Multi-Scale Vulnerability Assessment of Surge and Wind Hazards in Coastal Communities – Venice Island, Florida

Introduction

Management and protection of coastal areas worldwide is of particular interest as these areas are heavily populated, and are often subject to weather and climate-related hazards. In the US, approximately 30% of the total population resides in coastal communities [1], and the rate of population growth continues to increase steadily in these space-limited areas [2]. Another important element in coastal management includes the real estate market, which has appreciated at 7% a year over the last 50 years in US [3]. Krugman [4] also argued that, due to the high-density population and limited space in coastal communities, housing buyers are willing to spend more money on coastal real estate markets. Yet, these near-shore landscapes are also very dynamic due to variations in winds, tide, and ocean currents, including low frequency, high-impact events such as storm surge and flooding. Because of the potential of existing chances for economic losses and human casualties, it is critical for coastal communities' administrator to identify the potential impacts and extent of these hazards.

Scientists and researchers have used vulnerability assessment approaches to identify the potential damage from hazards and to develop plans for hazard mitigation. Vulnerability assessments have been conducted at different spatial scales, from the global [5, 6], national [7], and regional [8, 9], to the local [10, 11]. At the local level, i.e., the individual house or neighborhood, little research on vulnerability assessments has been conducted, primarily because implementation is often prohibited by logistical and financial constraints. Recent technological developments, such as Light Detection and Ranging (LiDAR) and Geographic Information System (GIS) software, provide more accurate and time-efficient tools that now make it feasible to conduct vulnerability assessments at local scales.

Understanding and implementing vulnerability assessments for multiple hazards is another priority for hazard management efforts. For example, multiple hazards, e.g., flooding due to storm surge and strong winds, can occur when hurricanes affect coastal communities. Although several studies have assessed vulnerability of multiple hazards for coastal communities [12, 13], the difficulty of combining and synthesizing complex data from multiple sources and scales makes multi-hazard analysis particularly challenging [14]. Despite these challenges, a comprehensive vulnerability assessment for multiple hazards at local scale is critical for coastal communities. The goal of my study is to determine the complex relationships between mapping scales and the estimates for multi-hazard using Hazards United States Multi-hazard (Hazus) software, a methodology developed by the US FEMA.

Hazus-MH model

Hazus combines socio-economic and environmental characteristics, and then applies a hazard scenario in such a way where the vulnerability of human properties can be assessed (Figure 1). Three levels of analysis can be performed based on the detail of user-provided information in Hazus: Level 1,

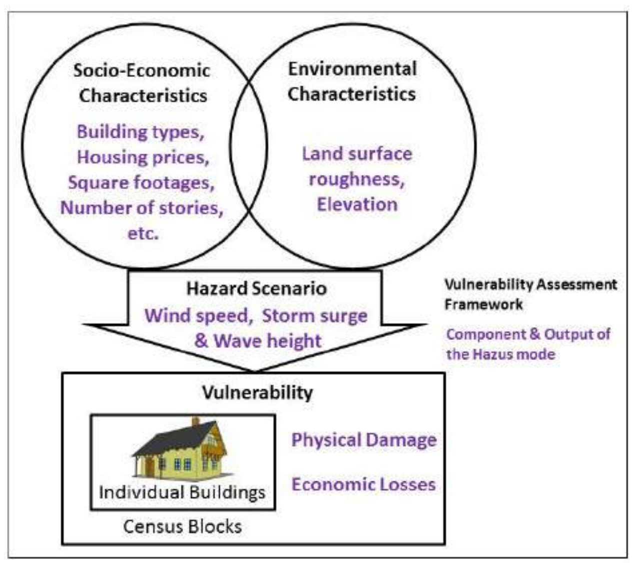

Figure 1. The framework of the Hazus model as a vulnerability assessment tool.

users apply the default inventory dataset and hazard scenario; Level 2, users are required to collect specific building and socio-economic attributes; and Level 3, users must import detailed engineering data, such as user-input damage functions for specific buildings [15]. Therefore, the more detailed the component of the Hazus model, the more accurate the vulnerability assessment will be. The current Hazus model includes three types of natural hazard models: Earthquake, Hurricane, and Flood, all of which run separately. In addition, FEMA also developed a combined model to assess multiple hazards to avoid overestimations from separate estimates of wind and storm surge damage in hurricanes [15, 16].

Several studies have applied the Hurricane and Flood model to assess vulnerabilities. Others have focused on a comparison and verification of the Hazus outputs [17-21]. Level 2 modeling results provides more reliable estimations than Level 1 [17, 22].The Hazus model has been shown to predict accurately inundation area after flood events at the county spatial scale and level of analysis [20]. While many of the previous authors focused on the comparison or improvement of environmental characteristics and hazard scenarios of Hazus, few have examined the socio-economic characteristics that constitute the inventory dataset of the Hazus model (Figure 1). In particular, not many have focused on examining the socio-economic inventory mapping scales. Most of the Hazus studies have applied the default mapping unit, which is the census block level in the Flood model and the census tract level in the Hurricane model. While users can import detailed building information as a *User Defined Facility* dataset to estimate possible damages and losses for individual buildings at the local scale, very few researchers have investigated this capability. In addition, few studies have combined a housing price model with the Hazus model in order to estimate housing market losses from multiple hazards, which is essential for real estate management in coastal communities. The key objective of my study is to compare Hazus modeling results with two socio-economic inventory-mapping scales for a multi-hazard vulnerability assessment in order to estimate the losses of housing prices.

To address this objective, this study focused on *how the mapping scales of socio-economic inventory (the census blocks versus individual houses) and hazard/environmental characteristics (wind, storm surge, and higher/lower resolution DEMs) affect the vulnerability assessment of multiple hazards*. I carried out a Combined Hurricane and Flood (CHFH) model (Level 2) in Hazus for Venice Island, FL, a barrier island along the west coast of Sarasota County and as part of Venice City. I selected single family properties for this study due to: (1) a hedonic model analysis that can be integrated to generate more accurate predictions of housing prices; (2) single family properties that are the most common residential occupancies in coastal communities; and (3) single family properties that are simpler to include in analyses because they have only one or two buildings per unit.

Method

Study Area

The highest ground elevation in study area is 33 feet to the southeast, and the closest and largest bay is Roberts Bay to the north. In 2010, the total population in Venice City was 20,784 with a median age of 67.6 years whereas approximately 57%of the population was over 65 years old [23]. Most of the residential and commercial properties are located on the northern and central part of the island, and Venice

Municipal Airport occupies most of the southern area. Of all the property parcels in Venice Island, 60% are single family properties (2020 houses).

Hurricane and tropical storms are the most critical natural hazard in Sarasota County [24]. The 1944 Cuba-Florida Hurricane was one of the costliest natural hazards [25] to impact the area. The hurricane formed in the Caribbean Sea approximately 18:30 (EST) on October 12, 1944, and made landfall near Venice Island at around 03:00 (EST) on October 19 as a Category 3 hurricane on the Saffir-Simpson wind scale. Severe damage from high tides was reported along the coast of Sarasota County [26].

Data Preparation

In this study, spatial data such as parcels, road networks, and digital elevation models (DEM) were collected from several sources: the Florida Geographic Data Library (FGDL), the National Hurricane Center (NHC), the Sarasota County Geographic Information System (SCGIS), and the Southwest Florida Water Management Water District (SWFWMD). Single-family sale records were acquired from the Sarasota County Property Appraiser (SCPA). I compiled these data in Excel spreadsheets, Access databases or ArcGIS shape files.

Assemble Inventory Datasets

Two mapping scales were processed and compared: the census block (CB) and the individual house (IH). I acquired detailed building information for each single-family property to build the IH dataset and aggregated it into census blocks as a CB dataset. To create an IH dataset, detailed attributes of single-family properties were compiled as an Access database and imported into the CHFH model. Most of the attributes were based on the parcel layer from FGDL and building information files from SCPA. To get more accurate housing prices for single family properties, the cost for each property was calculated based on the hedonic model analysis, which can be used to estimate the ideal bundle of housing characteristics for home buyers [27]. Data from 2005 were used because the largest number of transactions occurred in this year. To increase the sample size, 6,388 single-family properties near the coastal region of Sarasota County were incorporated in the model. I used the multiple regression method to model the influence of housing characteristics on housing price, which can be written as:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + \varepsilon_i, \quad i = 1, \ldots, n \tag{1}$$

where y_i is the market value of the property, β_0 is the intercept of estimated prices, β_1 to β_p are coefficients of housing characteristics (x_{i1} to x_{ip}), and ε_i denotes the random error (Table 1). To determine the best fit for the statistical model, logarithm transformations were applied to both dependent and explanatory variables.

Table 1. Description, mean and standard deviation of variables used in the hedonic model analysis.

Variable	**Unit / dummy**	**Mean**	**Standard Deviation**	**Characteristic Type**
Just market value in 2005 (dependent variable)	USD	207898	256187	
Land area of parcel	square feet	12099	17651	Structure
On barrier Island or not	dummy	0.05	0.22	Coastal-related
Effect building year	year	1984	17.38	Structure
Total living area	square feet	1802.68	798.31	Structure
With boat dock or not	dummy	0.33	0.18	Structure, Coastal-related
Have pool or not	dummy	0.38	0.48	Structure
Distance to public beach	feet	29688	12336	Coastal-related
Distance to Downtown Sarasota	feet	68457	47342	Accessibility
Distance to I-75 ramps	feet	24176	12732	Accessibility
Distance to shoreline	feet	9754	7850	Coastal-related
Ratio of population older than 65 years old[a]	percentage	0.3	0.2	Demography
In Flood zone V or not	dummy	0.0002	0.05	Coastal-related

[a] Here the ratio was based on the fraction of population older than 65-years-old divided by total population. The number of population was based on the 2010 Census Survey.

For each single-family property in the IH dataset, latitude and longitude coordinates defined at the center point of each building footprint, were used to represent one single-family property. For the CB dataset, three attributes were aggregated from the IH dataset: total square footage, building counts and housing prices. To update these attributes, the Comprehensive Data Management System (CDMS), was utilized to replace the original values in the default CB dataset.

In the Hazus model, the *mapping scheme* represents the general building characteristics for each census block and includes (1) the percentage of each building type and (2) building characteristics for the estimations. Except for the updated attributes described in the preceding paragraph, the default CB mapping scheme for the Hurricane model was applied because updating the mapping scheme for every individual census block manually would have been prohibitively time-consuming. For the Flood model, the default building type information was also applied. Unlike the Hurricane model, the Flood model focused on the first floor height, which was defined based on the general foundation type and assumed first floor elevation.

Define Hazard Scenario

The CHFH model requires data from a hurricane scenario to be able to model effects of wind and storm surge hazards associated with these storms. This study used data from the 1944 Cuba-Florida hurricane. These data are necessary to run the wind field model, which simulates wind speeds during a hurricane event. Wind speeds were calculated based on the parameters of the historical hurricane's specific characteristics. In addition to the wind field model, terrain roughness was another important parameter for damage estimation. In general, the rougher the terrain, the lower the wind speeds because friction reduces the hurricane winds near the surface. The roughness length in the study area ranges from 0.31 z_0 to 0.41 z_0, and it is categorized as a suburban land surface.

To model storm surge and wave heights, *Simulating Wave Nearshore* (SWAN) and *Sea, Lake, and Overland Surge from Hurricane* (SLOSH) were used. SWAN is a model for simulating two-dimensional waves in nearshore areas, and SLOSH is a model for estimating storm surge height. The SLOSH cell grids, which are the modeling units for storm surge height calculation, were directly applied in the SWAN model to 1) maximize consistency in two models utilizing equivalent bathymetry data and 2) reduce computing time. The wind field model of the selected hurricane scenario drove both models. Initial water level is another model input. This represents the height above sea level of the predicted astronomical tide at (storm) landfall plus the pre-storm tide anomaly. The initial water level was set to 5.9 feet, based as the mean high water level of the tidal station in Venice Island. Using a two-way coupling computation of SWAN and SLOSH to process the maximum storm surge and significant wave height, a grid file was created with the associated storm surge wave heights during the hurricane event.

Once the storm surge and wave height were estimated, flood depth was calculated based on the ground elevation of the study area. This study used two digital elevation models (DEMs) as the ground elevation models against which to compute the storm surge flooding depth: the National Elevation Dataset (30 feet cell resolution) and a LiDAR DEM (5 feet cell resolution). Two DEMs were used to compare the effect of higher versus lower resolution reference data on storm surge flooding estimates.

Estimation of Housing Price Losses

It is important to note that the Hazus model assumes buildings are evenly distributed inside a census block for the CB dataset results. Conversely, the IH dataset was estimated based on the center point of building footprints, and thus, damage to individual buildings could be calculated. For housing price loss estimation of wind hazard, loss functions for specific building types were applied. The loss function was based on the wind speed from the hurricane scenario selected to be used in the model, and roughness of land surface. These loss functions show the relationship between wind speed to the ratio of cost of damage to house value. For the study area, the loss function of suburban was applied. For the storm surge estimation, housing price losses were computed based on the relative flooding depth of buildings. Depth-damage functions designate the relationship between flooding depth and the ratio of cost of damage to housing prices, and these functions were then used to calculate housing price losses.

In addition to wind and storm surge only loss estimates, a combined wind and storm loss estimate was calculated:

$$\max(\mathrm{W}, \mathrm{F}) \leq \mathrm{C} \leq \min\,(\mathrm{W} + \mathrm{F}, 1.00) \tag{2}$$

where W is the wind- only losses ratios, F is the storm surge- only loss ratio, and C is the combined wind and storm surge loss ratio. The combined housing price losses must be equal to or larger than the sum of wind-only and storm surge-only losses, and equal to or less than 100% of housing prices.

Results

Hedonic Model

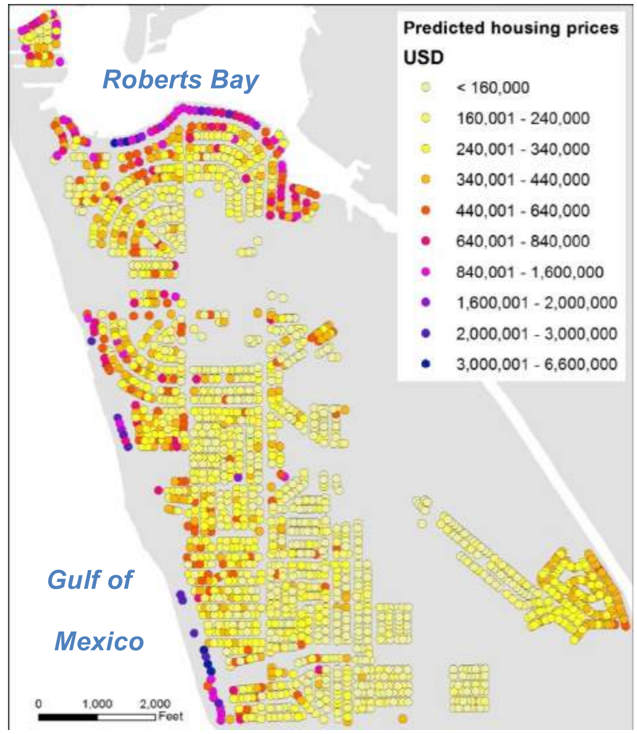

Figure 2. Predicted housing prices for single family properties in Venice Island, FL.

Results from the hedonic model showed that housing prices were strongly associated with coastal amenities, which led to extremely high housing values on beach and bay fronts. Five significant variables were related to coastal attributes (On barrier island or not, With boat dock or not, Distance to public beach, Distance to shoreline, In Flood zone V or not) at the 95% confidence level, which indicated the positive effects of coastal amenities on single family housing prices in the study area. Two accessibility variables were also significant: Distances to Sarasota Downtown and I-75 ramps, both of which indicated the importance of road networks and commercial services. Three basic structural characteristics (Land area of parcel, Effect building year, Total living area) were also significant with high T-values, which denote their importance of determining of housing values (Table 2). The adjusted R^2 of the model was 0.88. Spatial autocorrelation was considered through calculation of the Global Moran's I of estimated housing price residuals, which was -1.56. This value was less than the critical value of the null hypothesis, and indicates that the spatial autocorrelation was trivial. Figure 2 shows the predicted single-family housing prices in Venice Island. The most expensive properties were located along the beach and bay fronts. Property prices dropped as distance from shoreline increased. These predicted housing values were imported as one of the IH attributes and were aggregated into census blocks for the CB dataset.

Table 2. Regression coefficient, standard error, and t-values of variables in the hedonic model.

Variable	Regression Coefficient	Standard Error	T-value	Variance flation Factor
Intercept	-6.1889[a]	0.2396	-25.83	
Land area of parcel (log)	0.1591[a]	0.0081	19.73	1.57
On barrier Island or not	0.201[a]	0.0093	21.56	1.77
Effect building year	0.0044[a]	0.0001	34.64	2.01
Total living area(log)	0.9348[a]	0.0145	64.26	2.47
With boat dock or not	0.1511[a]	0.0108	13.94	1.57
Have pool or not	0.0545[a]	0.004	13.76	1.50
Distance to public beach (log)	-0.0394[a]	0.0059	-6.66	1.89
Distance to Downtown Sarasota (log)	-0.1136[a]	0.005	-22.56	1.52
Distance to I-75 ramps(log)	-0.0603[a]	0.0084	-7.20	1.52
Distance to shoreline (log)	-0.0504[a]	0.0043	-11.70	2.82
Ratio of population older than 65 years old	0.2431[a]	0.0095	25.49	1.51
In Flood zone V or not	0.2948[a]	0.0304	9.70	1.03
R^2	**0.8869**	**Global Moran's I of residual**		**-1.56**
Adjusted R^2	**0.8865**			

Note: [a] denote the significance of parameter at 1% level based on t-statistic.

Assessments of Housing Price Losses

The combined wind and storm surge assessment results demonstrated a complicated relationship between mapping scales and the detail of estimates. In general, *the more detailed the hazard/environmental characteristics, the larger the difference of the IH and CB estimates.* The CB dataset required less processing and computing time, but it was not able to capture the geographical variations across each census block. Conversely, the IH dataset required more processing and computing time but the estimate results were more detailed than the CB dataset. The pros and cons of the two datasets are listed in Table 3. The following sections will address the details of the housing prices losses due to the separate wind and storm surge and the combined housing price losses estimates for wind and storm surge hazards.

Table 3. Pros and cons of using the CB and IH dataset.

	CB dataset	IH dataset
Pros	Less computing time of Hazus (5 -6 hrs). The results are automatically computed.	Can capture much more details within census blocks The damage and loss can be estimated for every building.
Cons	Cannot reflect the geographic changes across census blocks. Tends to overestimate damage and losses.	Longer computing time of Hazus (> 10 hrs). Some calculations require manual computation in ArcGIS.

Wind-only Estimates

For the 1944 Cuba-Florida hurricane scenario, two estimated wind speed values were assigned 121 and 125 mph. Due to the coarse resolution of the wind field model, the estimated wind speeds did not vary greatly across the entire study area. Because the wind- only assessments were based on hazard characteristics (wind speeds) with a smaller mapping scale, the estimate results for the CB and IH datasets were similar. The loss estimates for the CB and IH datasets are shown in Figure 3. Compared to the CB result, the IH

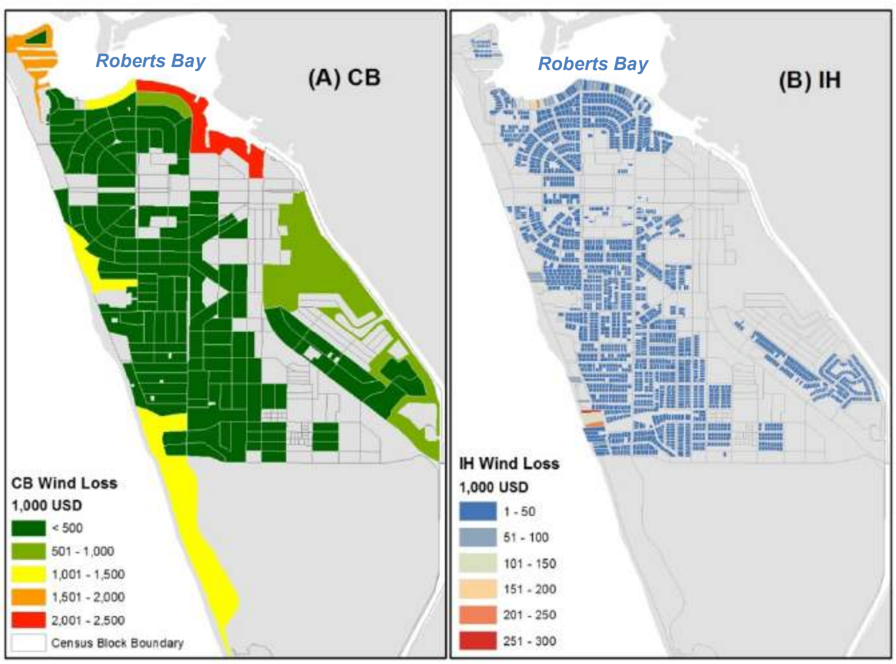

Figure 3. Housing price loss estimations for (A) the CB dataset and (B) the IH dataset.

results showed more variability in housing price losses across the study area which was because the IH estimated losses for individual houses. Furthermore, due to the relatively high predicted housing prices near Roberts Bay and on the beach front, housing price loss estimates in both the CB and IH datasets were higher, even though the damage ratios were similar for the entire study area.

Storm Surge-only Estimates

The storm surge damage results revealed the importance of data accuracy to vulnerability assessment, as well as a more complex relationship between mapping scales and estimates of hazard characteristics, specifically storm surge flooding depth. Figure 4 shows the estimated storm surge flooding depth based on the higher (HR) and lower (LR) resolution DEMs. The zoomed in areas of northern Venice Island further illustrates the detailed flooding depth distribution in Figure 4 (A') and 4(B'). The overall pattern of flooding depth for the HR and LR DEMs were similar; however, the HR results showed improved estimates. Figure 5 presents the estimated housing price losses for storm surge flooding based on the GBD dataset. The highest

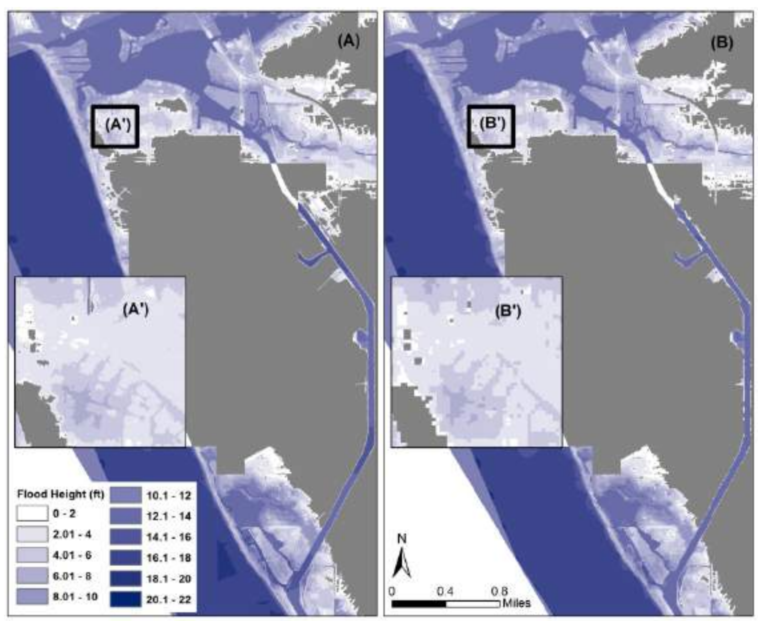

Figure 4. The estimated storm surge flooding depth: (A) the result using a higher resolution DEM (LiDAR), and (B) result using a lower resolution DEM (NED). A' and B' show a zoomed in map of areas in A and B, respectively. The higher resolution result (A') shows more accurate flood depth estimates and spatial flooding pattern.

losses (8-9 million USD) occurred on two census blocks near Roberts Bay. Figure 5(C) shows the difference between the HR and LR results. Most of the differences were between ± 100,000 USD, and the block with the largest difference, which is about 800,000 USD, was located in the census block on the bay-front of Roberts Bay.

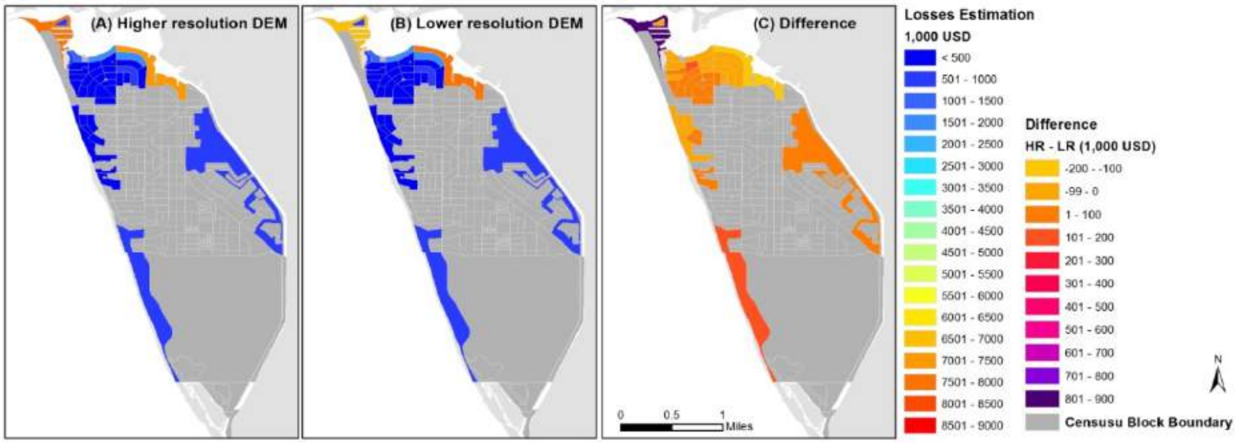

Figure 5. Storm surge loss estimates using the CB dataset based on the higher (A) and the lower (B) resolution DEM's. Panel C shows the difference between A and B.

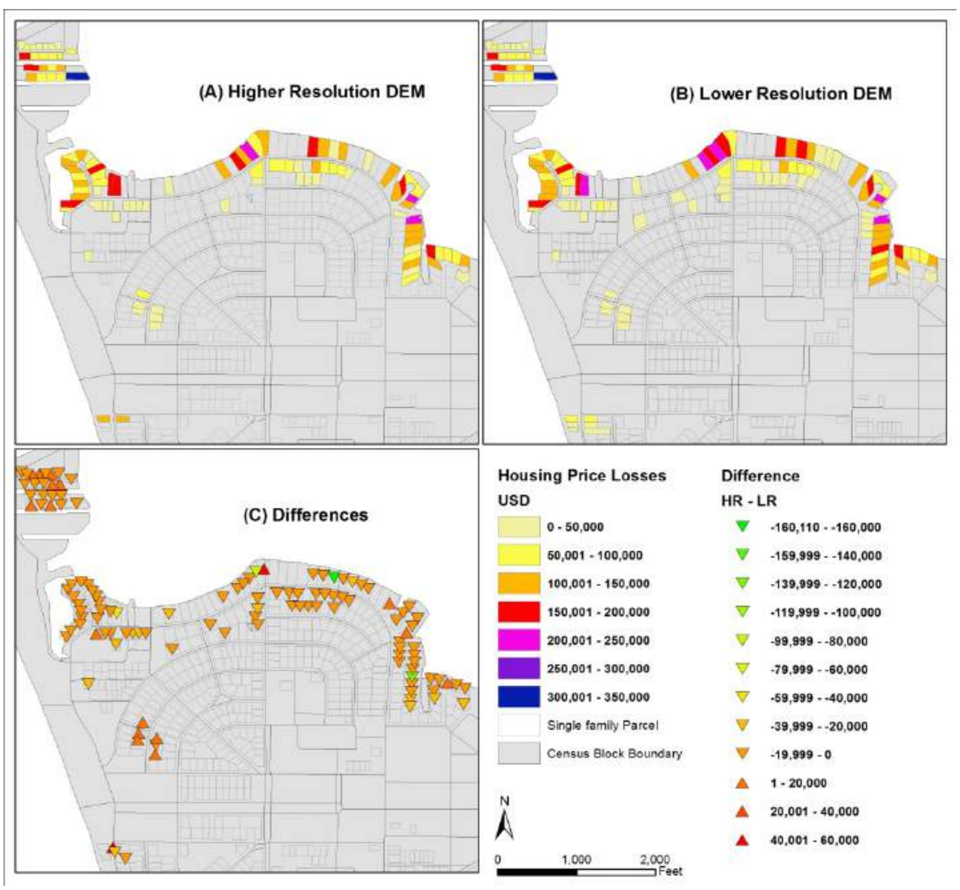

Figure 6. Housing price loss estimates from storm surge flooding using the IH dataset based on the higher (A) and the lower (B) resolution DEM's. Panel C shows the difference between A and B.

Figure 6 shows the estimated housing price losses based on the IH dataset. Most of the high losses were located on the bay front of Roberts Bay. The differences between the HR and LR results are shown in Figure 6 (C). Compared to the HR result, most of the loss estimates from the LR were higher. In addition, more properties were predicted to flood based on the LR result. This was because the HR DEM provided more detailed and accurate elevation information and, therefore had a greater ability to estimate the flooding depth, which was based on the center point of building footprints. The majority of the properties with higher loss estimates were located beside the bay and along beachfronts. Note that these properties were more *sensitive* to loss. For instance, the 50% value loss for a 6 million USD value, bay-front property is dramatically higher than the same percentage price loss of an inland property valued at 100,000 USD.

Combined Housing Price Loss Calculation

Finally, combined wind and storm surge housing price loss estimates were calculated based on the combined wind and storm surge function (Function (4-3)). Figure 7 shows the housing price loss estimates based on the CB dataset. The highest estimated losses were located on the bay-front area, which was where the storm surge was greatest. The combined calculation using the IH dataset is shown in Figure 8. Compared with the CB result, fewer properties were flooded; therefore, most of the combined losses resulted from wind damage. Again, properties located on the beach and bay fronts had the highest combined housing price losses, which is because the predicted housing prices of these properties were much higher than properties located relatively inland.

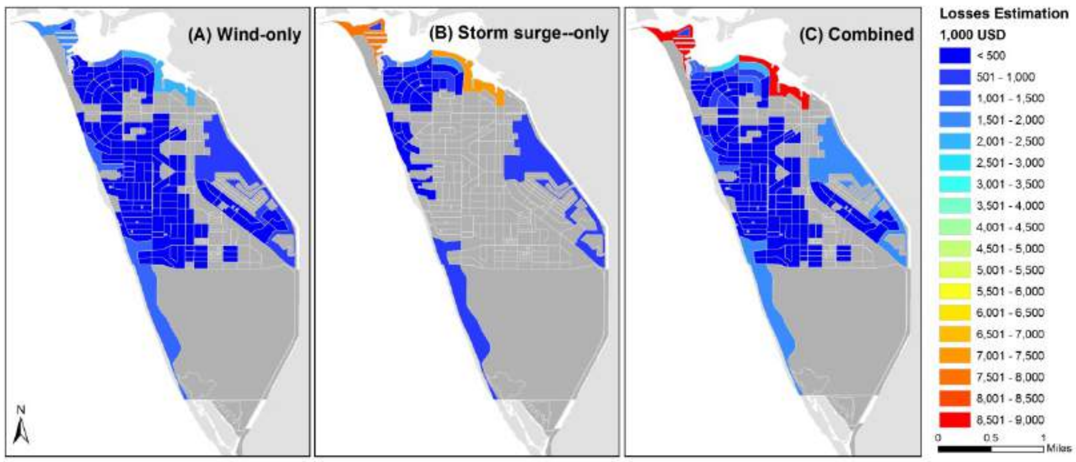

Figure 7. The housing price loss estimates using wind-only (A) storm surge-only (B), and combined (C) wind and flood using the CB dataset.

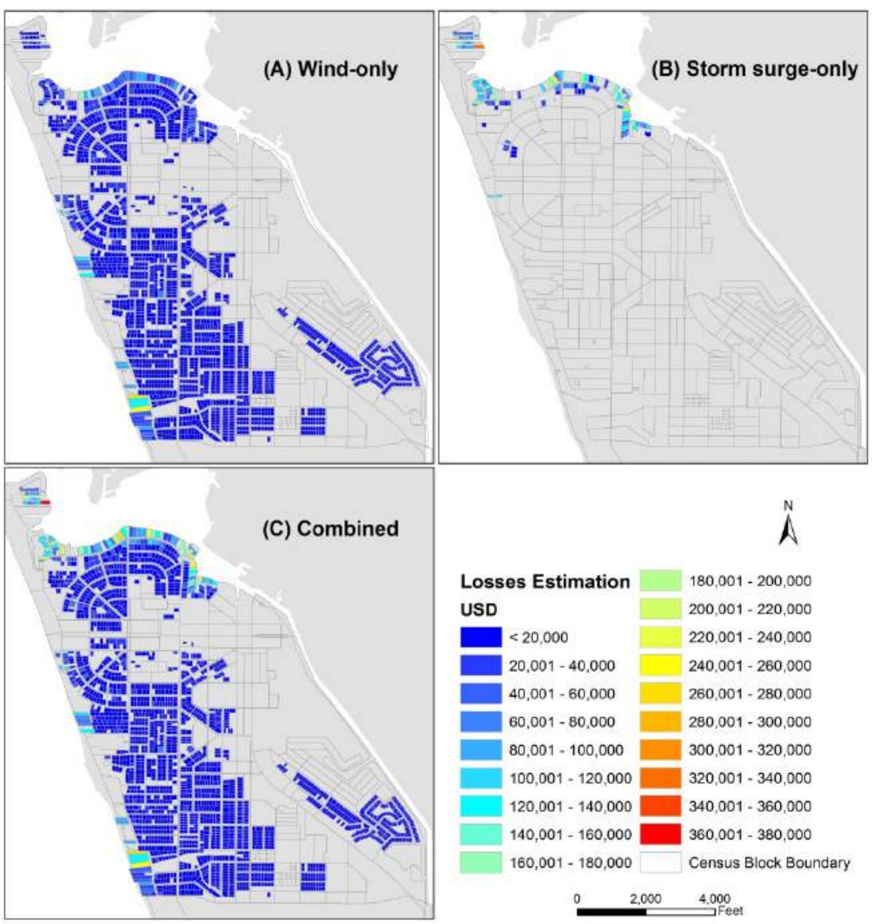

Figure 8. Housing price loss estimates of wind-only (A) and storm surge-only (B) and combined (C) wind and storm surge for the IH dataset.

To compare the CB and IH results, the IH results were aggregated as census blocks for comparison. Figure 9 presents the difference between CB and IH results, which was calculated by subtracting the IH estimates from CB. Compared with the IH dataset, the CB dataset had similar loss estimate results in wind-only damage, but tended to overestimate the losses of storm surge-only damage. For the wind-only estimates, most of the differences were under two million USD; for the storm surge result, the difference is higher, especially in two census blocks nearby Roberts Bay. The differences of combined loss estimates (from wind plus storm surge) had a similar pattern to the storm surge result, which indicated that most of the differences could be attributed to differences in the storm surge estimates. The average difference of loss estimates between CB and IH as census blocks for the wind- only estimate was -796 USD (standard deviation: 155,814), for the storm surge- only damage was 466,554 USD (standard deviation: 1,092,432), and for the combined damage was 117,812 USD (standard deviation: 688,428).

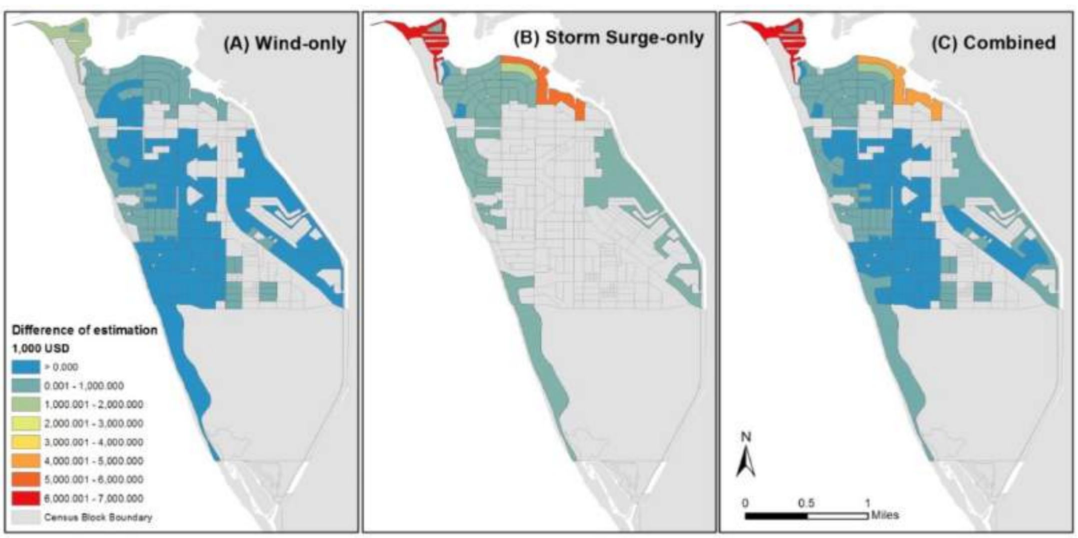

Figure 9. Comparison of the CB and IH datasets for wind-only (A), storm surge (B), and combined loss estimates.

The overall difference of wind-only loss estimate was much lower than the storm surge- only estimates (Table 4). This was because the mapping scale of the wind damage was much smaller than storm surge damage. As mentioned before, only two wind speeds were included in the study area (121 and 125 mph), which was because the wind speed distribution was determining using the regional scale model. For storm surge flooding, the distribution of flooding depth was more complicate: compared with results based on CB, the IH dataset was able to capture the complicated distribution of flooding damage. A conceptual framework for the relationship between mapping scale and detail of estimates is illustrated in Figure 10.

	CB	IH	Difference
Wind-only	27,609	24,940	2,669
Storm Surge-only (LR)	26,791	10,249	16,542
Storm Surge-only (HR)	24,825	9,053	15,772
Combined	49,593	33,576	16,017

Table 4. Estimates of total housing price losses in 1,000 USD. The combined estimates was based on the HR result.

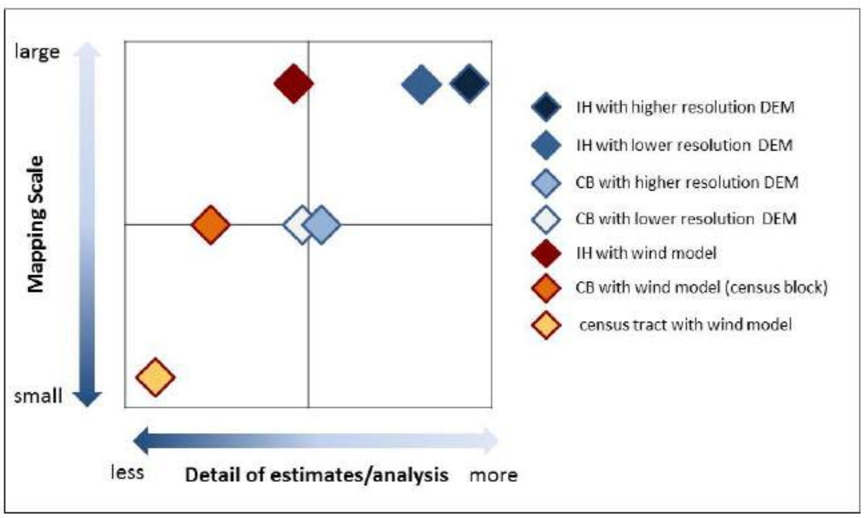

Figure 10. Conceptual framework of mapping scales and detail of estimates for the CB and IH datasets.

Discussion

Mapping Scale for Vulnerability Assessment

Previous multi-hazard studies rarely addressed the influence of mapping scales to the vulnerability assessments [12, 13, 28]. For example, Mahendra et al. [12] overlapped sea-level change rate, shoreline change rate, and estimated return periods of extreme storm surge layers and categorized results into hazard and safe zones to identify vulnerable buildings. My results showed a complex relationship between mapping scales and estimates of vulnerability for multi-hazard. I applied a built-in historical hurricane scenario in Hazus. The mapping scale of wind speed was small, which was because the model of the built-in scenario was designed for regional scale studies. For storm surge estimates, users are required to import DEM data. A higher resolution DEM from LiDAR and the IH dataset were imported and were used to compare with a lower resolution DEM and the CB dataset. Results showed that the storm surge estimates results are much more complex than wind estimates. The LiDAR data has been utilized for several flooding estimation studies and its reliability has been confirmed [17, 19, 20, 29, 30]. For instance, Tate et al., [19] studied the uncertainty of the Hazus Flood model. They concluded that DEM is the largest source of uncertainty among the model components, and argued that the census blocks in an urban area have better estimated results compare to rural areas, because they are smaller with more evenly distributed properties. Still, as the results showed in this study, compared with the CB dataset, the IH can predict estimates more realistically. Kappes et al., [14] reviewed several literatures of multi-hazard studies, and argued that the availability of data and methods, as well as scale issues are main challenges. The overall vulnerability might regard differently from vulnerability for single hazard.

It is possible to complete a more detailed and accurate modeling of wind and storm surge as a Level 3 Hazus model. For instance, Subramanian [21] compared the Hazus wind field model with 700,000 damage reports submitted after Hurricane Ike in Harris County, TX, using a machine learning method. They found the Hazus wind model had a predictive accuracy of only 29.5% with real damage, and suggested it was necessary to improve the Hazus model by using more detailed parameters and damage functions. However, applying a Level 3 analysis requires the expertise of one or more engineering and technical experts, and the expected modeling time is six months to two years [31]. It would not be feasible for a local manager to complete a Level 3 hazard analysis, particularly during a real-time hurricane evacuation management where notification time of a Category 1 Hurricane is 12- 24 hours[32]. The Level 2 model method presented in this study provides a more practical method for estimating losses from wind and storm surge.

Housing Prices for Economic Loss Estimation

The loss function in Hazus model were based on the damage records and surveys of hurricane events, therefore, most of previous Hazus studies applied building and content values to estimate the direct economic losses [33-35]. To investigate the potential impact of hurricane events to coastal real estate market, I applied housing prices, which was computed using the hedonic model analysis, to estimate the economic losses of wind and storm surge hazards. The hedonic model result showed that coastal amenities had positive and significant influences on housing prices, which lead to extremely high housing values for beach and bay- front properties (Figure 2), Some of these properties were also prone to storm surge hazard, which led to high housing price losses on the bay-front of Roberts Bay. Note that these houses were also essentially more *sensitive* to loss estimations.

Interestingly, in the hedonic model results, the dummy variable of Flood Zone V had a positive, significant relationship with housing prices, which was due to the fact that most of the single family properties located in the Flood Zone V had tremendous aesthetic benefits from water bodies, such as private access to beaches and ocean views. In fact, several studies have investigated the impact of hurricane [36, 37] and flood [3, 38] events as local housing real estate markets. For instance, Morgan [36] found average housing prices were 15% lower after Hurricane Ivan in Santa Rosa County, FL relative to prices before the hurricane. Venice Island has not been exposed to a severe hurricane event for decades; this study provides a benchmark for assessing the relationship between real estate markets and natural hazards and conducting a multi-hazard assessment for the area.

Conclusion

Multiple hazards might threaten coastal communities, especially during hurricane events. Therefore, multi-hazard vulnerability assessment, which has been utilized to identify hazard-prone areas and calculate possible costs of damages, is important for hazard management. Multi-hazard analysis is not an easy task because of complex methods and data from multiple sources scales. Thus far, there still lacks of a comprehensive study of determine the influence of mapping scales on vulnerability assessment for multiple hazards.

The main objective of this study was to utilize a Level 2 CHFH model to estimate the housing price losses using storm parameters from the 1944 Cuba-Florida Hurricane scenario. Two mapping scales of socio-economic inventory dataset were applied: CB (census block) and IH (individual building), note that few studies have applied IH scale for vulnerability assessment. This study also used DEMs with higher and lower resolutions for floodplain designations to determine the influence of DEM resolutions on results.

The results presented the complex relationships between mapping scales and the details of estimates. For the wind damage assessment, the wind field model was designed for application at a regional scale. Therefore, the distribution of wind damage was nearly uniform across the entire study area, and the losses estimates of using CB and IH were similar. For the storm surge assessment, the distribution of storm surge flooding depth was more detailed than that for the wind model, and the CB dataset was not able to estimate realistic damage because the buildings were assumed to be evenly distributed across the census block. This study also compared the storm surge flooding estimates with higher (HR) and lower resolution (LR) DEMs. For the CB dataset, the differences between HR and LR were similar; for the IH dataset, the HR provided a more accurate estimate of storm surge flooding because the HR DEM had a better ability to estimate the ground elevation of each building. The combined calculation of housing price losses showed that the highest losses occurred on beach- and bay- front properties due to the extremely high housing prices. Most of the difference of CB and IH results came from storm surge damage estimates (~15 million USD). Furthermore, the estimated housing prices losses presented the sensitive of estimation of high-housing prices properties, which mostly located on beach- and bay- fronts, and were more prone to storm surge hazard.

For future applications of the Level 2 CHFH model, the CB dataset would be sufficient for the wind- only assessment; however, for storm surge, the IH dataset with higher resolution DEM for assessment is strongly recommended. The housing price loss estimates can also provide a benchmark estimate for housing buyers and real estate manager. Future studies could complete a Level 3 CHFH model with more detailed wind model and damage functions to further examine the influence of mapping scales. Finally, the CHFH model only considers the wind and storm surge model; freshwater flooding from hurricane precipitation was not included. This can be an important factor, considering that approximately one-fourth of fatalities from Atlantic tropical cyclones result from freshwater flooding [39]. A combined estimate of damage from wind, storm surge, and freshwater hazards would better estimate vulnerability of coastal areas from hurricane hazards.

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