Considering Time-Varying Factors and Social Vulnerabilities in Performance-Based Assessment of Coastal Communities Exposed to Hurricanes

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Abstract: Climate change, population dynamics, the aging of built infrastructure, and their growing complexity have gradually increased the vulnerability of coastal communities around the world. Among the many critical coastal infrastructures, the residential coastal building stock has exhibited significant vulnerabilities in past storm and hurricane events. Beyond the initial impact of these hurricane events on the built environment, coastal communities struggle to recover even years after landfall. Moreover, the initial shock as well as the recovery phase do not evenly affect all sectors of the population and frequently uncover social vulnerabilities and inequalities in the preparedness, response, and recovery from disasters. This study explores and expands a performance-based coastal engineering (PBCE) framework that allows for consideration of time-varying aspects of the hazard, depreciation, and aging or deterioration of coastal structures and infrastructure systems by applying it to evaluate the future performance and recovery of a portfolio of residential structures subjected to surge and wave loads. Using the residential building stock of Galveston, Texas as a case study, a Bayesian network framework is leveraged to evaluate the uncertain damage and subsequent recovery of the portfolio for the years 2030 and 2050, and correlations with representative social vulnerability factors are drawn. The correlation analysis between immediate damage and social vulnerability factors, as well as between the recovery index and social vulnerability factors up to six years following the storm landfall, is pursued to expose potential disparities in the impact of the storm to different sectors of the community in the short- and long-term. Results show that changing climate conditions exacerbate the probability of failure of the building stock and associated housing recovery. Also, the correlations in the short- and long-terms show that the elderly and women might be most at risk in future hurricane events. The incorporation of multi-structure systems and time-varying factors in the performance assessment framework is of great importance to inform resilience and adaptation engineering models, in particular, when the effects of chronic hazards, a growing population, and increases in asset values are expected to grow in the future. The methodology and case study also provide useful tools to inform planning and decision-making, resilience assessment, and facilitate recovery efforts in coastal settings while accounting for the impact of the hazard on vulnerable populations. **DOI: 10.1061/(ASCE)ST.1943-541X.0003400.**

Introduction

Coastal regions are not strangers to the seasonal impact of hurricane hazards. However, during the last decades, the impact of storm and hurricane events on coastal communities has been growing at a significant pace and has exposed the high vulnerabilities and even unpreparedness of our modern societies to cope with the changes in storm frequency and intensity (Chu et al. 2021; Cui and Caracoglia 2016; Cutter 2020; Hallegatte et al. 2013; Pant and Jeong Cha 2019). As our societies thrive on the economic advancement and opportunities that coastal areas offer (e.g., port and trade activity, tourism, energy, and industrial sectors), the changing climate has been paralleled by significant growth in assets, businesses, and population. These rapid changes have not only increased the exposure in coastal areas but also have had a significant effect on the social systems and urban organization of these regions.

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Among the different infrastructure systems, the residential building stock has particular importance in the well-being and dynamics of a community, being the primary unit of household activity. Nevertheless, its performance in past hurricane events has been far from ideal, as seen in Hurricane Ike (2008) and Hurricane Michael (2018), where widespread damage was observed to the residential building portfolio across communities (CNN 2018; FEMA 2009; KFDM YouTube 2012; Siegal 2020). The loss of residences not only has implications on the structure, development, and economy of the region (Binder et al. 2015; Pais and Elliott 2008; Wasileski et al. 2011), but also has deep repercussions on individuals' and families' lives, promoting migration (Curtis et al. 2015; Hori and Schafer 2010), homelessness (Chakraborty et al. 2021; Doran et al. 2016; Ramin and Svoboda 2009), and psychological stress, especially in children and adolescents (Goenjian et al. 2001; Kim and Sutley 2021; Vernberg et al. 1996). It is well documented and acknowledged in the literature that natural hazards do not affect all sectors of the population uniformly, but rather highlight disparities in the social structures of the community, disproportionately affecting vulnerable populations immediately after the event and in the years to follow (Markhvida et al. 2020; Pais and Elliott 2008; Peacock et al. 2014; Sutley et al. 2017; van Zandt et al. 2012).

Methodologies are required to assess how coastal communities will perform in future hazard events while considering the dynamic nature and vulnerabilities of the built, natural, and social systems of these areas. Performance-based engineering strategies have been

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successfully used in the past to assess built environment performance and have recently been expanded to evaluate post-hazard performance by incorporating functional recovery, resilience, and sustainability performance objectives (Cook 2021; Ellingwood et al. 2018; Lin et al. 2016; Minsker et al. 2015). However, these strategies generally fail to capture the temporal variation and disparities in the impact of future hazards, which are of extreme importance on coastal regions.

This study extends and expands a recently proposed performance-based coastal engineering (PBCE) framework (González-Dueñas and Padgett 2021) to the community scale in support of evaluating resilience and adaptation strategies. Beyond the conceptual and methodological advancement of PBCE, this paper offers new insights on the spatial and temporal evolution of dynamic processes in this unique coastal setting using residential structural portfolios and housing as a focal point. Specifically, the PBCE framework allows for consideration of time-varying aspects of the hazard under climate change, of economic factors such as the discount rate or asset depreciation, and of coastal structures and infrastructure systems related to aging and deterioration. A Bayesian network approach is posed to assess the performance of a portfolio of typical residential structures subjected to surge and wave loads in the years 2030 and 2050, using the residential building stock of Galveston, Texas. The damage assessment is then used to inform a recovery model that follows the recovery process of the community up until six years after the storm. Moreover, correlations between damage and recovery are drawn with representative social vulnerability factors at the block group level, which acts as the neighborhood unit in this study. The correlation between the social vulnerability factors and the damage and recovery of the community aim to shed light into the connections between the short and long-term hurricane impacts and the social structure of the area. This allows disasters to be evaluated as a dynamic process, where the impact of the storm is assessed in different layers (natural, built, and social environment) that interact with each other in space (hurricane impact on the region) and time (effects of damage in the recovery and social dynamics of the community in the years following the storm).

In the subsequent section of this paper, the methodological approach and extension of the PBCE framework are presented. Then, the performance (i.e., damage and recovery) of the building portfolio of Galveston Island is investigated for the years 2030 and 2050, leveraging the expanded PBCE framework. The impact of the immediate damage and the recovery process in the community is explored by computing their correlations with representative social vulnerability factors at the block group level. Finally, a discussion of the study findings is presented followed by concluding remarks. Table S1 presents a list of the abbreviations used in this article.

Performance-Based Assessment of Coastal Communities

The evaluation of the performance of structures under multi-hazard conditions is a key component of the risk and resilience analysis of coastal regions. When analyzing the impacts of hurricane or storm events on the built environment, two stages can be identified: the immediate effects and the recovery phase. The former refers to the initial damage undertaken by the structures due to the effect of the loads acting upon them during the event, and the latter describes the process of structural and functional restoration. The immediate effects are mostly driven by the robustness of the system, while the recovery is a complex process where socio-demographic, political, structural, environmental, and economic factors interact dynamically. This study leverages and extends the PBCE framework proposed by González-Dueñas and Padgett (2021) to analyze the immediate and long-term effects of hurricane and storm hazards at a regional scale. Fig. 1 presents the proposed methodology.

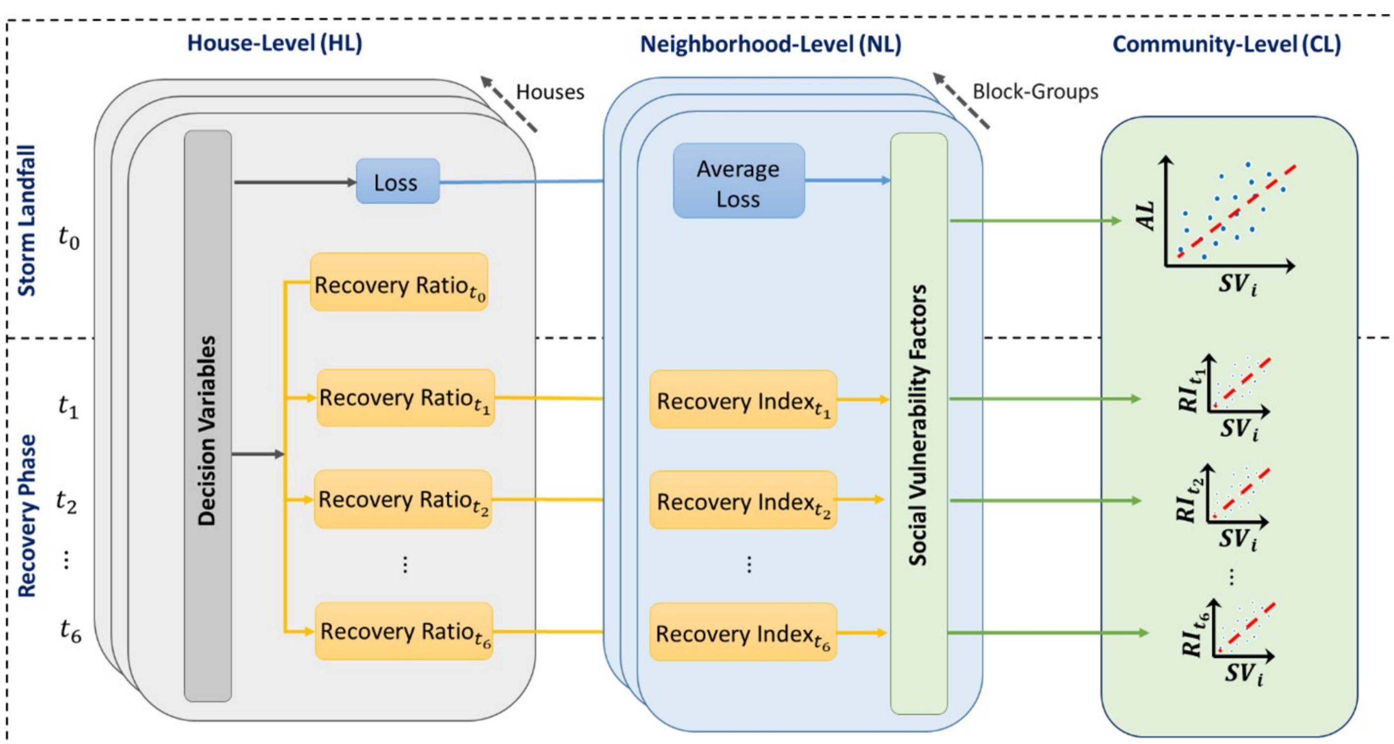

Fig. 1. Methodology proposed.

The performance of the built environment at a portfolio level is directly related to the individual building performance in the aftermath of a natural hazard event. Therefore, the first step of the methodology consists of computing the individual house performance, both in the short- and long-term, when subjected to surge and wave loads. In this study, the performance metrics of the built environment are associated with the losses in the aftermath of the event, and the building stock recovery in the years to follow.

Performance-based assessment of individual structures involves detailed information related to the loading conditions, the mechanical properties, the structural response, and damage sustained when compared to performance-objective targets or decision variables. In this study, the PBCE framework proposed by González-Dueñas and Padgett (2021) is leveraged to define the parameters of interest for the performance analysis of each house using a Bayesian network (BN) approach. A Bayesian network is a probabilistic graphical model defined by nodes and links, which represent the random variables of the system and their dependencies, respectively. This study leverages a BN (Fig. 2) to compute the marginal probability distribution of the loss and the recovery, the decision variables associated with the immediate and long-term effects of the storm. A numerical simulation is pursued using Markov chain Monte Carlo (MCMC) simulation, which allows estimation of the marginal distribution of any given random variable by generating samples from a Markov chain, avoiding the explicit computation of the integrals involved in the inversion of the joint probability density function of the network. Time-varying factors related to the hazard and mechanical properties of the structure are considered to compute the house expected loss and recovery ratio, which represent the two decision variables of the system, following a storm event in the years $t_0 = 2030$ and $t_0 = 2050$.

The first component of the PBCE consists of the hazard analysis, in which the intensity parameters are defined. As a proof of concept, the hazard in both years (2030 and 2050) is defined using a set of 19 synthetic variations of storm FEMA 33, which is a probabilistic storm that provides inundation levels of a 100-year return period storm in the Galveston, Texas region (Ebersole et al. 2017; Melby et al. 2017). Local sea level projections and the forward velocity of the storm are used to define the 19 storm combinations (Ebad Sichani et al. 2020), and are considered herein as the hazard parameters (i.e., parameters relevant to the numerical modeling of the hazard). The intensity parameters at a time t (the significant wave height H_s and surge depth S_d), are then defined using the polynomial regression models [Eq. (18) in the referred study] proposed by González-Dueñas and Padgett (2021), which provide the intensity parameters at the location of interest as a function of the hazard parameters. To probabilistically characterize the hazard parameters, a normal distribution is used to define the sea level rise projections and a uniform distribution to define the forward velocity of the storm. Leveraging the local sea level projections for Galveston provided by Kopp et al. (2014), a normal distribution is fitted for each year. A noninformative prior is used to define the forward velocity of the storm due to the high uncertainties on the effects of climate change on this variable. The limits of the uniform distribution are set as 3 m/s and 12 m/s, per Liu and Irish (2019).

The structural parameters for each house include the age (classified in age groups AG) and the elevation of the house with respect to the ground E_H, which are used to define the free-board height FB_{Hs} (distance between the wave crest and the lowest horizontal structural member of the house). The probability of failure P_f^{Fr} is assessed using Variant 5 of the fragility models proposed by Tomiczek et al. (2014), which is parameterized on the intensity parameters (H_s and S_d) and the structural parameters (AG and FB_{Hs}) of the house. The structural degradation is captured using a reduction factor R (Bjarnadottir et al. 2011), which modifies the value of the probability of failure obtained from the fragility model in such a way that $P_f = P_f^{Fr} \cdot (100 - R)/100$. Reduction factors of -15% (Nakajima and Murakami 2010) and -25% (Cavalli et al. 2016) are selected for 2030 and 2050, respectively (González-Dueñas and Padgett 2021). The assessed value of the structure in the year of analysis (2030 and 2050) is computed as the future value of the house based on the appraised value of the house in the year 2020 and the inflation rate per year, which is assumed as 3% in this study (Li and Ellingwood 2009). Finally, the replacement value of the structure UV, the housing characteristics HC (e.g., area, housing type), and neighborhood characteristics NC (e.g., income, race), inform the loss (DV_1) and the recovery ratio (DV_2), respectively. The loss represents the probable economic loss due to the structural failure of the house, which is computed as the product of the probability of failure of the house P_f and the replacement cost of the structure in the year under analysis UV. The recovery ratio computation is explained in the next section. More details on the model parameters and their dependencies can be found in González-Dueñas and Padgett (2021).

The second step of the methodology consists of aggregating individual building performance at the neighborhood scale. The short- and long-term effects of the storm in the built environment are neither uniform in space nor in time. For instance, neighborhoods might differ in their housing typologies, construction practices, and natural environment (e.g., presence of dunes, trees), which creates differences in the loading conditions and, in consequence, in the expected damage. Moreover, sociodemographic characteristics also vary across neighborhoods and these disparities lead to marked differences in the response and recovery of the community in the aftermath of natural hazards. To capture these changes, the performance of individual structures is aggregated at the block group level, which in this study is considered as the neighborhood unit. In the short-term (t_0), the average loss of the neighborhood is computed using the mean losses of the houses located in it. Moreover, the recovery per neighborhood is estimated based on the number of houses reaching a complete recovery state (i.e., recovery index) in the years following the event.

At a regional scale, the impacts of natural hazards are mostly associated with the ability of its inhabitants to cope with the disaster, which depends on factors such as income and their ability to get loans (Hamideh et al. 2021; van Zandt et al. 2012). Therefore, the last step of the methodology consists of computing the correlation of the performance metrics of the built environment at the neighborhood scale with relevant social vulnerability factors, to assess differences in the storm impacts to different sectors of the population. As a proof of concept, the next section explores the application of the proposed methodology to assess the impact of storm events in the residential building stock of Galveston Island for two future scenarios, 2030 and 2050, while considering time-varying factors related to the hazard, system strength, and sociodemographic variables.

Building Performance under Time-Varying Conditions

Damage Evaluation

In this study, a database of approximately 14,000 housing units located in Galveston Island was used to define the structural parameters (i.e., age group and elevation of the house with respect to the

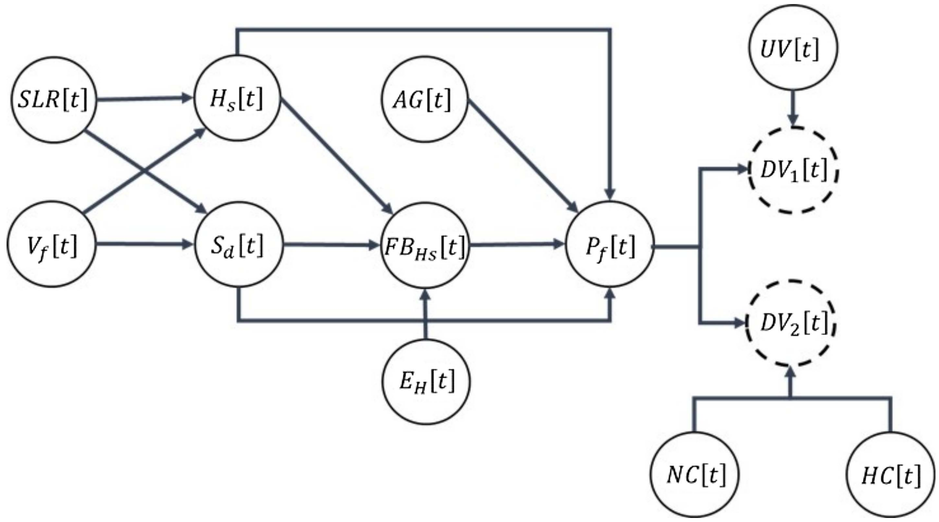

Fig. 2. Bayesian network of the system at time $t = 2030{,}2050$.

ground) of the building stock (Fereshtehnejad et al. 2021). For simplicity, the fragility model developed by Tomiczek et al. (2014) was used to compute the probability of failure of all the 14,000 housing units in the database since it is characteristic of the building stock of Galveston Island, its construction practices, and is representative of a hurricane event with predominantly storm surge and wave loads. It is acknowledged that this fragility function was specifically developed for elevated residential structures from a single storm event (Hurricane Ike 2008); thus, future work may seek to address the range of building archetypes and hazard conditions of interest since the PBCE framework and BN analysis are flexible to accommodate different fragility functions (Do et al. 2020; Hatzikyriakou and Lin 2017b; Masoomi et al. 2019; Massarra et al. 2019; Nofal et al. 2020). The python package PyMC3 (Salvatier et al. 2016) was used to analyze the Bayesian network model using an MCMC approach—an approximate inference algorithm (Yildirim 2012). For each house, five chains were used to obtain 50,000 samples after the tuning process (Gelman and Rubin 1992; Yildirim 2012), which discarded 5,000 initial samples from each chain.

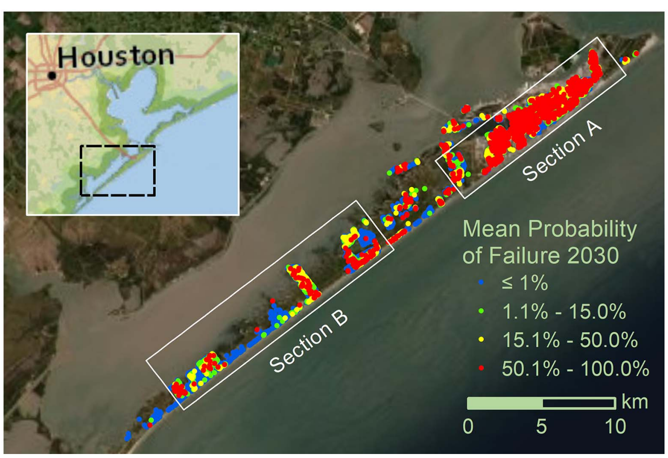

Fig. 3. Mean probability of failure of the building stock of Galveston Island, TX for the year 2030. [Upper left base map from Esri, DeLorme, HERE, USGS, Intermap, iPC, NRCAN, Esri Japan, METI, Esri China (Hong Kong), Esri (Thailand), MapmyIndia, TomTom; lower base map from Esri, DigitalGlobe, GeoEye, i-cubed, USDA FSA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community.]

Fig. 3 depicts the mean probabilities of failure obtained from the BN analysis of the residential structures for the year 2030. Moreover, Fig. 4 shows the comparison by zones of the estimated mean probability of failure of the building stock for the years 2030 and 2050. The houses located in the urban core of Galveston Island (Section A) presented a higher probability of failure compared to the southwest region (Section B), for both 2030 and 2050. This is due to the fact that the houses in the urban core are older, and therefore, were constructed with less stringent code requirements (e.g., lower elevation above the ground). Moreover, given that the mean probability of failure was mostly driven by the water level reaching the structure, the higher levels of surge depth in 2050 caused an increase in the probability of failure between the two years. For instance, the percentage of houses that do not suffer any damage ($P_f < 0.1$) decreased from 54% in the year 2030 to 45% in the year 2050. Similarly, the percentage of houses in intermediate ($0.15 < P_f < 0.5$) and extensive damage ($P_f > 0.5$) states increased from 8% to 13%, and from 16% to 20%, respectively.

To analyze the impact of the event on the community, the spatial distribution of the mean loss by the block group for the years 2030 and 2050 is presented in Fig. 5. The mean loss at the block group level was computed from the mean loss of its individual houses whose distribution was evaluated using the Bayesian network presented in Fig. 2. As expected, the losses by the block group were higher for the year 2050, due to the observed increase in the probability of failure of the building stock. More specifically, the percentage change between 2030 and 2050 in average loss per block group ranged from a minimum of an 86% increase to a maximum of a 245% increase. In terms of the total loss for the region, the mean average loss for Galveston Island increased from \$0.51 billion in the year 2030 to \$1.18 billion in 2050, showing an increase of approximately 57%. Fig. 6 shows the distribution of the total loss for both years.

Recovery Phase

The recovery process of the community was explored based on the gradual recovery of each house in the years following the event. As a proof of concept, the recovery model proposed by Hamideh et al. (2021) was used to compute the trajectory of recovery for

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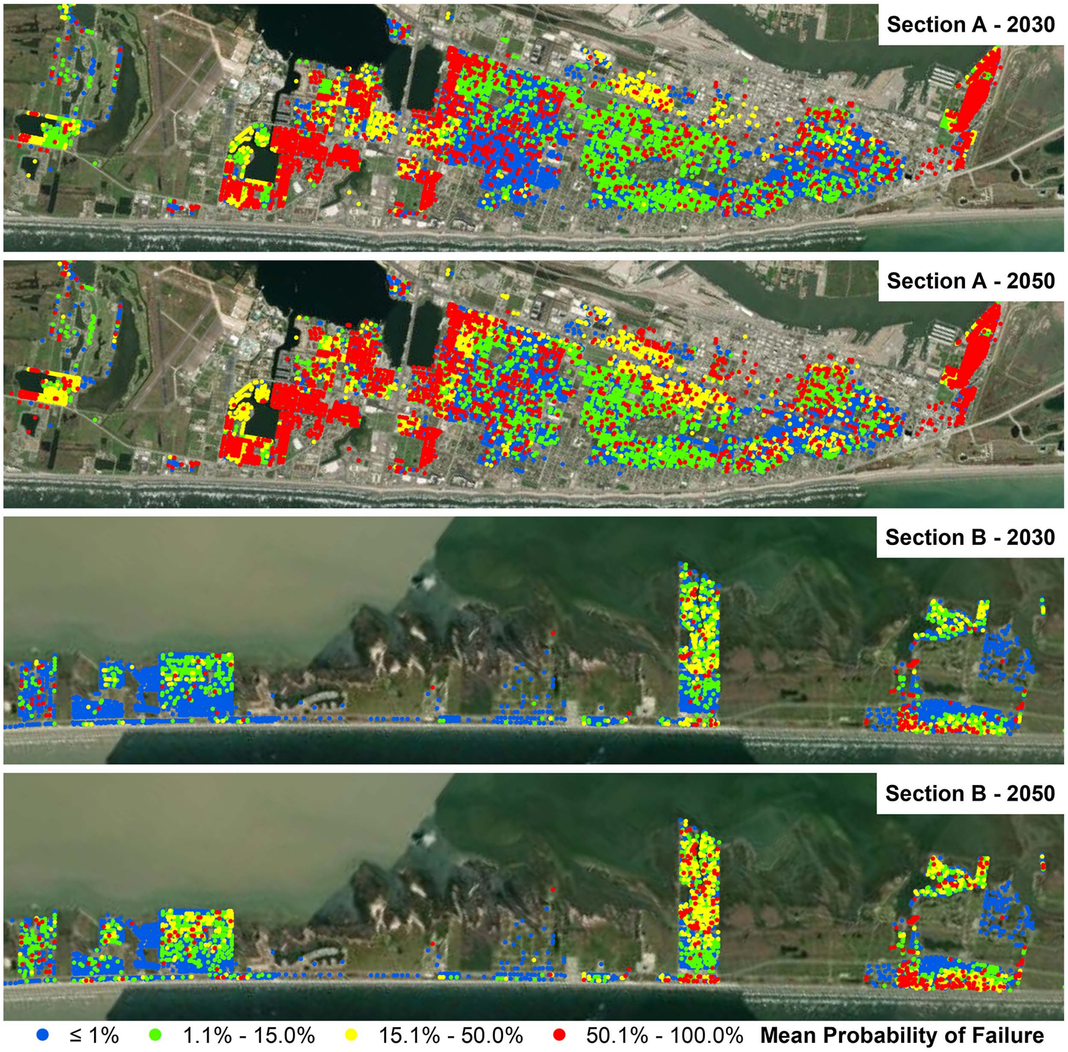

Fig. 4. Comparison of the mean probability of failure of the building stock of Galveston Island, TX for the years 2030 and 2050 by zone. (Base maps from Esri, DigitalGlobe, GeoEye, i-cubed, USDA FSA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community.)

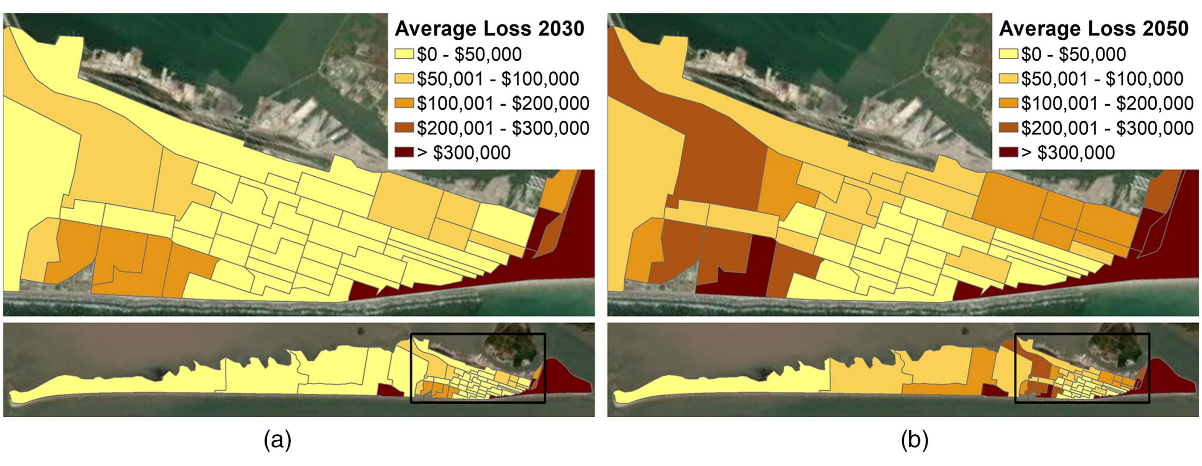

Fig. 5. Average loss per block group for the years (a) 2030; and (b) 2050. (Base maps from Esri, DigitalGlobe, GeoEye, i-cubed, USDA FSA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community.)

each house under analysis. This information was then used to compute a recovery index per block group, which allowed estimating the relative recovery of different neighborhoods up to six years following the event for the years 2030 and 2050. Nevertheless, the proposed methodology can be easily adapted to any model that provides a dynamic evaluation of the performance and recovery trajectory of the built infrastructure in the aftermath of hurricane events.

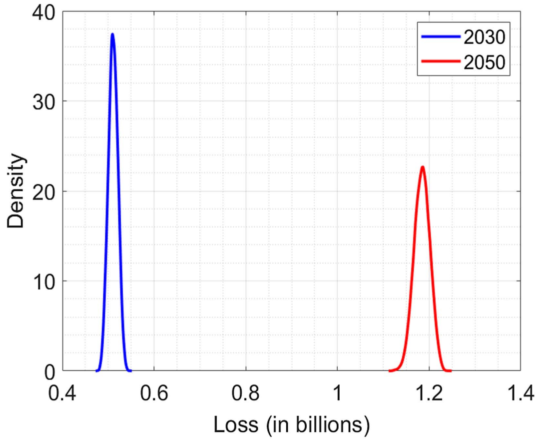

Fig. 6. Distribution of the total loss for the years 2030 and 2050.

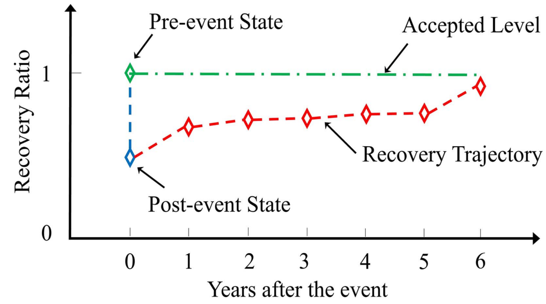

Fig. 7. Damage and recovery trajectories.

This recovery model tracked the changes in improvement value of more than 13,272 houses in Galveston County following Hurricane Ike, from 2008 (base year) until 2015, using publicly available data from the tax appraisal district, to formulate a predictive model of the house recovery rate. The multilevel linear regression model [Eq. (1) of Hamideh et al. (2021)] provides the natural logarithm of the assessed value in the years following the event and is parameterized on housing and neighborhood characteristics. The coefficients of the predictive model are provided in Table 5 of Hamideh et al. (2021). The housing characteristics include the housing type (single-family, multi-family, or duplex), the age of the house in each year, its size, the percentage damage, and housing tenure status (i.e., owner-occupied or not).

The neighborhood characteristics consist of the median income and the percentage of the non-Hispanic Black and Hispanic per block group. Once the assessed values were estimated for the years following the event, they were normalized using the base year assessed value, or improvement value of the property (i.e., assessed value not including the value of the land) in the year that the event occurs, to compute a recovery ratio that ranges between 0 and 1. Recovery was achieved once the recovery ratio reaches 1 again (i.e., once the assessed value was equivalent to the assessed value of the base year). In Hamideh et al. (2021), the recovery model captured the drop in performance in the first year following the event. However, in this study, it was assumed that the drop in price in the year following the event was based on the damage suffered by the house due to the hurricane event in the previous year. Therefore, the base year and the first year were combined to characterize the immediate effects of the storm (year 0) and represented the pre- and post-event states of the house. The different states of damage and recovery used in this study are presented in Fig. 7.

In this study, the housing characteristics of the model were assumed to remain invariant for the years 2030 and 2050. Therefore, the housing characteristics, besides the percentage damage, were obtained based on tax appraisal data of Galveston County for the year 2020 (Galveston Central Appraisal District 2020) and spatially joined to the building stock database using ArcGIS—a geographic information system (GIS) software. In order to couple the performance model with the recovery model, the percentage of damage of the house was assumed to be equal to the probability of failure (P_f) of the house in the year of analysis (2030 or 2050). For houses that experience extreme structural damage [$P_f > 0.5$ per Hamideh et al. (2021)], it was assumed that the drop in the assessed value could not fall below 10% of its original value.

The neighborhood characteristics, which are available at the block group level, were estimated for both years of analysis, 2030 and 2050, based on county-level projections of gross domestic product (GDP) and population characteristics (Gaffin et al. 2004; Hauer 2019). Since all the houses inside a block group share the same value of neighborhood characteristics, it was assumed that the database of housing units was a representative sample to evaluate the relative trajectory of damage at the block group level and that the change in the number of houses did not need to be projected. However, if data related to future construction developments, such as building permits, is available, projections on changes in the housing characteristics can be incorporated into the methodology.

The percent increase of non-Hispanic Black and Hispanic per block group was approximated using the projections proposed by Hauer (2019), which provides the framework, associated codes, and complete output database of population projections by shared socioeconomic pathway (SSP). The SSPs describe "alternative pathways for future society" (Hausfather 2018) considering how socioeconomic factors can affect future emissions and were designed to be complementary to the representative concentration pathway (RCP) scenarios, which consider different scenarios of future greenhouse gas concentrations (Hausfather 2018). In this study, SSP2—the "middle of the road" scenario—was selected, which represented a future with medium challenges to mitigation and adaptation. The database provided projections for the period 2020–2100 in five-year intervals and was categorized by race (Black and Hispanic), age, and sex at the county level for the United States. Using the data for the SSP2, the percent increase of population by race was computed as the change in the percentage of Black and Hispanic populations from the year 2020 to the years 2030 and 2050, respectively. Since the projections were at the county level, the percent increase of non-Hispanic Black and Hispanic for the years 2030 and 2050 was applied uniformly to all the block groups of Galveston Island. The percent change of Black population for the years 2030 and 2050, were −0.676% and −1.649%, respectively. In the case of the Hispanic population, the percentages corresponded to 2.467% for 2030 and 6.947% for 2050.

Following a similar methodology, the increase in median household income per block group was estimated using the projected GDP percentage increase of the United States for the years 2030 and 2050 (Wear and Prestemon 2019). This was done using downscaled projections of GDP (CIESIN 2002; Gaffin et al. 2004) for the B2 SRES scenario (a preceding version of the modern SSP scenarios), which was comparable to the SSP2 scenario (Hausfather 2018). The percent increase in median household income for the years 2030 and 2050 were 11.12% and 37.99%, respectively.

Fig. 8 shows the recovery trajectory and associated uncertainty for a typical coastal elevated house for the years 2030 and 2050. The model uncertainty in the mean recovery ratio came from the propagation of uncertainty in the probability of failure of the house

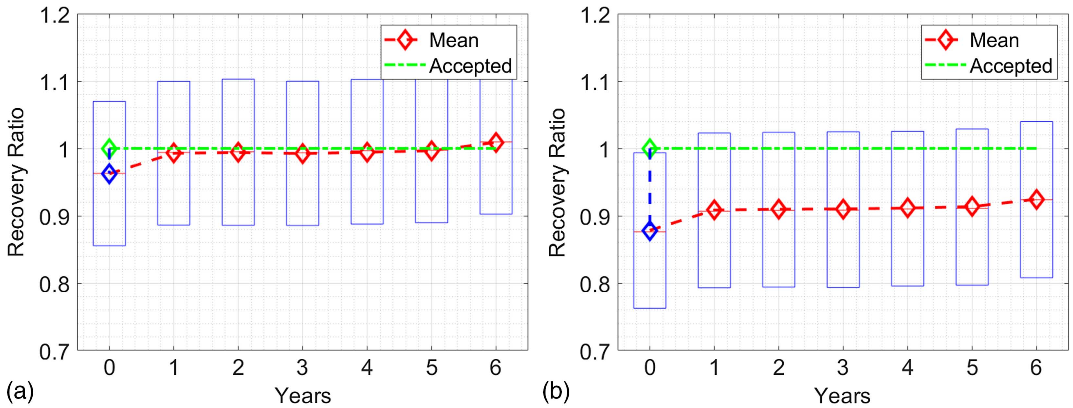

Fig. 8. Recovery trajectory and associated uncertainty for a typical coastal elevated house, for the years (a) 2030; and (b) 2050.

and from the error terms in the recovery model proposed by Hamideh et al. (2021). The house had an area of 124.86 m^2(1,344 ft^2), was a single-family house, and was owner-occupied. For the year 2030, its mean probability of failure was 32%, the median income was \$87,953.7, and the Hispanic and Black population percentages were 5.48% and 0%, respectively. For the year 2050, the mean probability of failure increased to 68%, the median income to \$109,221.8, and the Hispanic population to approximately 10%.

In the year 2030, the house did not experience a large drop in the recovery ratio in its post-event state and returned to pre-event levels approximately at the end of two years. However, the higher probability of failure in the year 2050 added to a larger drop in the recovery ratio in the base year and lead to the house not reaching its recovery target. Even though the driving factor on reaching target recovery levels was seen to be the probability of failure of the house, the model depended on many others that create differences between different types of housing and neighborhoods (Hamideh et al. 2021). For instance, in Hamideh et al. (2021), multi-family and duplex housing types reached lower recovery rates than single-family houses, and many of them did not recover even after 7 years following the event.

The recovery process at the neighborhood level for the years 2030 and 2050 was assessed through a recovery index that followed the ratio of houses recovered in the years following the storm event. The recovery index at the year i, (RI_i), was computed at the block group level based on the immediate damage of the housing units following the event and their recovery trajectory [Eq. (1)]

$$RI_i = \frac{(Number\,of\,houses\,recovered)_i}{(Number\,of\,houses\,damaged)_{t_0}}, \qquad i \in [1,6] \qquad (1)$$

where RI_i = recovery index i years after the event; $(Number\,of\,houses\,recovered)_i$ = count of houses that have reached a recovery ratio of 1 in the ith year following the storm; and $(Number\,of\,houses\,damaged)_{t_0}$ = number of houses in a post-event state (i.e., count of houses that experience a drop in recovery ratio immediately after the storm). This definition of recovery allowed representing the resilience of the building stock as a dynamic process, where each time step (year) was a snapshot of the state of the community after a hazard event. Therefore, the higher the recovery index, the more resilient the neighborhood.

As an example, Fig. 9 depicts the state of recovery for 33 representative block groups at the end of the third year after a storm event in the years 2030 and 2050. It is noteworthy to mention that the recovery state between the years 2030 and 2050 is not directly comparable since the recovery index depended on the number of houses suffering damage in the aftermath of the storm, their specific probability of failure and recovery trajectory, as well as their aggregation at the neighborhood level. However, since the climate conditions in the year 2050 were more severe than in the year 2030 and the

Fig. 9. Recovery index at the end of the third year following a storm occurring in 2030 and 2050. (Base maps from Esri, DigitalGlobe, GeoEye, i-cubed, USDA FSA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community.)

structural performance was affected by aging and deterioration, the number of houses damaged was higher. This means that houses fragile enough to experience damage in the year 2030 will experience the same or more severe damage in 2050, setting a lower bound for the number of damaged houses for this year. Following the same argument, the houses that did not experience any damage in the year 2030 were likely to suffer minor ($P_f < 15\%$) or moderate damage ($15\% < P_f < 50\%$) levels in the year 2050. Therefore, these houses were more likely to recover and lead to higher recovery indices in 2050. Table S2 presents the information of the number of houses damaged and recovered per block group at the end of 1, 2, 3, and 6 years for both 2030 and 2050 events.

Consequence of Disasters in Vulnerable Populations

To avoid the most adverse consequences of natural disasters, efforts need to be focused on the neighborhoods and people most at risk, which are oftentimes the vulnerable population. This issue encompasses a long history of urban planning discrimination, rapid and unplanned urbanization, and inadequate socioeconomic policies that have created spatial inequalities and marked differences in the ability of individuals to cope with the impact of natural hazards and climate change (Peacock et al. 2014; Witze 2021; Zurich Insurance Group 2015). Therefore, the last step of the methodology aims to expose underlying impacts of built environment performance and recovery pace on coastal communities, to better understand the possible consequences of future hurricane hazards on vulnerable populations. Thus, the correlations of damage and rate of recovery in the short- (immediate loss) and long-term (recovery period) with representative social vulnerability factors are computed and examined for potential trends or insights that may inform risk mitigation and resilience planning efforts.

Social Vulnerability Factors

The uniqueness of coastal communities, in their natural and built environments (e.g., the morphology of the coast, ecosystems, and construction practices), as well as in their cultural and socioeconomic aspects (e.g., economy and racial and ethnic composition), results in varied disaster impacts across regions and the need to analyze each community at a local scale (Liu et al. 2019; Pant and Jeong Cha 2019; van Zandt et al. 2012). In this study, social vulnerability factors with a potential influence on the disaster impact on the community were considered and computed at the block group level using US Census data for Galveston County (US Census Bureau 2020). The set is composed of 15 factors: (1) single-parent household, (2) renter occupied units, (3) non-White population, households with (4) Black and (5) Hispanic householders, (6) occupied housing units without a vehicle, (7) Black and (8) Hispanic population, (9) households with less than the median income, (10) elderly (above 65 years old), (11) female population, (12) presence of children and adolescents, (13) population with educational attainment less than high school, and with (14) no health insurance and (15) that do not speak English well or not at all. In previous studies, these factors have shown a relation with housing damage and restoration, casualties, response, evacuation, and ability to access recovery resources (Houston et al. 2021; van Zandt et al. 2012).

Short- and Long-Term Effects of Hurricane Hazard on Coastal Communities

From the landfall of a hurricane to the reconstruction and recovery phases, the social composition of the community plays an important role in the overall impact of the storm. For instance, the damage undertaken by the structure is related to aspects such as the spatial distribution of the building stock (e.g., proximity to the coast) and the robustness of the houses (e.g., age or construction type), which are dependent on urban planning policies, and on social aspects such as income, race, and ethnicity (Peacock et al. 2014; Sutley et al. 2017; van Zandt et al. 2012). Moreover, given the limitations on the recovery budget, the reconstruction and recovery phases are affected by the individual's income, their ability to get loans, if their house has insurance, and their social networks (Drakes et al. 2021; Houston et al. 2021; van Zandt et al. 2012). Therefore, it is expected that different dimensions of social vulnerability will be highlighted during different phases of the disaster.

To investigate the impact of future hurricane hazards in the community in the short-term, the correlation of the mean loss, obtained from the performance analysis of the building stock, with the set of social vulnerability (SV) factors was computed. Further, the correlation of the recovery index with the SV factors was calculated for each year of the recovery phase, to analyze the long-term effects of hurricane hazards on the community. To do this, 33 blocks out of the 54 block groups in Galveston County were selected. The 33 block groups were selected based on the sufficiency of samples to compute reliable results of correlations. Therefore, a block group was selected if the number of houses analyzed was at least one-third of the total number of houses surveyed in the US Census data (US Census Bureau 2020) for that block group. Moreover, the two southern-most block groups of Galveston Island were also disregarded from the analysis, given that these block groups were mostly composed of rental and vacation homes (Hamideh et al. 2021; van Zandt et al. 2012).

Tables 1 and 2 show Spearman's rank correlation coefficients for both short- and long-term, with the set of SV factors, respectively. The significance of the correlation coefficients was assessed using a p-value analysis with a 90% confidence level. When analyzing Table 1, it is seen that the SV factors of households with Black householders, population without health insurance, occupied housing units without a vehicle, and those receiving less than a median income had a significant negative correlation with the

Table 1. Correlation coefficients of social vulnerability factors with the average loss for 2030 and 2050

No.	Social vulnerability factor	2030	2050
1	Single-parent household (SP)	−0.060	−0.097
2	Renter occupied units (RT)	−0.066	−0.087
3	Non-White population (NW)	−0.214	−0.235
4	Households with Black householders (BH)	−0.362*	−0.370*
5	Households with Hispanic householders (HH)	−0.075	0.217
6	Occupied housing units without a vehicle (NV)	−0.435*	−0.442*
7	Black population (BP)	−0.200	−0.227
8	Hispanic population (HP)	−0.170	−0.184
9	Households with less than median income (LI)	−0.393*	−0.409*
10	Elderly (ED)	−0.120	−0.080
11	Educational attainment less than high school (HS)	−0.167	−0.165
12	Female population (FP)	0.360*	0.345*
13	Presence of children and adolescents (CA)	0.102	0.088
14	Does not speak English well or not at all (EN)	−0.125	−0.109
15	No health insurance (NH)	−0.409*	−0.426*

Note: $*p < 0.10$.

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average loss for both 2030 and 2050. Therefore, an increase in the proportion of these factors would lead to a lesser neighborhood mean loss, which has also been observed in previous studies (van Zandt et al. 2012). This can be explained by the fact that vulnerable neighborhoods generally have less expensive assets, which would lead to a lower loss compared to more affluent neighborhoods. Nevertheless, the proportion of the female population maintained a positive correlation with the average loss, indicating that neighborhoods with a larger proportion of women experience greater average loss.

Regarding social vulnerability correlations with the recovery index, the trend seemed to maintain, where the SV factors correlated with higher rates of recovery, as seen by the significant positive correlation coefficients in Table 2. Nevertheless, the elderly and the female population showed a negative correlation with the recovery index in the years 2030 and 2050. This suggests that women and people over 65 years old might experience lesser rates of recovery throughout the recovery phase.

Although counterintuitive, the positive correlation of vulnerable neighborhoods with recovery can attend to the social dynamics of vulnerable neighborhoods in the aftermath of natural disasters. As observed by Girard and Peacock (1997), Black householders often decide to stay in their houses after a hurricane despite the damage due to their limited options on alternative housing, their limited mobility, and because they depended on their local job for their livelihood. Therefore, is not surprising that the need itself to stay helps vulnerable populations to work toward the recovery of their houses (Hamideh et al. 2021).

These findings in positive correlation are also interesting when the correlations among the SV factors are analyzed (Fig. 10). For the year 2050, 7 SV factors showed a positive correlation: non-White population, Black householders, occupied housing units with no vehicle, Black population, low-income population, adults with educational attainment less than high school, and population without health insurance. In Fig. 10 it is apparent that households with Black householders and low-income populations have a significant positive correlation with the remaining 5 SV factors. This might indicate that Black householders and low-income populations might be driving the correlation in the recovery for the year 2050. Nevertheless, as observed in Fig. 10, the female population is not correlated with any other SV factor. This highlights the added importance of this negative correlation and suggests that in neighborhoods with a large female population and any other significant SV factor, the disaster impact might be exacerbated.

It is also noteworthy to mention the correlation trend in the recovery for 2030. Even when the Hispanic householders and the elderly showed a significant correlation throughout the recovery period, the SV factors related to single-parents (SP) and the presence of children and adolescents (CA) only showed a significant correlation for the second and last years of the recovery phase. By Fig. 10, it is seen that the elderly SV factor is negatively correlated with all the other 3 factors and that Hispanic householders are positively correlated with CA and SP and negatively correlated with the elderly. This might be the driving factor of the significant correlations in the year 2030, but also features the importance of assessing disasters as dynamic processes, following how they evolve.

Discussion

This study proposes to extend the PBCE framework to include not only temporally evolving structure or infrastructure performance during hurricane hazard events, but their dynamic interaction with the recovery of coastal communities, including features such as housing (value) recovery and its impact on vulnerable populations. Results show that the incorporation of climate change effects and degradation factors in the performance assessment of residential houses increased their probability of failure and associated loss, as observed in the differences between the 2030 and 2050 scenarios. This not only affects the immediate impact of hurricane hazards but has an important influence in the recovery phase, where it is seen that the damage suffered by individual houses drives its potential recovery in the years following the storm. Moreover, the correlations between short- and long-term performance of the built environment with sociodemographic variables exposed some of the underlying effects of hurricane hazards on coastal communities and, more specifically, on vulnerable populations.

The findings of this study are limited by the characteristics of the models used to assess the fragility of the houses, their restoration, and data availability. As previously discussed, the house fragility model is an empirical model developed based on the survival of elevated residential structures during Hurricane Ike (Tomiczek et al. 2014). Therefore, the fragility model can only provide a collapse limit state assessment and might have limitations when applied to coastal houses with different foundation types. The recovery model is also a data-driven model developed in the aftermath of Hurricane Ike that uses assessed values of the houses to track damage and

Table 2. Correlation coefficients of social vulnerability factors (SVF) with recovery index for 2030 and 2050

Year		2030				Year	2050			
No.	SVF	1	2	3	6	SVF	1	2	3	6
1	SP	0.279	0.299*	0.287	0.314*	SP	0.126	0.126	0.126	0.136
2	RT	0.103	0.109	0.102	0.117	RT	0.247	0.247	0.247	0.229
3	NW	0.194	0.196	0.193	0.167	NW	0.469*	0.469*	0.469*	0.468*
4	BH	−0.036	−0.043	−0.041	−0.064	BH	0.577*	0.577*	0.577*	0.571*
5	HH	0.320*	0.331*	0.325*	0.328*	HH	0.210	0.210	0.210	0.208
6	NV	0.027	0.033	0.030	0.028	NV	0.440*	0.440*	0.440*	0.452*
7	BP	0.061	0.052	0.056	0.039	BP	0.468*	0.468*	0.468*	0.490*
8	HP	0.223	0.233	0.227	0.223	HP	0.182	0.182	0.182	0.171
9	LI	−0.168	−0.162	−0.167	−0.182	LI	0.415*	0.415*	0.415*	0.401*
10	ED	−0.423*	−0.424*	−0.420*	−0.403*	ED	−0.211	−0.211	−0.211	−0.224
11	HS	0.094	0.093	0.090	0.070	HS	0.351*	0.351*	0.351*	0.350*
12	FP	0.078	0.093	0.085	0.120	FP	−0.302*	−0.302*	−0.302*	−0.330*
13	CA	0.244	0.261	0.250	0.296*	CA	−0.076	−0.076	−0.076	−0.085
14	EN	0.130	0.141	0.131	0.117	EN	0.288	0.288	0.288	0.282
15	NH	−0.054	−0.047	−0.050	−0.073	NH	0.328*	0.328*	0.328*	0.323*

Note: $*p < 0.10$.

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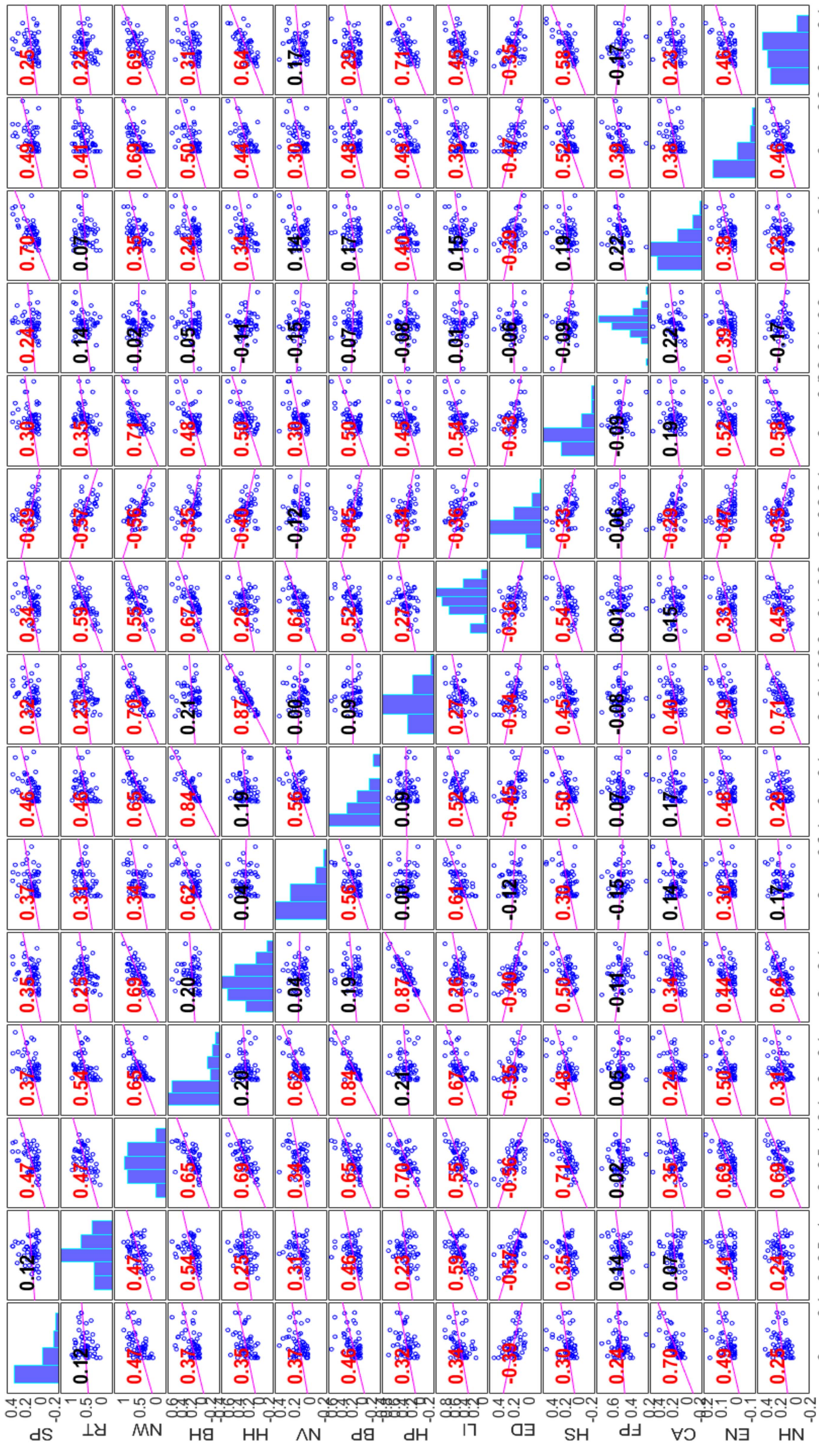

Fig. 10. Correlation plot among social vulnerability (SV) factors.

recovery. As noted in Hamideh et al. (2021), Hurricane Ike also coincided with the recession of 2008, which might have affected the prices of the residences in Galveston Island. Data constraints in storm simulations, projections of sociodemographic variables, and more precise building data might also affect the results of the model. For example, the elevations of the building stock are estimated based on minimum-elevation requirements of the houses at the time that they were constructed (Fereshtehnejad et al. 2021), and since the probability of failure is very sensitive to the water line reaching the structure (González-Dueñas and Padgett 2021), results might change with more precise measurements. Moreover, in this study, the SV factors used in the correlation analysis could not be projected due to a lack of information. Even though recent efforts have been made to estimate future projections of such SV factors at the country level (Lee et al. 2016; Ortman and Shin 2011; Ro et al. 2021), projections at a higher spatial resolution (Colby and Ortman 2015; Hauer 2019) are required to evaluate their effect in the results and analysis of the proposed study. These points highlight the need of more comprehensive databases and platforms that provide the opportunity to share and access data in the context of natural hazards research (Rathje et al. 2017; Wartman et al. 2020).

Nevertheless, data-driven models have added advantages with respect to physics-based models. For instance, data-driven models can capture specific characteristics of the construction practices of the region, the storm, and highlight important features of the built and natural environments, such as the added protection of dunes or the added increase in the probability of failure due to channel-induced erosion on foundations (i.e., the velocity of the water increases in the spaces between houses). On the recovery side, data-driven (e.g., tax appraisal data or surveys) models can capture to a certain extent how the dynamics of the population affect the way in which the community recovers after a storm (Hamideh et al. 2021) and even identify region-specific factors that played an important role in shaping the recovery process (van Zandt et al. 2012).

Finally, a transition from an individual structure–wise analysis to a system-level analysis needs to be promoted to identify cascading effects of damage in neighborhoods. For instance, the prices of houses that did not suffer any damage might be affected if they are located in a neighborhood where all the other houses collapsed (De Silva et al. 2008). Damage correlations among structures should also be considered in order to capture system-level dynamics in individual building performance such as shielding effects and waterborne debris impacts (Hatzikyriakou et al. 2016; Hatzikyriakou and Lin 2017a). This is also important when assessing social networks; if complete neighborhoods are dislocated due to the impact of the storm, social bonds might be broken, which in many opportunities are a core part of recovery and the livelihood of minorities and vulnerable populations (van Zandt et al. 2012).

From the insights of this study, some important issues are raised. When considering the added stress on the built environment posed by climate change and degradation and its increase with time (as seen in the differences in performance between 2030 and 2050), it is important to ask how are we going to mitigate the risk of structural and infrastructure systems imposed by the changing climate conditions of this century? When do we need to put these mitigation strategies in place? And, considering an economy of limited resources, how do we choose what systems need to be retrofitted first? Regarding these questions, innovative solutions are required that can not only effectively adapt our built environment to the new climate, but that are also sustainable and economically viable (Dong and Li 2017; Wang et al. 2020). The construction sector is one of the big contributors to carbon emissions in the world (Erlanger and Sengupta 2021), therefore, more sustainable construction and design practices need to be promoted to fit into a new adaptation engineering scheme. Also, life cycle methodologies that can include the time-varying characteristics of structural and infrastructure systems and that can incorporate more environmentally friendly strategies as viable options to reduce long-term costs and emissions (Angeles et al. 2021; Wei et al. 2016) need to be developed. Life cycle and adaptation engineering strategies can inform practical and achievable goals of mitigation and retrofitting strategies, considering both the available resources and the feasible time frame. The potential increase in the landfall frequency of tropical cyclones over the century (Xi and Lin 2021) could mean that coastal communities might not have enough time to recover from one event before another storm hits the area (Minsker et al. 2015). This is of particular importance when evaluating the long-term impacts of hurricanes events since the resilience of the community might depend on the pace of recovery in the aftermath of the storm. Finally, as could be observed from the correlation analysis of building performance and social vulnerability factors, disparities in damage and recovery of the built environment exist among communities. Hence, one of the most challenging questions is how the abovementioned strategies can be implemented without favoring the more affluent sectors of the economy and the population. Vulnerable populations are not only more exposed to the impacts of natural hazards, but also generally do not have the resources to adapt to the new climate conditions (e.g., expenses of structural retrofitting, relocating). Therefore, policies should aim for a fair transition into more sustainable practices, while protecting the most vulnerable sectors of the population (Drakes et al. 2021; Witze 2021). It is also necessary to propose adequate and practical metrics that can capture the social disparities of disasters in the region and their influence on risk and resilience assessments (Kim and Sutley 2021; Markhvida et al. 2020). For instance, metrics such as "household well-being losses" (Markhvida et al. 2020) and "hot households" (Fereshtehnejad et al. 2021) have been proposed to assess the coupling between building fragilities and social systems. This is not only important to perform more unbiased risk analyses [e.g., losses might be biased by more expensive assets (Markhvida et al. 2020) as discussed in the previous section], but also leads to more efficient and transparent communication with stakeholders and communities.

Conclusions

This study explores the application of the PBCE framework to support regional hurricane risk and resilience assessments while considering time-varying and social vulnerability factors. The methodology consists of three main steps: damage evaluation, recovery assessment, and the evaluation of the consequences of the disaster within vulnerable populations. First, the performance of the building stock of Galveston Island under surge and wave loads was assessed for future hurricane scenarios with changing forward velocity and local sea level rise projections in the years 2030 and 2050 in terms of damage and recovery. The average loss and the relative recovery (i.e., recovery index) of the houses were used as performance metrics to analyze the short- and long-term impacts at a neighborhood scale, respectively. The introduction of the recovery phase analysis within a PBCE framework allowed evaluating recovery as a dynamic process, where the recovery trajectory of the neighborhood was analyzed up to six years following the event. Finally, to assess the consequences of the damage of the houses (short-term) and their recovery over time (long-term), correlations were computed with a set of representative social vulnerability factors. Results show and quantify the changes in the probability of failure of the building stock and their recovery due to the effects of a changing climate on the hazard conditions (i.e., changes in the forward velocity of the storm and local sea levels). The correlations in the short- and long-terms show that the elderly and women might be most at risk in future hurricane events, given the models and conditions assumed in this study. In this scenario, resilience strategies and policies should be promoted to mitigate the potential adverse consequences both in the long- and short-term to these two population sectors. Moreover, correlations among social vulnerability factors should be also considered while interpreting results, since underlying hidden factors might be driving the correlation with both damage and recovery.

This study has also shown the importance of considering time-varying factors when assessing the performance of structural systems and how it correlates with the sociodemographic characteristics of the region. The need to address disasters as dynamic processes becomes more evident when considering the cascading effects of natural hazards in damage disparities across a region and its consequences in the recovery process. Moreover, the added risk caused by climate change and aging of structural and infrastructure systems and the complex dynamics of socioeconomic systems call for creative adaptation strategies that consider sustainability, climate justice, new policies in urban planning, and infrastructure investments that consider social vulnerability, as well as changes in building design codes that can ensure structural performance beyond collapse prevention for future climate conditions.

While this paper presented a framework for extending notions of PBCE to community-scale recovery and consideration of social vulnerability, future work should address limitations and gaps such as the differences in building archetypes when evaluating performance at a regional scale, the incorporation of evidence to reduce uncertainty in the estimates, the adoption of alternative decision variables, such as carbon emissions or dislocation, as well as the incorporation of a fully probabilistic hazard model. Opportunities for improvement also include more accurate region-specific projections of climate change effects on hurricane hazards, socioeconomic projections considering different climate scenarios, as well as future built environment development. For instance, in this study the impact of climate change in the hazard was only captured by two parameters, local projections of sea level rise and changes to the forward translational speed of the storm in order to showcase the methodology. In the future, the effects of climate change in other relevant storm parameters (e.g., intensity, size, track) should be assessed to perform a fully probabilistic hazard analysis and better predict the effects of a changing climate in tropical cyclones and their impacts on coastal communities. A future opportunity also relies on the use of historical storms to leverage and test the proposed framework. To this end, data collection and dissemination efforts in the aftermath of hurricane events that assess not only the immediate damage but the recovery process for individual houses in the years following the landfall of the storm should be promoted.

Moreover, in this study the houses were considered as independent units, therefore opportunities exist to model the interactions between housing units leveraging deep probabilistic graphical models to better capture their complex behavior in the aftermath of natural hazards. This methodology can also be expanded to different testbeds, in order to analyze differences in performance depending on the region and unveil the specific sociodemographic interactions that are key for managing risks in the future. Opportunities also include the integration of the proposed methodology with a life cycle analysis of the system, which can inform adaptation strategies for coastal communities. Finally, the investigation of the impact of different retrofitting measures and policies specifically designed for neighborhoods considering their characteristic social vulnerabilities should also be explored.

Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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Supplemental Materials

Tables S1 and S2 are available online in the ASCE Library (www.ascelibrary.org).

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