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Advancing Scenario Planning through Integrating Urban Growth Prediction with Future Flood Risk Models

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Abstract

High uncertainty about future urbanization and flood risk conditions limits the ability to increase resiliency in traditional scenario-based urban planning. While scenario planning integrating urban growth prediction modeling is becoming more common, these models have not been effectively linked with future flood plain changes due to sea level rise. This study advances scenario planning by integrating urban growth prediction models with flood risk scenarios. The Land Transformation Model, a land change prediction model using a GIS based artificial neural network, is used to predict future urban growth scenarios for Tampa, Florida, USA, and future flood risks are then delineated based on the current 100-year floodplain using NOAA level rise scenarios. A multi-level evaluation using three urban prediction scenarios (business as usual, growth as planned, and resilient growth) and three sea level rise scenarios (low, high, and extreme) is conducted to determine how prepared Tampa's current land use plan is in handling increasing resilient development in lieu of sea level rise. Results show that the current land use plan (growth as planned) decreases flood risk at the city scale but not always at the neighborhood scale, when compared to no growth regulations (business as usual). However, flood risk when growing according to the current plan is significantly higher when compared to all future growth residing outside of the 100-year floodplain (resilient growth). Understanding the potential effects of sea level rise depends on understanding the probabilities of future development options and extreme climate conditions.

Keywords

Scenario planning; prediction modeling; sea level rise; land transformation model; climate change

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1. Introduction

As the built environment, population locations, and technology rapidly change, the future becomes more complex and unpredictable (Kok et al., 2007; Rotmans et al., 2000). High uncertainty in both flood risk and urban growth make planning for future urbanization difficult. Observed temperature increases and sea level rise have created unprecedented situations which must now be addressed (Pachauri et al., 2014; Newman et al., 2020). The National Oceanic and Atmospheric Administration (NOAA) reports the global mean sea level will rise between 0.2 meters and 2.0 meters by 2100 (Parris et al., 2012). Simultaneously, the United Nations (2017b) reports that the global population will increase by 29% between 2017 and 2050 (7.6 billion). Sea level rise due to climate change makes coastal populations more susceptible to flood risks while urban expansion and land use alterations due to population growth can worsen climate conditions and place more people in hazard zones.

Worldwide, more than 600 million people live in coastal regions currently lower than 10 meters above sea level, and nearly 2.4 billion people live within 100km of the coastline (United Nations, 2017a). In the U.S., 254 counties (8%) out of 3,142 are located on the coast. However, 39% (123.3 million people) of the county's total population live in coastal counties, and 52% (163.8 million people) live in coastal watershed counties (Wilson & Fischetti, 2010). Shoreline county populations have grown steadily since 1970 and are projected to continue do so (Crossett et al., 2013).

Land use change. the result of interaction between human activity and natural resources, plays a pivotal role in preparing the built environment for the future uncertainty through planning processes (Agarwal et al., 2002). Land change modeling (LCM) is a planning support system integrating future land use prediction models into the planning process (Berke et al., 2006). LCM creates the opportunity to mold uncertain futures into more succinctly determined conditions, when coupled with scenario planning (Harwood, 2007). Traditional "predict-and-plan" approaches allow for only singular growth trajectories and fail to adequately address the future complexities (Quay, 2010; Van der Heijden, 2011). Through better understanding of historic land development processes, LCM can be used to predict accurate future urban growth scenarios supporting urban planning for potential future flood risk mitigation. Over the past few decades, urban LCM has significantly advanced, addressing urbanization issues and their impacts in multiple related and distinct fields (Güneralp, 2011).

Scenario planning, a flexible approach to making long term plans based on options for future growth (Berke et al., 2006; Masterson et al., 2019), has been actively integrated with LCM, but most LCM studies do not integrate urban growth predictions with future sea level rise projects, fully incorporate the existing arsenal of model calibration methods, explore the possibilities of extreme change possibilities, implement multi-scalar analytics into their evaluations, or gauge the successfulness of city growth plans. This study advances LCM research using scenario planning by analyzing the effectiveness of a current land use plan and comparing the plan with predicted growth options. Using the Land Transformation Model (LTM), a popular and proven accurate LCM (Pontius et al., 2008), we predict potential future urban growth and flood risk scenarios in Tampa, Florida, and assess future urban flood exposure at city and neighborhood levels.

2. Literature Review

2.1. Defining Scenario Planning

As Van der Heijden et al. (2002, p.277) posits, “It is not simply what you know that matters, but how you react to what you do not know.” Scenario planning is a decision-making process which identifies and plans for various future options (Van der Heijden, 2011); it helps stakeholders (e.g. agencies, local officials, developers, land owners, general public) to make better decisions for possible future conditions by comparing and assessing different and plausible stories (FHWA, 2011). Ringland and Schwartz (1998, p.2) define scenario planning as the “part of strategic planning which relates to the tools and technologies for managing the uncertainties of the future.”

2.2. Scenarios in Urban Planning

In the field of urban planning, Quay’s (2010) “predict and plan” approach is used to predict future populations or employment trends to arrange future necessary infrastructure. In both land use and transportation planning, a single preferable future state/trend (e.g. population estimation) has been used as a standard to forecast future urban change; this approach works well when society and the environment are stable and predictable (Chakraborty et al., 2011; Quay,2010). However, high uncertainty and complexity due to climate change and population relocation dynamics can decrease accuracies in singular prediction approaches (Van der Heijden,2011).

In urban planning, scenarios have been widely utilized for land use, transportation, economic development, environmental systems, resilience, and other fields (Goodspeed, 2017). Researchers have made significant efforts in improving scenario development processes, tools, and evaluation. Postma and Liebl (2005) specified a conventional scenario planning approach, identifying a set of common predeterminants and unknowns and ranking levels of impacts and levels of uncertainties for unknowns (Van der Heijden et al., 2002). They suggested methodological adaptations for future scenario construction through considering and weighting uncertain or unique factors. Couclelis (2005) suggested that this could be created through better synergies with computer techniques in land-use models.

Further, Hopkins and Zapata (2007), when planning a three-county metropolitan area, promoted what they referred to as contingent scenarios – an approach to investigating a compendium of plans and comparing them with sustainable forecasting tools. Quay (2010) posited that anticipatory planning could be used as a model to combine future predictions and analyses to explore broader ranges of possible scenarios. However, to increase accuracies and probabilities in broader scenario development, a broader array of driving forces must also be utilized. Chakraborty et al. (2011) promoted an approach for increasing accuracies through largescale scenario analysis which adopted both internal (controllable) and external (uncertain) driving forces behind prediction models. Through such an approach, both robust plans covering future predicted scenarios as well as contingency plans supporting specific future were created and analyzed. Recently, Goodspeed (2017) proposed adding additional factors for urban scenario planning, including psychological, institutional, and system-related drivers and outcomes. However, though scholar's efforts in developing scenarios in urban planning, there are still some deficiencies in considering uncertainties, predicting for and assigning impacts of only a single preferred scenario/plan, and an unwillingness to predict for and entertain extreme circumstances (Chakraborty & McMillan, 2015; Chakraborty et al., 2011).

2.3. Urban Growth Scenarios and Sea Level Rise

LCM has been shown to be an effective tool to develop and evaluate future urban growth scenarios. LCM can project future land change and the outcome of natural and human systems based on relationships among historic land cover and explanatory factors to estimate the mostlikely patterns (Brown et al., 2013). Many LCM studies have examined forecasted urban growth scenarios and their subsequent impacts to identify optimal future growth directions. However, scenarios have been limited primarily to typologies which compare a business as usual (same growth pattern as previous patterns) output (Shi et al., 2017) to scenarios which only offer alternatives for urban growth which do not fully encompass the broader options and possible extreme circumstances related to climate change (Song et al., 2017; Goodarzi et al., 2017; Shi et al., 2017; Te Linde et al., 2011; Liu et al., 2011).

Only a handful of studies have estimated climate change/sea-level rise (SLR) impacts on future urban growth in LCM studies (De Moel et al., 2011; Song et al., 2017; Te Linde et al., 2011; Zhao et al. 2017). When examining flood risk, SLR scenarios (Song et al., 2017), riverflood probabilities (Te Linde et al., 2011), or existing flood risk maps (De Moel et al., 2011) have been examined using multiple growth scenarios according to site conditions. For instance, Zhao et al. (2017) examined the efficacy of land use adaptation strategies by comparing two growth scenarios (baseline and adaptation) with low/medium/high SLR scenarios by 2030 and 2080. Song et al. (2017) assessed flood damage area using different urban growth density scenarios (historic growth, urban sprawl, and compact growth) in the 500-year floodplain under two SLR scenarios (0.2m and 0.9m). Te Linde et al. (2011) predicted potential flood damage using two socio-economic growth scenarios (high/low economic and population growth) with river flood probability by 2030. De Moel et al. (2011) compared socio-economic growth scenarios in 2040 and 2100 with existing maximum flood inundation capabilities. The previously identified articles utilized different flood risks due to available data or particular site conditions. However, for scenario analyses, each existing study only estimated flood damage areas within a single study scale (e.g. country, watershed, or city) at to identify a preferred growth scenario. Few studies have actually employed urban growth and flood risk scenarios.

2.4. Literature Gaps and Research Question

This research adds several contributions to the existing computational literature involving prediction modeling. The literature review revealed several needs accolated with current LCM research including 1) ranking levels of variable influence through the consideration of factors (Postma and Liebl, 2005), 2) better synergies with computer techniques in land-use models (Couclelis, 2005), 3) a need to better investigate and evaluate the successfulness of existing plans (Hopkins and Zapata, 2007), and 4) the need to explore broader ranges of possible scenarios based on extreme circumstances due to climate changes (Quay, 2010). This study fills these needs by 1) ranking the influence of driving factors utilized to predict through drop one experiments, 2) integrating and analyzing LCM scenarios with SLR scenarios, a rare coupling in the current literature, 3) evaluating the successes and drawbacks of the current comprehensive plan for Tampa through flood risk evaluation rather than simply analyzing whether the plan's goals were accomplished or through post-occupancy evaluation measures, and 4) forecasting extreme urban growth options (such as no growth in the future 100 year floodplain) and linking these forecasts with extreme SLR projections.

Methodologically, our approach advances gaps in existing prediction modeling literature, also in a myriad of ways. First, we combine 5 different calibration methods to ensure model accuracy (PCM, Kappa, OA, AUC, and drop-one experiments); most research primary relies on Kappa statistics and PCM for validation (Pontius, 2011). Further, we uniquely calibrate the model by first predicting for existing circumstances (for the year 2011) and comparing the prediction outputs with the urban growth circumstances for 2011 (expanded upon later). Second, we use both municipal and local scaled analytics to assess impact. Current research relies primarily on a single scale, mostly only city or regional. Finally, this research incorporates 15 different driving forces to predict urban growth. The average amount of driving factors utilized in the current literature is only around seven variables. As far as we know, this research is the most comprehensive approach to integrate urban growth and SLR scenarios and fills several gaps in the current research.

The research asks, how can combining urban growth predictions into scenario analyses help inform preparedness for flood risks due to climate change in urban planning? To answer this, we determine the effectiveness of the current land use plan by comparing it to other urban growth options when considering future flood risks. The research articulates and illustrates a scenario development process, coupling both urban growth and flood risk scenarios (including SLR), and suggests two new types of growth scenarios (planned and resilient urban growth) to examine each scenario's efficacy to future flood risks at multiple scales using Tampa, FL, USA as a study area.

3. Methods

Based on the literature, we developed a process for analyzing the impact of climate change on three future urban growth scenarios: business as usual (BU), growth as planned (GP), and resilient growth (RG) (each explained in detail later). As Fig. 1 illustrates, the research process is divided into two parts: scenario making and impact analysis. Scenario making comprises 1)the prediction of urban growth scenarios using the LTM, and 2) delineation of future flood risks based on sea level rise scenarios using Geographic Information Systems (GIS). Then, impacts are evaluated using area of predicted urban growth exposed to flood risks at both city and neighborhood levels.

3.1. Scenario Making and Impact Analysis

3.1.1. Exclusionary Layers—As stated, the urban growth scenarios in this research employ the three categories: business as usual (BU), growth as planned (GP), and resilient growth (RG). The future urban growth in the BU scenario is natural growth without development regulations. It is based on the premise if new development occurs according to current development patterns. In the GP scenario, the growth projection follows the current land use plan for Tampa, reflecting how the city government and/or community prefer to develop. The RG scenario is an extreme scenario where no development occurs within the future 100-year flood plain. To restrict urban growth predictions into specific areas, the LTM uses exclusionary layers (Kim & Newman 2019). This approach creates the ability to controlling land development according to spatial rules. An exclusionary layer includes areas where no development will occur during an LCM, allowing for the exclusion of future areas for urban growth when predicting.

In this research, the BU scenario employs minimum exclusions including existing built parcels and water surfaces. It is assumed that, if a building already exists on a surface, another building will not occur on the same spot, although growth could occur around such an area; it is also assumed that development will not occur within a current warmer body, but could occur tangentially. The GP's exclusionary layers includes preservation areas (e.g. environmentally sensitive areas) according to the land use plan as well as those include within the BU scenario. Finally, the RG incorporates the BU and GP's exclusionary layers and also adds future flood risk zones an exclusionary layer.

3.1.2. Sea Level Rise Projection—For projecting the SLR scenarios, NOAA provides future potential sea levels with relative sea level (RSL) projections and different heights of the sea surfaces at different locations in the U.S., based on historic sea level changes (Parris et al., 2012). NOAA (2017) includes six future sea level scenario projections, each with a 95 % confidence level: low, intermediate low, intermediate, intermediate high, high, and extreme SLR options (Parris et al., 2012). The low scenario is a linear estimation based on the historical SLR tide records since 1900, showing a 1.7mm increase per year, on average. The intermediate low (IL) scenario is an optimistic scenario estimating minimum ice sheet melting and ocean warming and is based on more recent observations. The high (HI) scenario calculates maximum glacier and ice sheet loss and is a standard for highly vulnerable facilities such as power plants and high-risk industrial facilitates. The extreme (EX) scenario combines extreme weather and climate patterns to project the worstcase scenario (Parris et al., 2012). SLR records for St. Petersburg, FL were used for this research. NOAA's projection shows that SLR by 2040 for St. Petersburg vary from 0.18 meters (low) to 0.62m (EX). This study uses the IL scenario (+0.22m) as a primary risk, the HI scenario (+0.54m) as a less likely, but probable risk, and the EX (+0.62m) as worst case, but slightly possible, risk for SLR. The use of these scenarios has been shown to be a highly effective range of multiple future conditions with the high prediction confidence based on local SLR records (Arkema et al., 2013; Parris et al., 2012).

SLR projections are developed based on the National Flood Insurance Program's 100-year floodplain from the Flood Insurance Rate Maps. The 100-year floodplain signifies a 1% chance of flood in any given year. SLR scenarios were delineated by using a modified bathtub method, considering sea level height and hydrologic connectivity (Marcy et al., 2011), as seen in Berke et al.'s (2015) hazard mapping. As Fig. 1 shows, the urban growth and SLR scenarios combine to create nine potential future options. The BU and IL scenario combinations indicate urban growth with no regulation and intermediate- low flood by 2040. The GP and HI scenario combination include future urban areas following the land use plan with SLR by 2040 according to NOAA's high flood risk. The RG and EX scenario combination includes no future development under the future 100-year flood plain with an extreme SLR 2040 scenario. The impact analysis is based on flood exposure calculations at both city and neighborhood scales. The flood exposure calculation compares the existing urban area and the predicted future urban area through urban growth scenarios at a city and neighborhood levels.

3.1.3. Urban Flood Exposure at Multi-Scales—We also calculate urban flood exposure at both city and neighborhood levels. At the city level, existing urban area, predicted future urban growth scenarios, and future flood risk scenarios are calculated. The results show how each urban growth scenario (BU, GP, EX) is differently impacted by each SLR scenario (IL, HI, and EX). At the neighborhood level, the total tally of neighborhoods exposed to future flood risk and the total area under future flood risk by different urban growth scenarios are compared.

3.2. Urban Growth Prediction using the Land Transformation Model

The LTM is a tool to predict future land uses which examines relationships between driving factors of urban growth and land use changes through GIS and a machine learning process known as an artificial neural network (ANN) (Pijanowski et al., 2002). The LTM shows one of the highest current performances among some of the most used prediction models (Pontius et al., 2008). Its approach identifies non-linear relationships using a multi- layered ANN and includes input, hidden, and output layers. The LTM has the capability to predict future urban land change while integrating physical, socio-economic, and other growth-related variables through spatial transition rules (Pijanowski et al., 2002).

As Fig.2 shows, the LTM process incorporated 15 variables to predict future urban growth; performance and calibration methods were calculated to ensure accuracy of the model. Rasterized predictor variables linked to a geographical location (such as proximity and density data), referred to as driving factors, were inputted with rasterized historic land cover data sets for two the years 2001 and 2011 (referred to as base maps). The LTM literature recommends 250,000 training cycles, while 4,000 cycles are the minimum, to stabilize error levels (Pijanowski et al., 2002). More than 250,000 training cycles do not typically show much greater prediction accuracy (Lee et al., 2017; Pijanowski et al., 2005). Thus, this study used 250,000 training cycles. To better validate the model before predicting for future circumstances, after computing the output of expected change between 2001 and 2011, we compared this output to the actual land use between 2001 and 2011. To validate the model, we used four accuracy metrics including percent correct metric (PCM), kappa coefficient (Kappa), overall agreement (OA), and area under curve (AUC) of receiver operating characteristic (ROC). We also confirmed each driver's prediction capability and contribution with drop-one tests (Brown et al., 2013). All accuracy metrics concluded that the model was valid and the drop one tests confirmed the utilized drivers. Then, the future urban growth forecast for each scenario was forecasted and the same metrics were used to validate each scenario.

The 15 driving factors untiled in the LTM are proven contributors to urban growth in the literature and include slope (Berke et al., 2006), land value (Alonso, 1964), population density (Losiri, 2016), population increase (Veldkamp & Fresco, 1996), poverty (Hu & Lo, 2007), employment (Amano et al., 1988), proximity to roads (Daniels, 1999), watersurface, waterfront, parks (Correll et al., 1978), existing urban (Jafari et al., 2016), residence (Zhao et al., 2017), commercial (Munshi et al., 2014), central business district (Al-sharif & Pradhan, 2016), and public schools (Ku 2016). All driving factors were obtained from open-source data. Proximity variables were obtained from the City of Tampa Geo Hub and the U.S. Geological Survey, land value from the Hillsborough Appraisal District, and socio-economic data from the U.S. Census Bureau.

As noted, each driving factor's contribution to the model are proven by the calibration approaches statistical outputs as well as the drop-one experiment (Brown et al., 2013) (see Table 1 in Appendix). As noted, this research uses the four most common types of spatial statistical measures to validate spatial patterns: PCM, Kappa, OA, and AUC. PCM is the percentage of the cells correctly predicted to change divided by the total cells actually changed during the study period (Pijanowski et al., 2005; Pijanowski et al., 2014). Kappa is a widely used index in accuracy assessment and designates the proportion of agreement removing expected chance agreement (Cohen, 1960). However, because of limitations in only using the Kappa index (Pontius, 2000), this study also employs Overall Agreement (OA) and Area Under Curve (AUC, also known as ROC) calibration methods. Quantity disagreement is the difference in changed cell numbers without considering location, and allocation disagreement is the spatial difference in transition (Lee & Newman, 2017; Pontius & Millones, 2011). OA can be drawn by removing the quantity disagreement and allocation disagreement. Receiver Operating Characteristics (ROC) is a two-dimensional graph, plotting the true positive rate (sensitivity) on the Y axis and the false positive rate on the X axis, with 1 – the true negative rate (specificity), and it explains relative tradeoffs (Fawcett, 2006; Streiner & Cairney, 2007). AUC is the areas under ROC. The outputs from these calibration methods are explained in the results section.

3.3. Study Area

To select a case site, we used three prerequisites: the city 1) must have a comprehensive plan, 2) must be growing in population, and 3) must be coastal/flood-vulnerable. Like other cities in Florida, Tampa has a strong local comprehensive plan (Brody, 2001). As illustrated in Fig. 3, Tampa is located on the western coast of Florida in Hillsborough County. Southern Tampa is enclosed by three Bays; Tampa Bay, Old Tampa Bay and Hillsborough Bay. The climate is humid subtropical with a large amount of summer rainfall and hot temperatures due to the oceanic location. Due to its climate and geographic location, Tampa is ranked the most vulnerable U.S. city to hurricanes (Climate Central, 2012). The area is 170 square miles ($440km^2$) and the land elevations vary from sea level along the coastline to 55ft (16.7m). It is the third largest city in Florida with a population of 304,200 people in 2000, and 336,800 in 2010. The city's population has grown steadily, and is projected to grow in the future to 481,128 in 2040 (Hillsborough County, 2016). Due to the shallowness of Tampa Bay and the city's flat terrain, SLR will make more residents susceptible to increased flood risk.

4. Results

4.1. Model Validity

The LTM output showed that there was a change of 8,917 pixels of urban growth between 2001 and 2011, indicating a change of approximately 32,600 people. The future urban growth scenarios project a change of 48,395 pixels (30×30m), corresponding to a 176,928 population change between 2001 and 2040. The forecasted pixel numbers are the same for all scenarios, but the locations of the pixels are different based on the different exclusionary layers utilized for each scenario. As illustrated in Fig. 4, the total existing urban (light gray) in 2011 was 172.8km^2 (57% of the total Tampa area), the increased urban area (black) between 2011 and 2040 is 35.6km^2 (12%), and the rest of the area (white) within the Tampa boundary was 96.3km^2 (31%) was used for agriculture, wetlands, forests, water, and other uses.

The drop-one experiment runs the prediction model a series of times, with one driving factor missing. This is done until each driving factor has been removed for the model to see if the PCM increases if a variable is removed. If this occurs, it can be assumed that the removed variables decrease the accuracy of the model. As the drop-one test result shows (see Table 1 in Appendix), each variable used in the model positively contributes to the prediction capability and accuracy. This is indicated by the PCM values of each drop-one test being below the PCM value of the full 15 variable model. For the accuracy result of the full model, the PCM is 52%, and the kappa coefficient is 48%. All values are within acceptable and good ranges in prediction (Newman et al., 2016), justifying this as a proper model. The highest Kappa Statistic and PCM value from each 1,000th training cycle in each model varies from the 30,000th to 250,000th cycle. The distance to roads and distance to parks showed to be the most influential determinants in changing land cover. The next strongest factors are distance to existing land use, commercial, public schools, and residential. Though population density and land value have prediction capability, they appear to be less influential than other determinants in this model.

The model accuracy outputs (see Table 2 in Appendix) are measured to validate the accuracy of the prediction model. The BU scenario has a PCM of 52%, a Kappa of 48%, an OA of 93%, and an AUC of 74%; the GP scenario has a PCM of 55%, a Kappa of 5 0%, an OA of 91%, and an AUC of 75%; and the RG scenario has a PCM of 68%, a Kappa of 63%, an OA of 91%, and an AUC of 82%. All measures in each scenario show an acceptable or good level of prediction (Lee & Newman, 2017; Newman et al. 2016). When comparing the prediction accuracy values of each scenario, the results show that RG is the most accurate, and GP is more accurate than BU. In the fixed variable prediction, the total pixel numbers influence the prediction performance. In this approach, the rule is the more pixels, the less accurate, but, all are acceptable models.

4.2. Prediction Outputs: Future Urban Growth and Flood Risk

The prediction result (see Fig.4) shows different development patterns for each scenario. Future urban growth in the BU scenario is primarily located in northern Tampa (19.3km^2) with some development in the central (11.8km^2) and south regions (4.5km^2) of Tampa. The urban growth in the GP scenario involves evenly distributed development including 12.3km^2, 16.0km^2, and 7.2km^2 in the north, central, and southern regions, respectively. Urban growth in the RG scenario, however, focuses primarily on the central (17.5km^2) and north Tampa regions (15.6km^2).

For the SLR projection (see Fig. 4 and Fig. 2 in Appendix), the current 100-year floodplain covers 90.9km^2, or 30% of Tampa's area. The intermediate- low SLR scenario (0.22m) will enlarge the floodplain to occupy 108.5km^2 of Tampa (36%). The 0.54m SLR (high scenario) and the 0.62m SLR (extreme scenario) would expand the floodplain coverage to 113.4km^2 (37%) and 114.4km^2 (38%), respectively.

4.3. City Scaled Urban Flood Exposure

Urban flood exposure is calculated by overlapping existing urban and projected future urban scenarios with the projected future flood risk zones. In the existing urban exposure to future flood risk scenarios (the upper left in Fig. 4), as the sea level rises, more urban areas will be vulnerable to flood risk. In the inter-low (IL) SLR scenario at 47.3km^2, 27% of the total existing urban area would be susceptible to flood risk. In the high (HI) and extreme (EX) SLR scenarios at 51.0km^2 and 51.8km^2 of existing urban areas would be vulnerable to future flood risks. Fig. 4 shows that a large number of urban areas are under the current 100-year floodplain. More than 20% of existing urban areas are under the current floodplain, and future urban development would occur in the current flood zone, 30% of future urban development in BU and 22% in GP.

Fig. 4 also shows three urban growth scenarios (BU, GP, and RG) under different future floodplain scenarios; IL, HI and EX SLRs. Under the IL (+0.22m) SLR scenario, 11.9km^2 of BU and 9.5km^2 of GP would be endangered by flood risk. RG would be free from flooding due to new development oly outside the floodplain. Under the HI (+0.54m) and EX (+0.62m) SLR scenarios, areas vulnerable to flooding would increase 12.4km^2 and 12.5km^2 in BU, and 10.0km^2 and 10.1km^2 in GP. In the EX SLR case, more future urban areas would be under the sea level rise floodplain by 2040: 0.6km^2 in BU and 0.3km^2 in GP. In all SLR scenarios, the RG scenario is safer from future flood risk. Similar to the existing urban case, the higher the sea level rises, the more future urban areas are exposed to flood risk, except RG.

Since Tampa's geography ranges from 0 to 55 feet above sea level (Hillsborough County, 2016), a small change in the SLR can affect large areas of land. Existing urban areas would increase from 47.4km^2 in the IL scenario to 51.8km^2 in the EX one. BU's flood vulnerable urban area would enlarge from 11.9km^2 in the IL scenario to 12.5km^2 in the EX scenario. GP would be relatively smaller, with only 9.5km^2 in the IL scenario and 10.1km^2 in the EX scenario. RG is safer from all the SLR impacts. In the result between the HI and EX scenarios, the number of urban areas exposed to flood risks are not much different because the gap in the sea levels is small (+0.08m) between the scenarios.

Overall, in regards to flood risk reduction of future urban areas, the GP scenario shows to be better than BU, but much worse than RG. The number of flood vulnerable areas in the GP scenario is less than those of BU in all flood risk scenarios. However, the gap between the areas in BU and GP is not as obvious compared to that of GP and RG in all SLR scenarios.

4.4. Urban Flood Exposure at a Neighborhood Scale

The neighborhood scaled analysis examines how much future urban area in each neighborhood would be under future flood risks by comparing BU and GP, since RG lowers flood risk across all SLR scenarios. So, due to RG's floodplain free design, it is excluded from the comparison. For flood risk, this section uses a fixed HI SLR scenario to compare urban flood exposure in the BU and GP scenarios.

The results of potential flood impacted urban areas by neighborhood (see Table 3 in Appendix) indicate that 71 out of 127 neighborhoods are in existing urban areas. In the existing urban areas, two neighborhoods (#103 and #68) are the most vulnerable, with the largest amount of impacted areas (7.6km^2 in #103 and 6.3km^2 in #68). In the future urban scenarios, 55 neighborhoods in BU and 58 in GP would be exposed to flood risks. In BU, future flood risks would impact more than 1km^2 of new development in four neighborhoods (#13, #40, #68, and #113). In the GP scenario, future flood risks would impact more than 0.6km^2 in three neighborhoods (#28, #68, and #113). Neighborhood #68 is the most vulnerable to floods in both existing and future urban scenarios.

In the urban flood exposure comparison within a neighborhood between BU and GP (see Table 3 in Appendix), as Fig. 5 illustrates, 27 neighborhoods in the BU scenario have a larger number of urban areas exposed to floods than does the GP scenario. However, 30 neighborhoods in GP have a larger number of urban areas exposed to floods than does BU. This suggests that, when future urban development follows a land use plan (GP), the 30 neighborhoods (see the right map in Fig. 5) would have a larger amount of area under flood risk zones than urban development without a plan (BU).

At the city level, a large number of existing urban areas are under the current 100-year floodplain, 21% of the existing urban areas (36.5km^2). This would be enlarged by up to 51.8km^2 (or 30%) in the extreme SLR scenario. Out of the total future urban development of 35.6km^2 by 2040, 10.7km^2 (30% of future urban areas) in BU and 7.9km^2 (22%) in GP are projected to be developed in the current 100 year floodplain, with 12.5km^2 (35%) in BU and 10.1km^2 (29%) in GP under the future extreme SLR scenario. In the comparison of total urban flood exposure, existing urban areas are problematic, and urban growth as with no plan (BU) would cause more floodplain development than growth as planned (GP). When examining the results of the city level analysis, GP is better than BU in all the SLR scenarios, the total urban area exposed to flood risks in GP is less than in BU.

The neighborhood level analysis shows opposing results. There are 71 neighborhoods comprising the existing urban area, and more than 50 neighborhoods with future urban predicted growth (55 neighborhoods in BU and 58 in GP) would be impacted by future HI SLR risk. More neighborhoods in GP would be vulnerable to floods than in BU due to predicted floodplain development. Further, when comparing BU and GP, more numbers of neighborhoods in GP would have larger areas vulnerable to flood than in BU. Corollary, 30 neighborhoods in GP have larger areas of predicted development in high risk flood zones than in BU, but the 27 in BU have larger urban areas exposed to flood risks than in GP. Thus, planned urban growth in Tampa would be better to minimize potential flood damage at a city level than a growth with no plan, but it could be worse for some neighborhoods.

5. Discussion and Limitations

This research sought to determine how combining urban growth predictions into scenario analyses can help inform preparedness for climate change in urban planning. The results showed that urban growth scenarios forecast different growth patterns and flood risks will increase in response to rising sea-levels. The analyses indicate that regional solutions can sometimes have negative implications at the neighborhood scale. To address this circumstance, when making or updating comprehensive plans, planners and local stakeholders should work together to make better decisions by examining plausible scenarios and identifying their impacts. The findings reveal several impacts that provide a basis for a series of recommendations for future climate adaptation planning.

First, both context and local scaled analyses should be employed across each scenario created. Results in Tampa show that the area of future urban flood risk differs by scenario, and impacts differ depending on the scale of analysis. The current land use plan (GP) works well at the city level, but not as strong at the neighborhood level when compared to no growth regulations (BU), but much worse when compared to all future growth residing outside of the flood risk (RG). Through the scenario-based approach, the possibility to reduce potential flood damage in the current land use plan and its related policies can be exposed. Regarding the results of the multi-scaled analyses, some neighborhoods seem to be sacrificed (in regard to increased flood risk) for the greater good. Despite the fact that land use plan is primarily defined the use of ESA zones, the total urban flood exposure of the land use plan (GP) is still less than without a plan (BU). However, at a neighborhood level, more neighborhoods will be endangered by GP than BU. Thus, some neighborhoods would become more vulnerable to flooding due to the current plan. Once the current plan is fully implemented, local-level strategies (e.g. green infrastructure, storm-water management, etc.) (Ahiablame et al., 2012) to decrease potential flood risk should be prepared (especially for the flood-vulnerable neighborhoods) through local/community engagement. Planners should make decisions at multi-scales based on feedback from different scales (Agarwal et al., 2002; Demuzere et al., 2014).

Second, the suggested method in this research can be utilized to analyze/interpret the effectiveness of current land use plans and policies. For example, our findings show that the ESA land uses and their related development restriction policies help to decrease floodplain development. However, ESAs may force more floodplain development in areas outside of ESA overlays, which can result in future development in flood risk areas when considering SLR. The allowance of development within the future floodplain will endanger more people and assets. In Tampa, floodplain development is allowed by following current building codes and controlling the base flood elevation (BFE). This approach is based on the 100-year floodplain elevation under ENV Policy 2.1.3 and CM Policy 1.3.4 (Hillsborough County, 2016). However, due to changing climate patterns and increasing impervious surfaces due to new development and as shown in this research, the BFE standard may not always guarantee safety; this creates a false sense of security from flood risk (Tobin, 1995) which, then, can encourage increased floodplain development. The best way to minimize flood damage, of course, is to restrict floodplain development with land use management and policies. As a strong flood adaptation tool, land use regulations can guide future development locations outside current and future flood risk areas (Berke et al., 2015). Considering the forecasted urban flood exposure and future SLR impacts, better development regulations (e.g. restricting floodplain development, building codes) should be prepared before a flood disaster event occurs. During the planning process, the suggested scenario planning method in this research can be utilized to visualize where future urban will grow and how much area will be endangered by future SLR scenarios, should growth occur as predicted.

Thirdly, to help address uncertainties associated with a changing climate, future scenarios should continue to incorporate extreme growth prediction and SLR circumstances instead of being so reliant upon conservative outputs. In the case of Tampa, in this research, as a land use plan evaluation tool, the results show locations that are most vulnerable to future flood risk at multiple scales in different urban growth and SLR scenarios. Based on the results, planners can prepare for robust and contingent strategies (Chakraborty et al., 2011) for the entire city as well as specific neighborhoods (Goodspeed, 2019). This process can also be used during the plan making stage. As noted, especially in Florida, comprehensive plans are legally binding (Brody, 2001), so a GP scenario would be the most probable urban future. RG is the most desirable urban future in regards to sustainability, but may be difficult to tully realize due to planning priorities or stakeholders' rights of properties. For the flood risk scenarios, with a 95% confidence interval, NOAA's SLR prediction IL, HI and EX conditions were employed for a broader potential range of increased future flood risk. If there are other types of more plausible or extreme conditions (e.g. between/beyond GP and RG, more than EX), they should be included to take full advantage of scenario planning.

There are some limitations in prediction accuracy and impact evaluation that can be improved upon in future studies and advancements in prediction accuracy and impact assessments. First, future urban growth prediction has more room to raise its accuracy. In this study, the performance of urban growth prediction by LTM was tested with four different measures such as PCM, Kappa, OA, and AUC, showing a good range of prediction accuracy. Also, this study justified 15 driving factors contributing to Tampa's urban growth using drop-one tests (Brown et al., 2013). However, employing more influential drivers and multi-year land cover (e.g. land cover 2021) comparisons would enable the ability to predict with higher accuracy. Second, future flood risks were not fully represented through only adding SLR scenarios to the current 100-year floodplain using the bathtub approach. To increase plausibility, future research should consider increases in impervious surfaces impacting hydrology and a new floodplain integrating future run-off and peak flows (Gori et al., 2019). When open space land uses are converted to urban land uses, flood risk can increase due to increased floodplain areas and impervious surfaces. Moreover, as climate changes, rainfall patterns become severe, exceeding a 100-year rainfall. It is necessary to develop a more accurate flood risk delineation approach since the current 100-year floodplain does not capture dynamic conditions extremely effectively (Blessing et al., 2017). Third, to increase accuracy in the impact evaluation, planning policies need to be assessed and updated to determine how plan policies prepare for future flood risks. The results of this study also estimate future urban growth areas and urban flood exposure. This does not mean that all the flood vulnerable areas will be flooded nor all predicted areas will be developed. The probability of both occurrences is simply higher in these areas. Proper preparation (e.g. protection plan, policies) can reduce/eliminate future flood damage to create more resilient communities. Lastly, incorporating vulnerability assessment, “the characteristics of a person or group and their situation that influence their capacity to anticipate, cope with, resist and recover from the impact of a natural hazard (Winser et al., 2004, p.11),” can help understand actual flooding conditions. Vulnerability is based on an asset’s exposure, sensitivity, and adaptive capacity to a hazard event (Cutter 1996). If an exposed asset is highly sensitive to the harmful impacts of a hazard event, with a low adaptive capacity, the asset is considered vulnerable (Marin County, 2017). The same risk can impact areas differently depending on the personal/asset’s adaptive capacity. To be a more accurate assessment, adding to the future urban prediction and flood exposure of this study, physical/social vulnerability should be considered.

6. Conclusion

The process identified in this paper facilitates the aggregation of multiple sources of SLR and urban growth data, allowing for the creation of prediction maps which estimate the probability of growth occurrence by scenario, given a sea-level rise event. Understanding the potential effects of SLR depends on understanding the probabilities of future development options and extreme climate conditions. The framework presented in this research provides a pathway towards creating useful tools for decision makers with the capabilities to operate LCM and integrate their outputs into scenario-based urban planning. If future plans are created, based on this or similar processes, decision makers should aim to create more accurate growth and sea-level rise prediction methods and begin analyze outputs versus actual growth impacts to confirm specifcs of the approach. Relatedly, creating future scenarios with potential users of the information, through a co-creation or participatory process would allow the capabilities to test scenarios grounded in the realities of the place under investigation.

Appendix

Table 1

Drop-one test with 15 driving factors.

Excluded input factors	Highest training probability	PCM	Kappa	Influence
Population Density	200,000 th	51.50	0.48	Least
Land Value	90,000 th	51.28	0.47	
Population Increase	250,000 th	50.43	0.46	
Distance to Waterfront (sea)	100,000 th	50.30	0.46	
Central Business District	80,000 th	50.26	0.46	
Poverty	200,000 th	49.73	0.46	
Distance to Water Surface	80,000 th	49.69	0.46	
Slope	30,000 th	49.48	0.45	
Employment No.	200,000 th	49.25	0.45	
Distance to Existing Urban	100,000 th	49.12	0.45	
Distance to Residence	150,000 th	48.95	0.45	
Distance to Public School	250,000 th	48.58	0.44	
Distance to Commercial	250,000 th	48.49	0.44	
Distance to Park	90,000 th	48.13	0.44	
Distance to Roads	90,000 th	47.92	0.44	Most
Full Model (15)	**200,000 th**	**52.19**	**0.48**	-

Table 2

Prediction accuracy for urban growth scenarios.

	PCM	Kappa	OA	AUC
Business as Usual (BU) in the 200,000th cycle	52.19	0.48	92.85	0.74
Growth as Plan (GP) in the 40,000th cycle	55.04	0.50	90.93	0.75
Resilient Growth (RG) in the 150,000th cycle	67.63	0.63	91.24	0.82

PCM = percent correct metric, Kappa = kappa coefficient, OA = overall agreement, and AUC = area under the ROC curve

Table 3

Existing and future urban (BU and GP) flood exposure under the future floodplain.

NH No.	Existing Urban Flood Exposur e	BU Urban Flood Exposur e	GP Urban Flood Exposur e
1	0.000	0.000	0.000
2	0.000	0.000	0.000
3	0.000	0.000	0.000

NH No.	Existing Urban Flood Exposur e	BU Urban Flood Exposur e	GP Urban Flood Exposur e
4	0.000	0.000	0.000
5	0.000	0.000	0.000
6	0.002	0.000	0.000
7	0.122	0.000	0.002
8	0.000	0.000	0.000
9	0.000	0.000	0.000
10	0.129	0.120	0.075
11	0.181	0.015	0.018
12	0.000	0.000	0.000
13	0.122	1.290	0.162
14	0.000	0.000	0.000
15	0.008	0.000	0.024
16	0.072	0.000	0.000
17	0.000	0.000	0.000
18	0.215	0.004	0.001
19	0.274	0.018	0.059
20	0.000	0.000	0.000
21	0.000	0.000	0.000
22	0.048	0.001	0.022
23	0.050	0.000	0.000
24	0.000	0.000	0.000
25	0.209	0.000	0.134
26	0.066	0.000	0.000
27	0.000	0.000	0.000
28	2.038	0.862	0.632
29	0.000	0.000	0.000
30	0.000	0.000	0.000
31	0.000	0.000	0.000
32	0.120	0.001	0.015
33	0.023	0.000	0.004
34	0.009	0.000	0200
35	0.000	0.000	0.000
36	0.000	0.000	0.000
37	0.000	0.000	0.000
38	0.080	0.152	0.103
39	0.226	0.021	0.150
40	0.244	1.231	0.432
41	0.000	0.000	0.000
42	0.000	0.000	0.000
43	0.000	0.000	0.000
44	0.042	0.000	0.005
45	0.000	0.000	0.000

NH No.	Existing Urban Flood Exposur e	BU Urban Flood Exposur e	GP Urban Flood Exposur e
46	0.162	0.085	0.016
47	0.000	0.000	0.000
48	0.000	0.000	0.000
49	0.000	0.000	0.000
50	0.058	0.002	0.087
51	0.006	0.000	0.000
52	0.000	0.000	0.000
53	0.060	0.100	0.017
54	0.043	0.118	0.041
55	0.000	0.000	0.000
56	0.000	0.000	0.000
57	0.232	0.045	0.000
58	0.344	0.024	0.020
59	0.000	0.000	0.000
60	0.000	0.000	0.000
61	0.000	0.000	0.000
62	0.000	0.000	0.000
63	0.000	0.000	0.000
64	0.180	0.001	0.001
65	0.000	0.000	0.000
66	1.256	0.000	0.000
67	1.803	0.478	0.513
68	6.273	1.128	0.867
69	0.292	0.002	0.107
70	0.000	0.000	0.000
71	0.026	0.663	0.002
72	0.000	0.000	0.000
73	0.000	0.000	0.000
74	0.000	0.000	0.000
75	0.000	0.000	0.000
76	0.000	0.000	0.000
77	0.130	0.000	0.000
78	0.000	0.000	0.000
79	0.000	0.000	0.000
80	0.000	0.000	0.000
81	0.723	0.053	0.053
82	0.301	0.003	0.223
83	0.484	0.042	0.055
84	1.404	0.134	0.175
85	0.000	0.000	0.000
86	0.000	0.000	0.000
87	0.970	0.215	0.247

NH No.	Existing Urban Flood Exposur e	BU Urban Flood Exposur e	GP Urban Flood Exposur e
88	0.139	0.322	0.011
89	0.070	0.077	0.378
90	0.610	0.011	0.081
91	0.000	0.000	0.000
92	0.775	0.069	0.091
93	0.000	0.000	0.000
94	0.606	0.002	0.002
95	2.155	0.106	0.463
96	0.326	0.061	0.030
97	0.892	0.534	0.516
98	0.497	0.027	0.247
99	0.286	0.019	0.007
100	0.785	0.230	0.227
101	0.014	0214	0.231
102	0.440	0.035	0.035
103	7.642	0.004	0.006
104	2.536	0.247	0.205
105	1.456	0.194	0.313
106	0.026	0.007	0.000
107	1.564	0.177	0.361
108	2.131	0.236	0.348
109	1.116	0.252	0.176
110	0.850	0.399	0.351
111	1.903	0.075	0.206
112	0.100	0.158	0.135
113	0.492	1.640	0.641
114	0.096	0.098	0.016
115	0.210	0.039	0.109
116	0.000	0.000	0.000
117	0.033	0.000	0.039
118	0.000	0.000	0.000
119	0.000	0.000	0.000
120	0.000	0.000	0.000
121	1.494	0.570	0.506
122	0.000	0.000	0.000
123	0.012	0.000	0.000
124	0.000	0.000	0.000
125	0.000	0.000	0.000
126	1.161	0.000	0.000
127	0.309	0.000	0.000
Total	**51.0**	**12.4**	**10.0**

NH: Neighborhood, Unit km^2

a neighborhood where urban flood exposure in BU is larger than in GP

a neighborhood where urban flood exposure in GP is larger than in BU

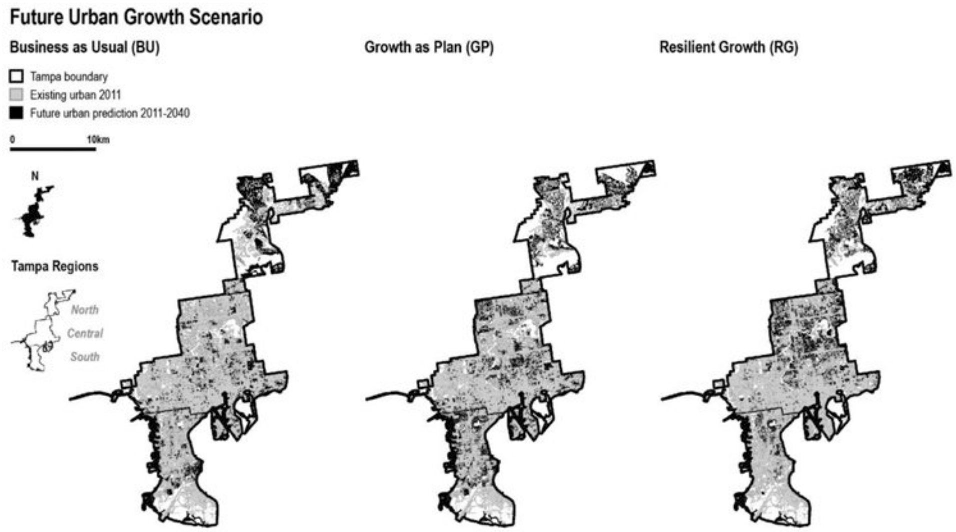

Fig. 1.
Future urban growth scenarios in Tampa, 2040.

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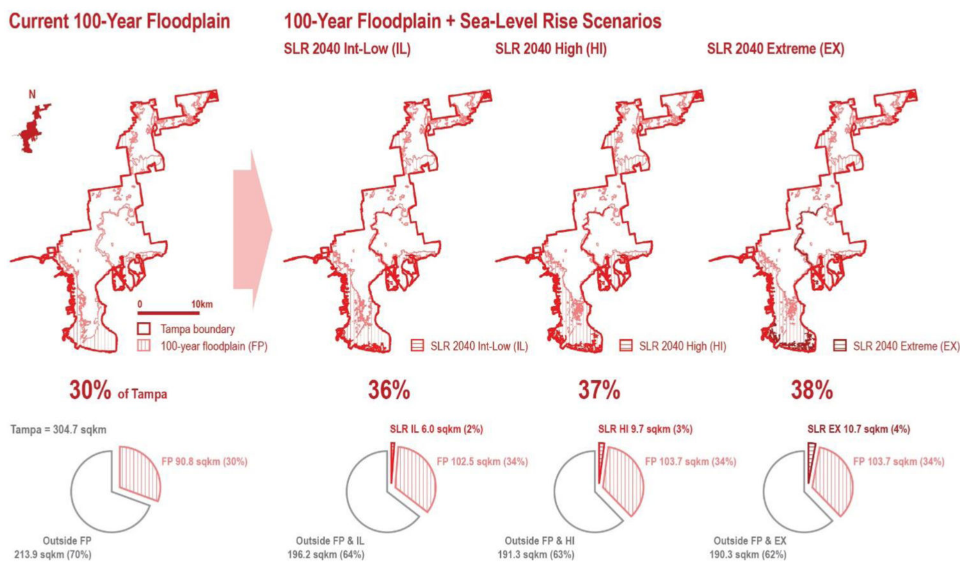

Fig. 2.

Future flood risk scenario based on the 100-year floodplain and sea level rise scenarios in 2040.

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Highlights

- Increasing future uncertainty calls for a better scenario planning approach rather than traditional predict-and-plan.
- Scenario planning has not been effectively linked to land change modeling.
- Integrating sea level rise and predictions into scenarios increased flood preparedness.
- A regional solution can result in adverse effects at the neighborhood scale.

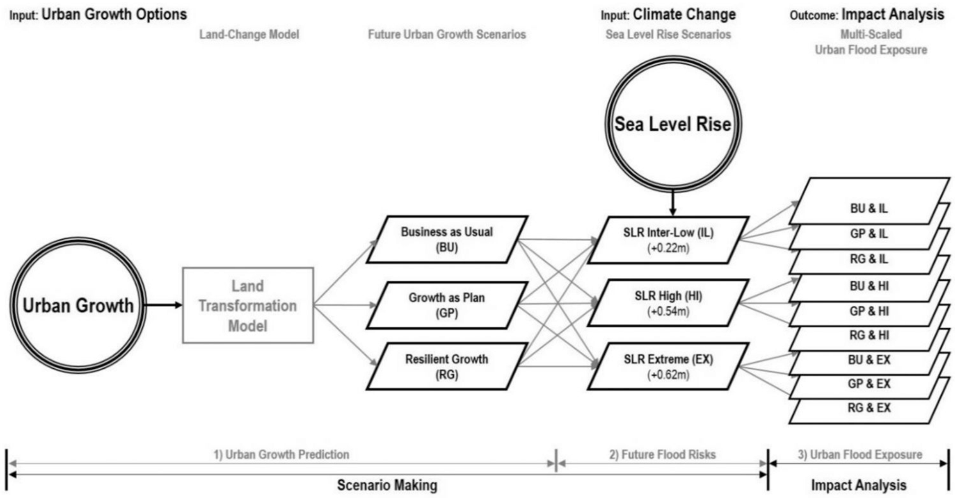

Fig. 1.

Research process showing the matrix integrating future urban growth and sea-level rise scenarios, creating nine different future scenarios.

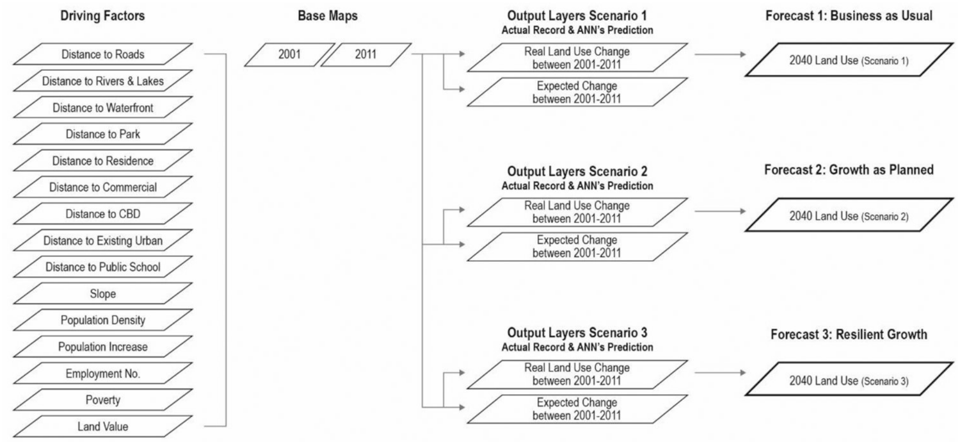

Fig. 2.

The LTM prediction modeling process showing driving factors, base maps, output comparison, and forecasted urban growth scenarios.

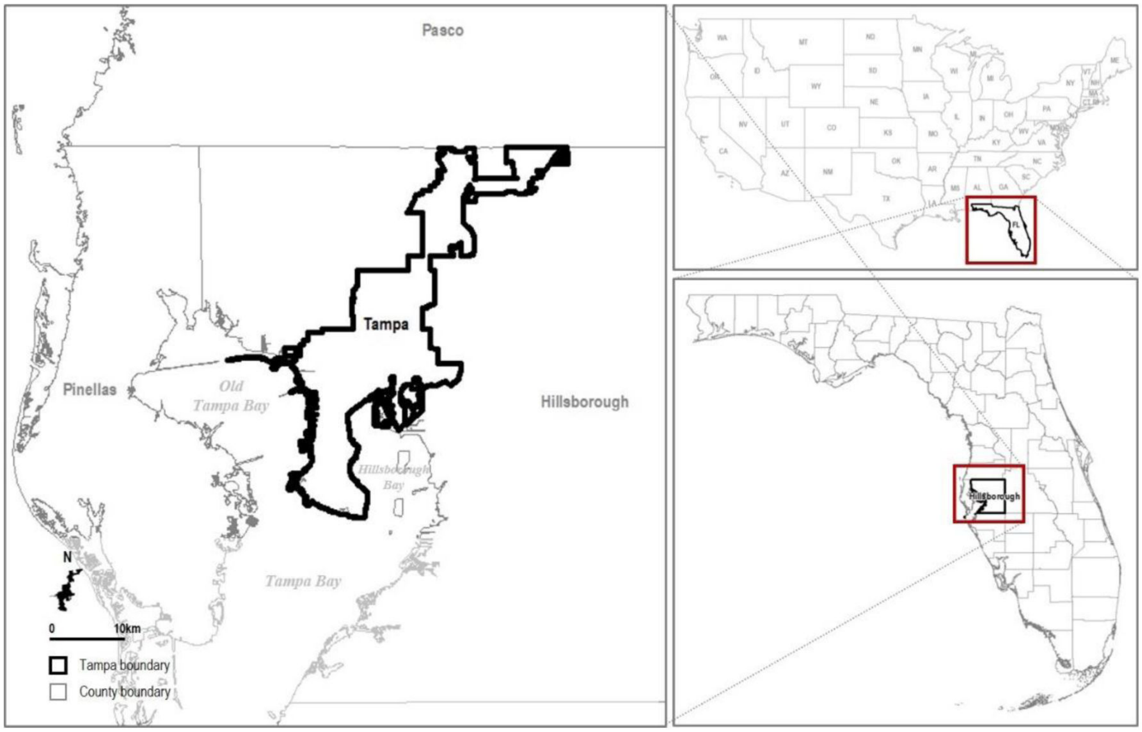

Fig. 3.
Location of Tampa, Florida.

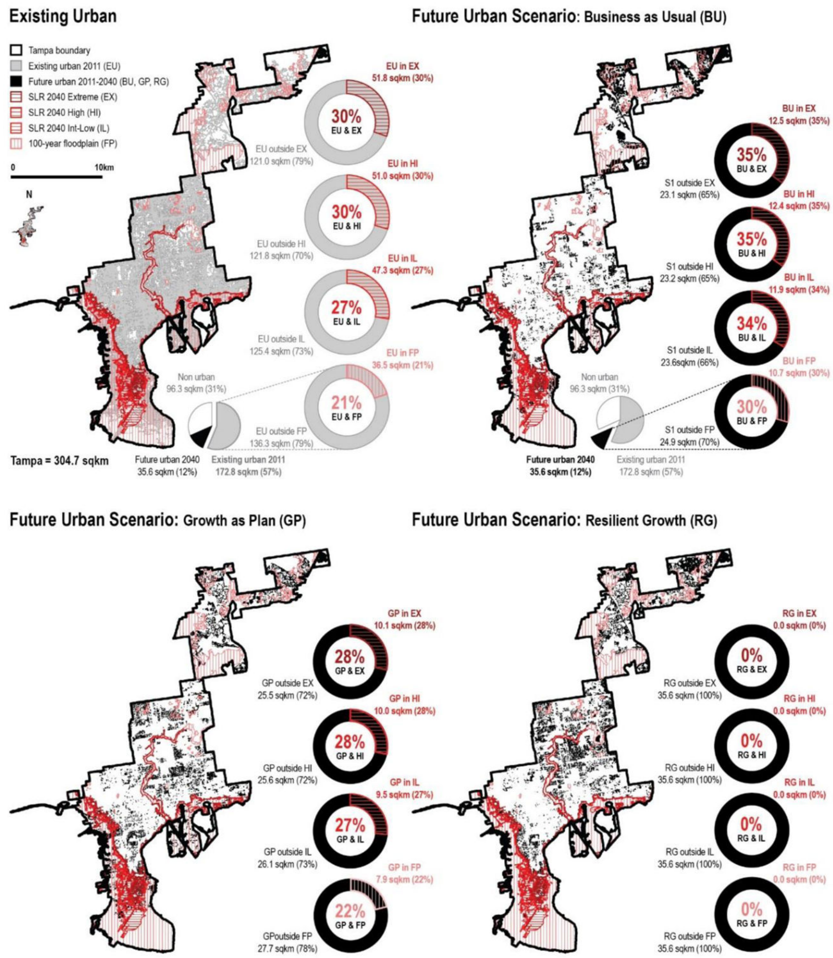

Fig. 4.

Flood exposure of existing urban and future urban growth scenarios.

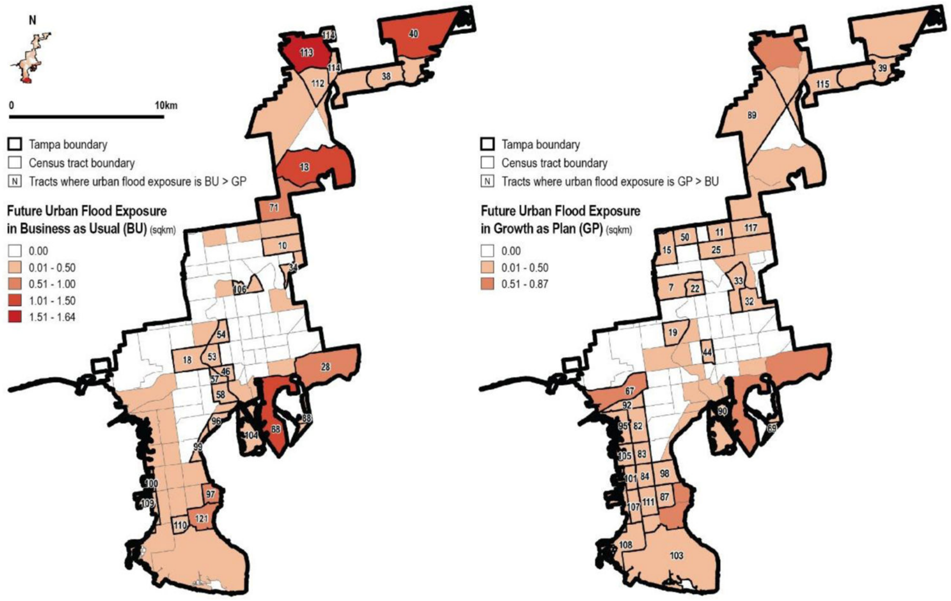

Fig. 5.

Comparing future urban (business as usual and growth as plan) flood exposure under the high SLR. The choropleth maps indicate urban areas exposed to flood risks in BU (left) and GP (right). A total of 127 neighborhoods in Tampa are identified by census tracts, numbering from #1 to #127. On the maps, tracts with numbers show where urban flood exposure in BU is larger than in GP, and where GP is larger than in BU.