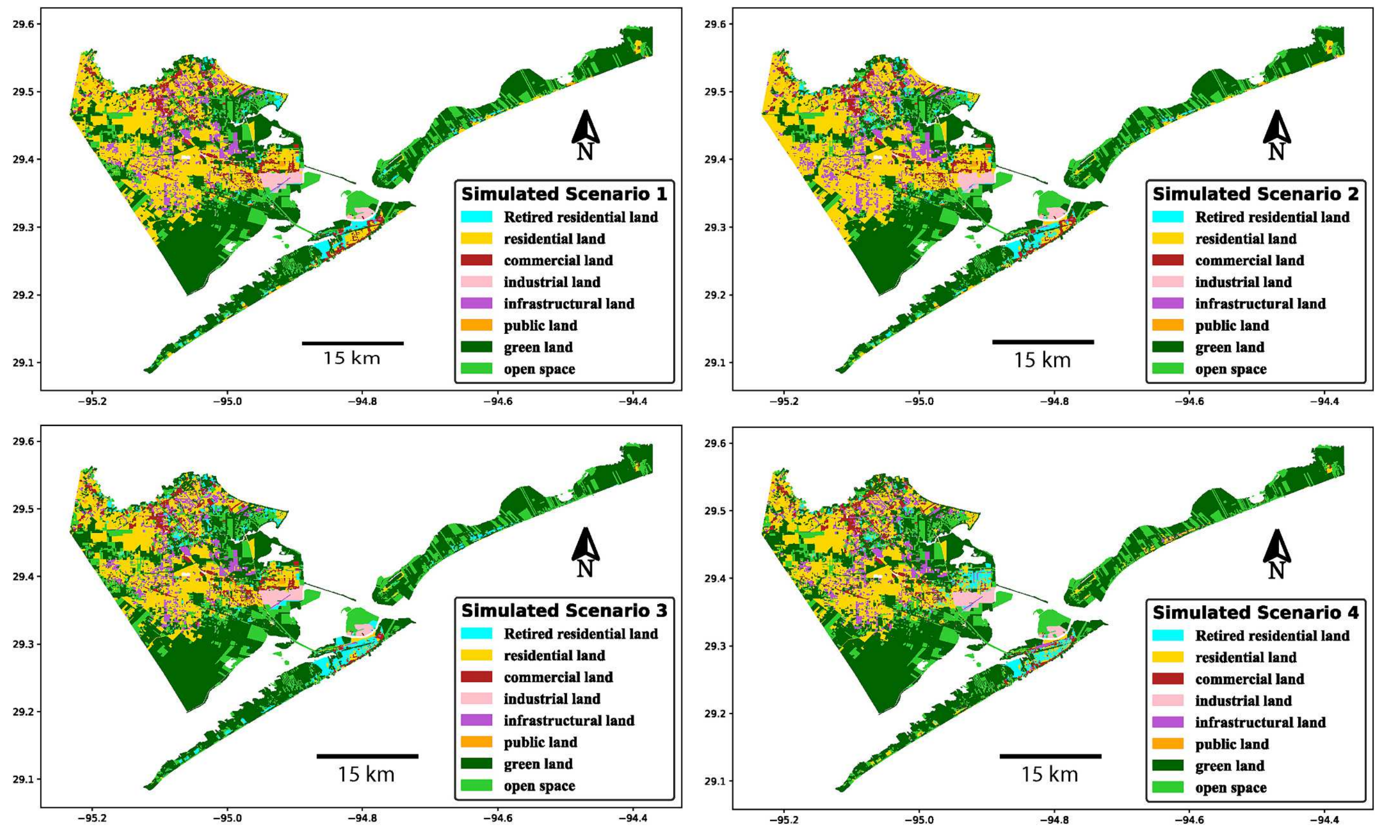

Fig. 6. Land use projections in 2050 excluding building first floor heights in different relocation scenarios.

the population forecast and the sea level rise projection to simulate four scenarios of future land uses by 2050. To forecast future population trends, we applied a linear predictive model, and for projecting future sea level rise, we utilized the SARIMAX time series model based on historical relative sea level data dating back to 1900. We measured the population change as net household growth and sea level trends in millimeters, as depicted in Fig. 5. Fig. 5(A) indicates an overall increasing trend of population migration for both in state migration and total migration, while there are fluctuations, including abrupt declines and subsequent recoveries in net population growth. A comparison with annual flood damage claims from FEMA's flood insurance dataset for Galveston County reveals a correlation that significant population drops tend to follow years with high flood damage claims. This pattern indicates that coastal disasters could temporarily reduce population in the area. Fig. 5(B) presents yearly mean sea level data dating back to 1900. It is evident that a significant temporal trend of rising mean sea level is observed in history, with the mean water level having increased by more than 1 m over the course of the past century. To incorporate impacts of future sea level rise in the area, we analyzed over a century's historical daily relative sea level observations from Galveston. We applied the SARIMAX regressors model to estimate the mean, the maximum, and the minimum temporal trends of sea level, as depicted in Fig. 5(B). The projected maximum and the minimum sea level trends offer insights into potential extreme events. Our focus for accessing future impacts of sea level rise is on the projected mean sea level trends. This approach provides a more accurate prediction of the impact of mean sea level rise, rather than extreme and less frequent occurrences.

Despite we estimated the average first-floor heights of buildings using a linear model, it is possible that not every building will meet retrofit requirements for first-floor elevation from the FEMA. To understand the impacts of first-floor elevation on simulation outcomes, we analyzed the simulated model results under different scenarios, both including and excluding first floor elevations. Fig. 6 and Fig. 7 show simulated scenario results excluding building first floor heights. Fig. 6 presents the projected land uses by 2050 under different relocation policies. In scenario 1, we considered relocating only high-risk properties, which have flood risk damage to building value ratio above 1. This led to new urban land developments primarily in green land and open space on the central and northwest of the county. In Scenario 2, the government acquires high-risk residential buildings within 2 km of coastal flood zones. As a result, more buildings in flood-prone areas would be relocated due to high flood risk and utility costs. Subsequent urban development are observed in areas with higher ground elevations. Scenario 3 outlines a long-term, dynamic relocation plan with a forward-looking approach. Buildings will be dynamically evaluated their flood risk within 30 years based on the latest information on sea level rise and once the projected future risk exceeds the property value, the building will be retired. In Scenario 3, all residential properties that are within flood A zones or flood V zones will be considered in the buyout plan. Consequently, many properties in Galveston Island and the northeast coast are changed to retired buildings. Scenario 4 focuses on mitigating flood risk by removing buildings with repetitive flooding. This scenario, resembling a managed retreat, leads to significant property buyouts and relocation to higher grounds, especially for residents of Galveston Island and the eastern coast. This results in urban shrinkage in these coastal areas. Fig. 7 uses Monte Carlo simulation to depict community flood risk, taking into account the year of construction of new urban land. These dynamic assessment results indicate an increasing flood vulnerability in Galveston County, exacerbated by ongoing urban development and sea level rise. Scenarios 1 and 2 result in similar flood risk at the end of simulation period, suggesting that merely relocating properties without considering building elevation, as in Scenario 2, doesn't significantly reduce community flood risk. Community flood risk in Scenario 4 is markedly lower than other scenarios, attributed to extensive managed retreat. It suggests that even minor flood occurring frequently, also known as nuisance flooding during sunny days, could

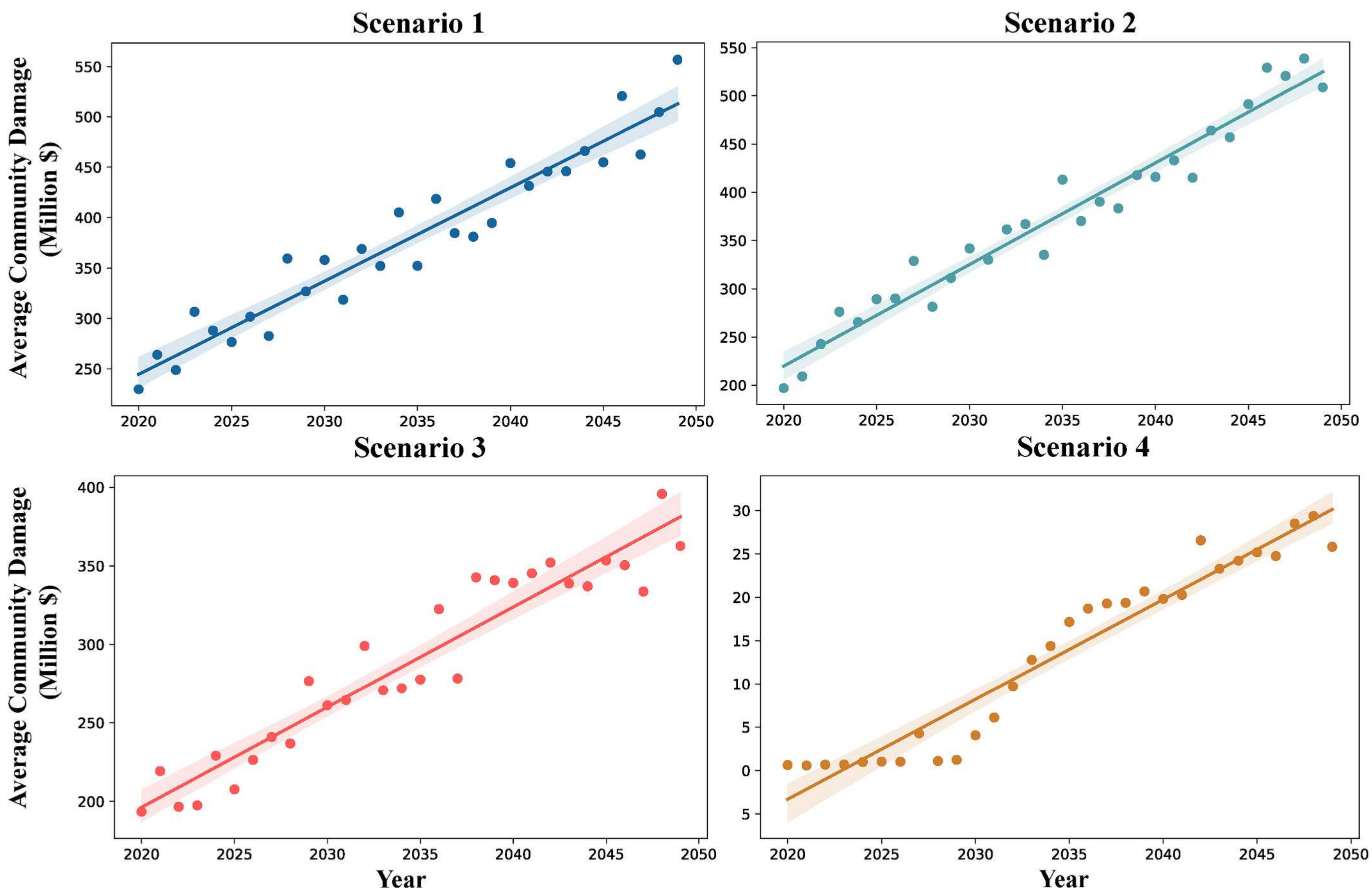

Fig. 7. Monte Carlo projections of community average flood damage in different relocation scenarios: impact of urban development and sea level rise, excluding building first floor heights.

lead to significant cumulative damage in vulnerable areas.

Fig. 8 and Fig. 9 present the outcomes of simulated scenarios that include buildings' first floor heights. These findings suggest that elevating buildings in vulnerable areas can effectively reduce overall flood risk, and lessen the costs need for extensive managed retreat. Fig. 8 shows that the whole county has few retired buildings under the current situation. However, a moderate number of buildings in coastal areas are projected to relocate under Scenario 2 and 3, with an increased number of retired buildings in Scenario 4, which indicates a proactive response in high-risk areas.

In Fig. 9, we observe that the average community damage in all scenarios is significantly lower than those depicted in Fig. 7, due to the elevation of properties in flood-prone areas. Notably, Scenario 4 in Fig. 9 demonstrates an annual community flood risk less than 4 million dollars after 30 years. This scenario indicates the most favorable adaptation outcome, combining managed retreat and private risk mitigation.

Table 2 presents results across all scenarios, both including and excluding the elevation of building first floors. Simulated results include the areas of vacant land, the developed land in different time periods, the area and the number of retired urban land, and the total costs associated with retired land. In the first decade of simulation, there is notable increase of urban land in Scenario 1 and 2 attributed to the compensation of relocated land areas. Consequently, the growths of new land from 2020 to 2030 in these Scenarios are significantly more pronounced compared to subsequent periods. When buildings' first floor elevations are considered, the area of retired land are considerably less than in scenarios excluding building first floor heights. This, in turn, leads to substantially less total costs in relocation.

6. Discussion

Although land-based adaptation strategies, like property buyouts and managed retreat, are often critiqued for being inefficient, costly, and political controversial, they are increasingly important due to the escalating risk of populations to coastal flooding (Hauer et al., 2021). Above modeling results reveal the disparate impacts of coastal flooding under different relocation policies and individual risk mitigation efforts in reducing community flood vulnerability under sea level rise.

The extreme value analysis indicates that the non-stationarity in historical sea level data primarily stems from the trends in sea level rise. By removing these trends, the sea level data is stationary. This allows us to model the coastal flooding risk through modeling the extreme value distributions and the temporal trends of sea level rise separately. This approach enables us to incorporate effects of both extreme events and sea level rise into flood risk modeling. A limitation of our analysis is the exclusion of the high uncertainty surrounding future sea level rise due to climate change. We based our model on a stable environment following historical trends. Nevertheless, even without considering the uncertainty, the risks of coastal floods and sea level rise pose significant challenges to coastal communities. Private adaptation measures are essential for mitigating existing flood risk. Thus, integrating effective enforced risk mitigation and property buyout policies in vulnerable areas is crucial to foster resilient communities.

Federal programs often require cost-share or investments in technical staffs by local governments. For example, the Hazard Mitigation Assistance statistics from FEMA shows cost-sharing ratios between federal and local governments for various acquisition projects, ranging from 50 % to 90 %, which can be challenging for financially limited local governments (Bukvic & Borate, 2021). Our scenario results show that

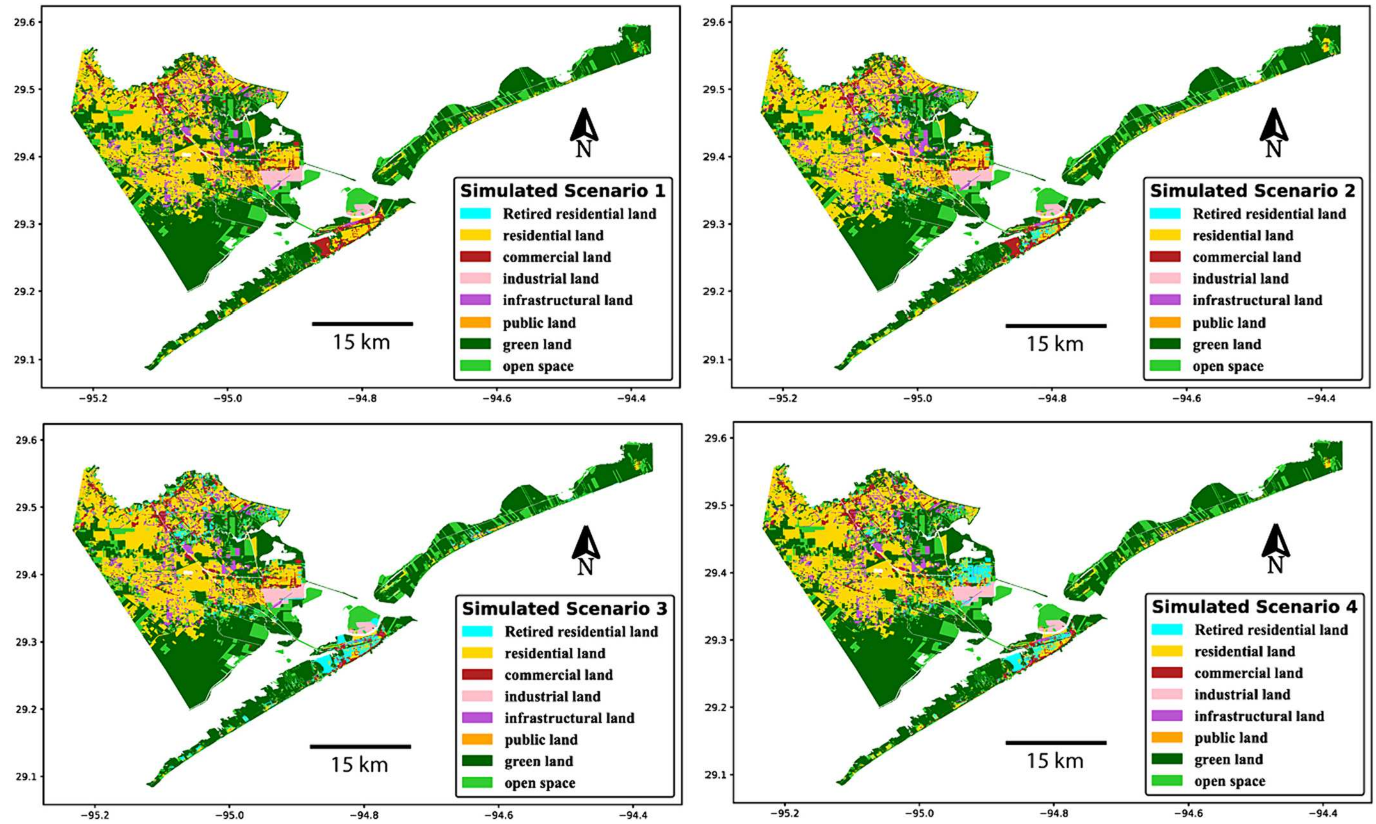

Fig. 8. Land use projections in 2050 including building first floor heights in different relocation scenarios.

community flood risk can be significantly mitigated by removing buildings with repetitive flood risk, especially when this is combined with strategies for raising buildings' first floor heights. To balancing long-term sustainability needs with the challenge of rising sea levels and increasing flood risk, it is crucial to promote private adaptation through incentives for property owners and to develop a tailored relocation strategy that addresses the distinct needs of individual stakeholders and the capabilities of local governments. Our scenario analysis also indicated that if buyout participants relocate to lower-risk areas within the county without pursuing private adaptation, government-supported buyouts alone may not be able to effectively mitigate community flood risk. Nevertheless, if properties are successfully relocated outside of the hazardous area, the property tax base of the local government would be reduced. Incorporating these financial considerations into future model simulation would be important for developing effective climate adaptation strategies for Galveston County.

7. Conclusion

This study developed a comprehensive parcel-level land use change model encompassing various components and scenarios of land use and flood risk mitigation in Galveston County, Texas. By incorporating population change forecasts and future extreme events modeling using empirical datasets, our model results paint a picture of dynamic and evolving landscape in response to environmental changes in a highly vulnerable coastal community of the US. Our findings offer valuable insights into the efficacy of future urban development patterns and community flood risk under population growth, sea level rise, and managed retreat strategies. The validated model results show a high accuracy and provide a reliable approach for future urban planning. The developed cadastral parcel-based model could reflect ownership of land units and facilitate coastal land management in response to sea level rise.

Our results reveal that elevating first floor of buildings significantly reduce the extent of required land relocation and associated costs. This adaptation for buildings not only reduces community flood risk, but also makes managed retreat more manageable and less expensive. In scenarios where building first floor elevation is considered, the retired land area and total community flood damage are markedly lower. Under relocation policies, especially in Scenario 3 and 4, the land development patterns indicate a shift toward more resilient urban development. Despite the effectiveness of these strategies, the financial burden on local governments to implement large scale managed retreat strategies highlights the need for a holistic approach to policy-making that considers both economic and environmental sustainability. Future studies could more focus on developing affordable managed retreat strategies (Siders, 2019b), incorporate social equity in relocation analysis (Shi et al., 2021), and also include future sea level rise uncertainties under climate change (White et al., 2021). Nevertheless, the dynamic interactions between flood risk, sea level rise, and population changes in coastal communities cannot be ignored. The findings observed in this study in response to sea level rise and population migration could build a foundation for future research on local adaptation actions to climate change challenges.

In conclusion, measuring community resilience under different adaptation policies require a multidisciplinary approach to integrate urban planning, hydrological simulation, climate science, and social science in the modeling process. Our developed model demonstrates that a multifaceted approach in flood risk mitigation, combining private adaptation measures such as building elevation with government-led initiatives like managed retreats and property buyouts, is crucial for building resilient communities.

Funding

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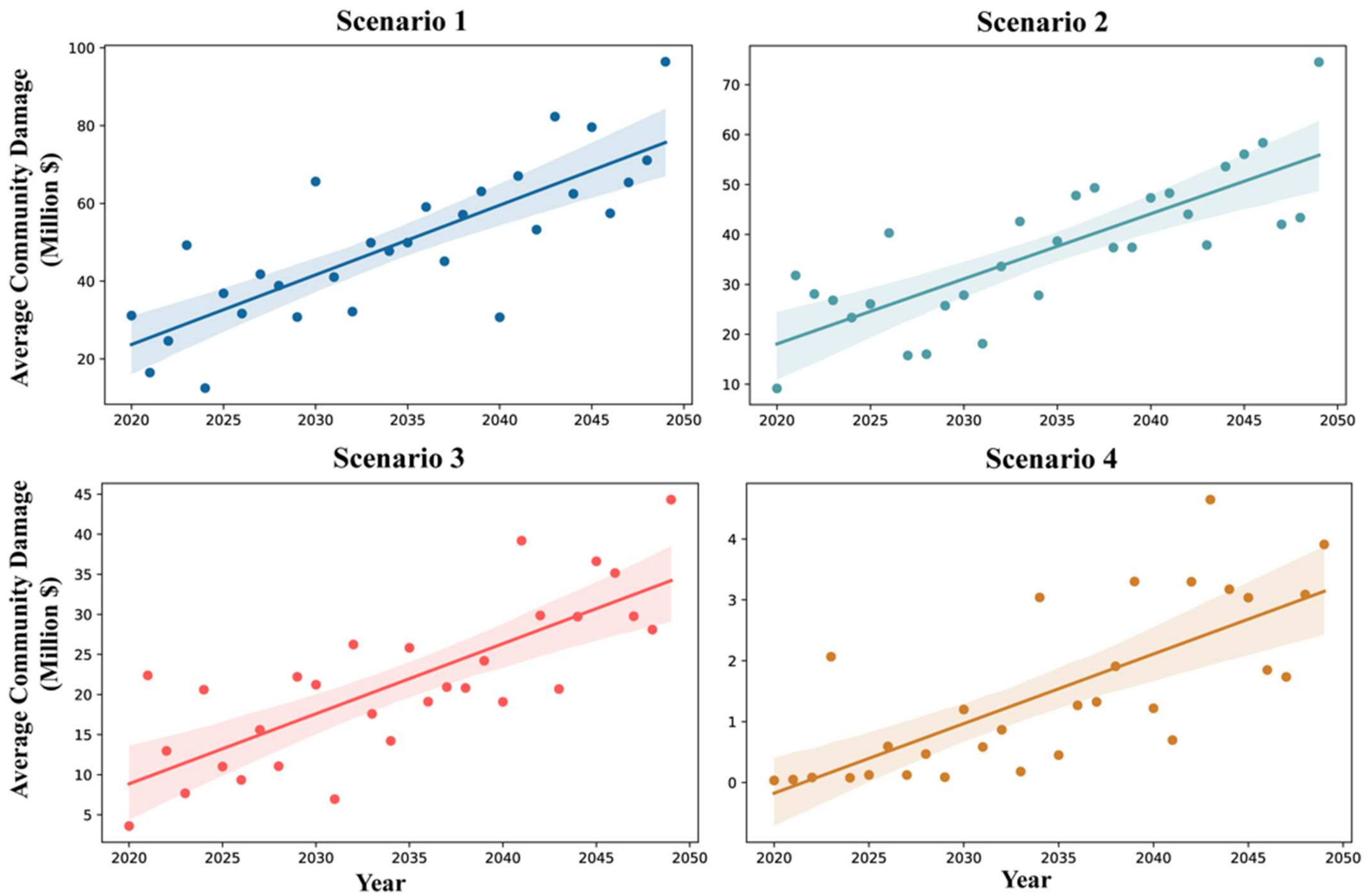

Fig. 9. Monte Carlo projections of average flood damage in different relocation scenarios: assessing impacts of urban development, sea level rise, and building first floor heights.

Table 2
The simulated areas of developed undeveloped, and retired land in different scenarios.

Land use change	First floor height	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Area of undeveloped land (km^2)	Excluding First Floor Height	539.53	517.45	497.70	516.14
	Including First Floor Height	530.10	504.15	505.07	521.51
Area of developed land Before 2020 (km^2)	Excluding First Floor Height	254.80	220.46	245.59	224.79
	Including First Floor Height	276.50	256.60	248.42	245.23
Area of developed Land 2020–2030 (km^2)	Excluding First Floor Height	94.24	171.39	55.99	62.10
	Including First Floor Height	64.10	82.07	57.87	58.40
Area of developed Land 2030–2040 (km^2)	Excluding First Floor Height	56.16	51.62	57.45	57.68
	Including First Floor Height	51.56	55.41	54.80	59.96
Area of developed Land 2040–2050 (km^2)	Excluding First Floor Height	48.54	69.47	51.46	47.27
	Including First Floor Height	47.66	48.76	53.71	44.38
Area of retired land (km^2)	Excluding First Floor Height	39.41	58.60	62.36	62.58
	Including First Floor Height	0.63	23.56	50.69	41.09
Number of retired land parcels	Excluding First Floor Height	23,490	39,773	44,076	47,898
	Including First Floor Height	198	23,695	34,217	37,298
Total costs of retired land parcels (million)	Excluding First Floor Height	2443.53	5517.16	6804.28	8848.93
	Including First Floor Height	2.78	3142.66	4938.25	5531.11

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CRediT authorship contribution statement

Yu Han: Conceptualization, Data curation, Formal analysis, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Xinyue Ye:** Project administration, Writing – review & editing. **Kayode Atoba:** Writing – review & editing. **Pallab Mozumder:** Writing – review & editing. **Changjie Chen:** Visualization. **Bastian van den Bout:** Writing – review & editing. **Cees van Westen:** Writing – review & editing.

Declaration of competing interest

The author is an Editorial Board Member/Editor-in-Chief/Associate Editor/Guest Editor for Cities and was not involved in the editorial review or the decision to publish this article.

Data availability

The datasets supporting the findings of this study are comprehensively included within the article and its supplementary data. The analytical figures and results were generated using Python, with the corresponding code available at our Github repository: https://github.com/yuh2017/retreatfromfloodzone.git.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cities.2024.104953.

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