ADVANCING SCENARIO PLANNING TO PREPARE FOR UNCERTAIN CLIMATE CHANGE:

FUTURE URBAN GROWTH PREDICTION AND FLOOD VULNERABILITY

A Dissertation

by

YOU JUNG KIM

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Chair of Committee,	Galen D. Newman
Committee Members,	Philip R. Berke
	Wesley E. Highfield
	Burak Güneralp
Head of Department,	Shannon S. Van Zandt

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ABSTRACT

The people and assets endangered by flood risks due to sea level rise and coastal population increase are increasing. Complex and unpredictable future circumstances necessitates a better scenario-based planning; helping to make better decisions through examining plausible future probabilities. Though it has value in urban planning, scenario planning has been limited to a single preferred plan and impact evaluation. To advance scenario planning for uncertain future urban growth and climate change, this research exemplifies scenario making and impact evaluation using the city of Tampa as a case site. It answers "How prepared are U.S. coastal cities for future urban growth and flood risks?"

In scenario making, this research creates flood risk and future urban growth scenarios in lieu of sea level rise using the Land Transformation Model, a GIS-based Artificial Neural Network land use prediction model. For impact analyses, first, three different urban growth scenarios are evaluated by comparing urban flood exposure at a city and neighborhood level. Second, plan policies are examined with predicted urban growth and flood risks in eight highly clustered future urban neighborhoods.

The findings show that the growth as land use plan scenario places less urban areas exposed to flood risks than the growth as business as usual, but much larger urban flood exposure than the resilient growth scenario at the city level. Even at the neighborhood level, more amounts of neighborhoods in the planned growth scenario are vulnerable to flood risks than in the business as usual scenario. In plan preparation, the findings show that Tampa's policies do not do enough to prepare for future climate change since the policies are based on the current climate pattern, and some policies are assigned in wrong locations. The scenario matrix (urban growth and flood risk scenarios) enables the ability to examine planning problems at multiple scales. The results of the impact analyses confirm dilemmas in urban planning: a regional solution can be worse in a neighborhood, and a good policy in the wrong place can work negatively.

DEDICATION

To my family,

Yooan, Jooho, Lia, and Seryeong.

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NOMENCLATURE

ANN	Artificial Neural Network
AUC	Area Under Curve
BFE	Base Floor Elevation
BU	Business as Usual
CTEDNA	Changing Tampa's Economic DNA
ESA	Environmentally Sensitive Areas
FEMA	Federal Emergency Management Agency
GIS	Geographic Information System
GP	Growth as Planned
HCLMS	Hillsborough County Local Mitigation Strategy
HLRTP	Hillsborough Long Range Transportation Plan
Kappa	Kappa Coefficient
LTM	Land Transformation Model
MLP	Multi-Layer Perception
NH	Neighborhood
NLCD	National Land Cover Database
NOAA	National Oceanic and Atmospheric Administration
PCM	Percent Correct Metric
RG	Resilient Growth
ROC	Receiver Operating Characteristic

RSL	Relative Sea Level
S1	Scenario 1
SLR	Sea Level Rise
TCP	Tampa Comprehensive Plan
TOD	Transit Oriented Development
USACE	United States Army Corps of Engineers

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1. INTRODUCTION

1.1. Background

As environment, society, and technology rapidly change, the future becomes more complex and unpredictable (Lincoln Institute, 2017). High uncertainty in climate change and urban growth make forecasting difficult to plan with a traditional "predict-and-plan" approach (Van der Heijden, 2011; Quay, 2010). Observed temperature increase and sea level rise since 1950 are unprecedented due to climate change (Pachauri et al., 2014). The National Oceanic and Atmospheric Administration (NOAA) reports future sea level rise scenarios that the global mean sea level will rise between 0.2 meters and 2.0 meters by 2100 (Parris et al., 2012). The United Nations (2017a) reports that 2.2 billion global population will increase between 2017 and 2050, which is 29% more of the population in 2017 (7.6 billion).

Currently, in the globe, more than 600 million people live in coastal regions, lower than 10 meters above sea level, and almost 2.4 billion people live within 100km of the coastline (United Nations, 2017b). In the U.S. 254 counties (8%) out of 3,142 are located on the coast. However, 39% (123.3 million people) of the total population live in coastal counties, and 52 % (163.8 million people) live in coastal watershed counties (Wilson & Fischetti, 2010). The shoreline counties' population has grown steadily since 1970 and is projected to grow in the future (Crossett et al., 2013). Sea level rise due to climate change make coastal population more susceptible to flood risks, and urban expansion due to population growth can worsen climate conditions and enlarge hazard zones: when open space land uses are converted to urban land uses, flood risk can increase due to increased floodplain areas and impervious surfaces. If we do not prepare properly for the future urban growth and climate change, more people will be at flood risk.

Land change modeling (LCM) is a planning support system to supply future land prediction to land use planning process (Berke & Kaiser, 2006). Land use change is the result of interaction between human activity and natural resources (Agarwal et al., 2002). Understanding historic land development processes in order to better predict future circumstances helps support urban planning for potential future flood risk mitigation. Over the past few decades, urban LCM has been developed significantly, addressing urbanization issues and its impacts in many fields (Verburg et al., 2015; Güneralp, 2011). It creates the opportunity to mold an uncertain future into determined conditions via scenario planning.

This research seeks to advance scenario planning for future urban growth and climate change in scenario making and scenario analysis. It uses the Land Transformation Model (LTM), a popular and accurate land change model, to predict potential future urban growth of a study area. In most land change prediction studies, there is a lack of explanation of driving factors, scenario types, and scenario analysis. To fill this gap, this research identifies driving factors of urban growth from previous prediction and empirical studies. In developing scenarios, this research adopts a land use plan and a local comprehensive plan in both scenario making and analysis to assess how a local comprehensive plan prepares for future growth scenarios.

1.2. Research Purpose

The overall aim of this dissertation is to examine future urbanization using prediction modeling coupled with scenario planning. It exemplifies a scenario planning process for climate change adaptation; examines multiple urban growth and sea-level risk scenarios and evaluates the impact of urban scenarios including local comprehensive plans at city and community scales. The main purposes of this research are; 1) to determine driving factors of urban growth in Tampa, Florida; 2) to validate future urban growth projection; 3) to examine the current land use plan with other growth scenarios; and 4) to assess a local comprehensive plan for future urban growth and flood risk.

1.3. Research Justification

The values of this research can be justified by three key points; scenario planning, a local comprehensive plan, and LCM/LTM models.

First, uncertainty in urban growth and climate condition calls for better scenario planning approaches. Scenario planning is a decision making process and identifies various future options helping stakeholders make a better decision for possible future conditions by comparing and assessing plausible stories (Lincoln Institute, 2017; FHWA, 2011). The future becomes more complex and unpredictable and such changes make less reliable to practical experience and conventional judgement as a guide to policy making (APA, 2017; Kahn & Wiener, 1967). Scenario Planning has been used in urban planning since 1960. However, many plans stay in the initial planning stage, predict-and-plan (Quay, 2010). They ignore uncertainty and deal with only a single preferred scenario (Chakraborty et al., 2011, Hopkins & Zapata, 2007), and fail to provide a detailed process of scenarios development and the future impact of scenarios (Woodruff, 2016).

Second, though natural disasters cannot be prevented, proactive actions can reduce their impact (Godschalk et al., 1998). A local comprehensive plan is a good tool to reduce damage from natural disaster by controlling future development areas based on current and forecasted hazard areas (Berke et al., 2015; Burby et al., 1999). Local governments are given the authority to control development and plan from the Growth Management Act of 1985 and the 2011 Community Planning Act (Hillsborough County, 2016). Especially in Florida, each community prepares for legally binding local comprehensive plans, and the plans provide city's land use and management decision (Brody, 2001). A local comprehensive plan guides a city or community's desirable future land use and development (Kang, 2009). Examining a local plan's preparedness based on potential future growth scenarios and flood risk will help to make more sustainable and resilient communities.

Third, LCM is a good tool to create future urban growth scenarios, but it produces limited types of scenarios, and its subsequent impact assessment is also limited such as total damage area calculation. Many prediction tools typically produce similar scenarios such as business as usual (same growth pattern as previous pattern), environmental growth (development outside environmental preservation areas), and sprawl/smart growth (development density control). In the case of the LTM, no study has applied scenario making. Land use planning and planning policies are influential determinants for future land change, but few studies have considered scenario making. Moreover, impact analysis in disaster related scenarios is limited to the total damage areas.

1.4. Research Process

Chapter 2 reviews several literature references to form an understanding of land change modeling and scenario planning and to lay the foundation for a conceptual framework for scenario making and analysis. The first part reviews 144 prediction articles to identify driving factors of urban growth, subsequent topics, and scenario making with land change models. The second portion reviews a specific land change model, the Land Transformation Model. The final section reviews the literatures associated with scenario planning in urban planning.

Chapter 3 addresses the research design, methods, and variables. The first section explains the overall conceptual framework in scenario making and impact analysis. The second section illustrates spatial frame and data. The variable selection section explains driving factors of urban growth from existing empirical studies, detects each variable influence using drop-one experiment of LTM in prediction capabilities of the study area, and finalizes variables.

Chapter 4 presents the results of scenario making and impact analysis. The first subsection detects each variable influence using drop-one experiment of LTM in prediction capabilities of the study area, and finalizes variable selection for urban growth prediction. Then, three urban growth scenarios are created with validation. The second subsection illustrates future flood risk scenarios based on NOAA’s SLR estimation. The third subsection compares each forecasted urban flood exposure by future flood risks at a city and neighborhood level. The final analyses show how plans prepare for future urban growth and flood vulnerability.

Chapter 5 summarizes the key findings of the dissertation, and concludes with study limitation and future research.

1.5. Research Question

Primary:

The overarching research question for this study is “How prepared are U.S. coastal cities for future urban growth and flood risks?” This research question consists of the following sub-questions.

Subsidiary:

- “How well-suited is the LTM in predicting future urban growth related to flood risk?”
- “How effective is the current comprehensive plan in adapting urban growth to climate change?”
- “How well-suited are neighborhoods to absorbing predicted growth based on current policy and vulnerability?”

The first sub-question will be answered with variable selection for the study area, Tampa, Florida, and four accuracy assessment measures (e.g. PCM, kappa, OA, AUC) will justify the LTM prediction capability. The result, the urban growth prediction scenarios will be a basis for the second and third sub-questions. The second sub-question examines the current land use plan, growth as planned, with other growth scenarios such as business as usual and resilient growth. To show the effectiveness of the current land use plan, future urban areas exposed to flood risks will be compared at a city and community scales. The last question will be answered by specifying policy preparation of the Tampa Comprehensive Plan 2040 based on current physical/social vulnerability evaluation for highly clustered future urban neighborhoods. Finally, the sub-questions will answer the primary question, the preparedness of a coastal city for future urban growth and flood risks.

2. LITERATURE REVIEW[1]

This section outlines and reviews the critical areas of research literature necessary to build an understanding of land change modeling and scenario planning. The first part of this section covers a 144-prediction article review assessing the driving factors of urban growth, prediction models, disciplines, location, sub-sequent topics, and scenario application. The second part reviews the Land Transformation Model (LTM) and its origin, process, and application. Scenario planning and its application in urban planning are reviewed in the third part. A summary of the research findings and limitations conclude this section.

2.1. Driving Factors of Urban Growth

To uncover the driving factors of urban growth and urban land-change modeling, a searched was conducted for land use prediction articles with land cover changes in an electronic database with backward and forward searches (Xiao & Watson, 2017). SCOPUS was used as a main search database on September 21, 2017. The search keywords were "future urban growth" or "future land use," "land use prediction," and "future urban expansion." The search covered the years from 1945 to 2017, and subject areas were environmental science, agriculture and biological science, social science, earth and planetary sciences, computer science, economics, econometrics and finance,

[1] Part of this chapter is reprinted with permission from "Climate Change Preparedness: Comparing Future Urban Growth and Flood Risk in Amsterdam and Houston" by Kim, Y. and Newman, G., 2019, *Sustainability*, 11(4), 1048, Copyright 2019 by the authors.

and neuroscience. Document types were limited to peer reviewed articles, reviews, and book chapters written in English. In the first round, 11,231 articles were searched, and after reviewing titles and abstracts, the second round resulted in 1,970 articles. After reviewing full texts, the selected land cover prediction related articles totaled 116. Through backward and forward search during the full-text review, 28 additional articles were found so the total number of articles to review for land use prediction model was 144 containing land change predictions, prediction models, and driving factors of urban growth.

The questions for this literature review are: What kind of prediction models have been used? What/how many times have driving forces have been applied to urban growth? What disciplines focus on land-change studies? Where the locations are for prediction studies? and What are the purposes of prediction studies?

2.1.1. Prediction Models

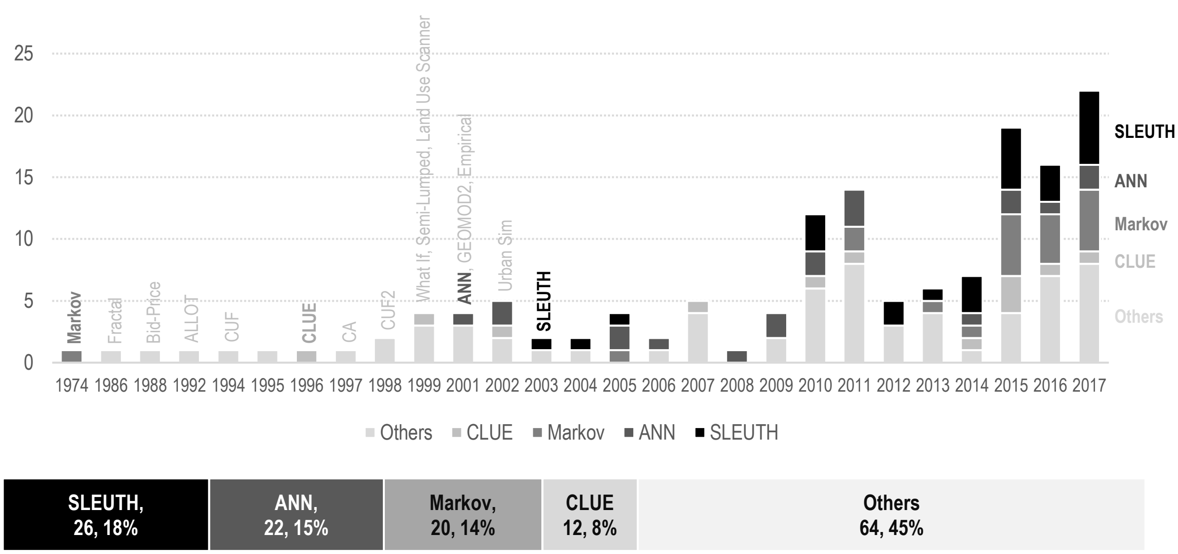


Figure 2.1. Number of articles by year that contain urban prediction models.

As seen in Figure 1, since 1974, urban prediction began with the Markov model (Bell, 1974). Many prediction models were introduced in the 1990s and early 2000s: CUF (Landis, 1994), Cellular Automaton (Clarke et al., 1997), Land Use Scanner (Hilferink & Rietveld, 1999), What IF (Klosterman, 1999), CLUE (Verburg et al., 1999), LTM (Pijanowski et al., 2002), SLEUTH (Silva & Clarke, 2002), and Urban Sim (Waddell, 2002). After the introduction of the various prediction models, performance and calibration methods were developed for each model, and, in 2010, many hybrid tools were created by combining various techniques: statistical regression, machine learning, cellular automata, exogenous quantity, and pure pixels (Pontius et al., 2008).

Land change models studies have been actively applied since 1999, and recently, from 2010 to the present, the study numbers have increased. In the last three years, 2015-2017, almost 20 papers were published each year. The four most popular prediction models as found in the 144 reviewed articles are SLEUTH (26), ANN (20), Markov (20), and CLUE (12).

The SLEUTH model (the former Clarke Urban Growth model), named from the first letters of the input layers (Slope, Land use, Exclusion, Urban extent, Transportation and Hillshade), uses a cellular automaton procedure on a gridded map (Clarke et al., 1997). The procedure is controlled by diffusion, breed, spread, slope, and road coefficients, and four types of urban growth patterns are revealed: spontaneous, diffusive, organic, and road-influenced (Silva & Clarke, 2002). The Land Transformation Model (LTM) is a representative artificial neural network (ANN) based land change prediction model using GIS (Pijanowski et al., 2002). Due to the ANN's capability in a non-linear model, it can be applied for natural, social, economic, and political factors. However, a primary limitation is that the model does not show causality for each factor's relationship to urban growth (Brown et al., 2013). The Markov-CA modeling is a hybrid model of Markov chains and Cellular Automaton. The Markov model uses a stochastic process (Bell, 1974) to describe the probability of change from non-urban to urban land within a given time (Shafizadeh-Moghadam & Helbich, 2013), following continual historic trends (Brown et al., 2013). A transition matrix summarizes the probability results, and the Cellular Automaton simulates the matrix into a spatial map. The Conversion of Land Use and its Effects (CLUE) predicts land use change based on the empirical relationships between land use and driving factors. The model consists of a non-spatial demand module that calculates the area of land use change area and a spatial allocation module that translates the demand into land use changes (Verburg, 2010). CLUE was initially developed for national scale land use predictions (Verburg et al., 1999), and CLUE-S (at small regional extent) was developed for land change at small scales such as watersheds and provinces (Verburg et al., 2002). Dyna-CLUE (dynamic) and CLUE-Scanner are advanced versions of the CLUE model.

2.1.2. Driving Factors of Urban Growth

Table 2.1. List of predictor variables and their usage in 144 reviewed articles.

Driving Factor		No. of Use	Driving Factor		No. of Use
Topography	slope	93	**Service**	distance to hospital	2
	elevation	41		sewer service	7
	aspect	10	**Amenity**	distance to water	49
	hill shade	26		distance to lake	6
	soil type	23		distance to green space	8
Transportation	distance to road	122		distance to recreational	8
	distance to highway	24		distance to sea	10
	distance to highway exits	4		distance to natural scenery / view	2
	distance to railway	13	**Preservation**	environmental preservation	16
	distance to railway station	5		forest density	3
	distance to airport	9	**Economic**	GDP	11
	distance to tollgate	2		Income	4
	distance to bus transit system	3		poverty rate	1
	distance to metro (subway)	5		property value	11
Land Use	distance to built-up area	73	**Population**	population	10
	distance to residential	13		population density	30
	land use	46	**Climate**	temperature	8
	distance to forest	9		precipitation	10
	distance to agriculture	8	**Disaster Risk**	flood risk	9
JOB	distance to cities	18		seismicity	3
	distance to urban center (CBD)	41	**Others**	policies and legislation	6
	distance to district / town center	18		race (white population)	1
	employment	7		neighborhood quality	1
	distance to industrial	8		crime	1
Service	distance to commercial	16		northing parameter (coordination)	8
	distance to institutional / school	9		easting parameter (coordination)	5

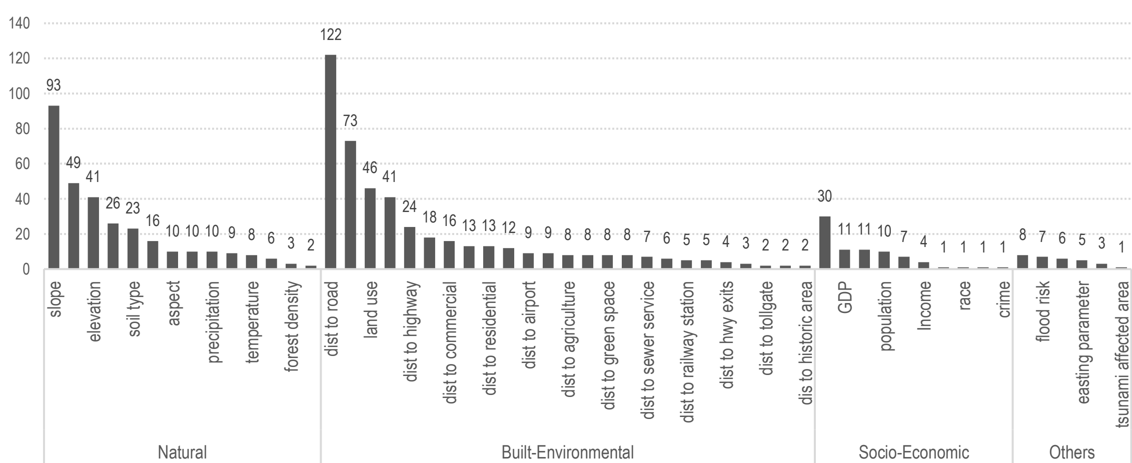


Figure 2.2. List of predictor variables and their usage in 144 reviewed articles.

Among the 144 reviewed articles, two studies (Bell, 1974; Conway, 2005) use only 1 factor, land use, to predict future urban changes. Variable amounts vary from 1 to 17, with an average of 7.3 per article. While general LCMs use infinite variables, the SLUETH model uses six fixed variables: slope, land use, exclusion, urban extend, distance to road, and hillshade.

As illustrated in Figure 2, natural and built-environmental variables have been popularly applied as major driving factors in urban growth. Distance to a road, slope, distance to existing urban, and distance to water are the most popularly used variables. Natural variables are slope, distance to a waterbody, elevation, hillshade, environmental preservation, aspect, distance to the sea, etc. Built-environmental variables consist of distance to a road, existing urban, urban center, highway, land use, etc. The popular variables in the socio-economic sector are population density, gross domestic product (GDP), property value, employment, and income. Some studies consider disaster impacts as land change determinants; floodplain (Bright, 1992; Conway, 2005; Munshi et al., 2014; Nourqolipour et al., 2015; Nourqolipour et al., 2016; Pettit & Pullar, 2004; Te Linde et al., 2011), tsunami (Achmad et al., 2015), and seismicity (Landis, 1994; Terzi, 2015). Northing and easting coordinates have also been used as growth driving factors in several studies (Al-sharif & Pradhan, 2015; Hao et al., 2015; Hu & Lo, 2007; Jafari et al., 2016; Shafizadeh-Moghadam et al., 2017) maybe due to indicating tendency of urban growth location.

Compared to natural and built-environmental variables, few studies consider socio-economic variables (Agarwal et al., 2002). This can be because of data stationarity and availability. Natural and built environments do not change as quickly as socio-economic factors and their static status may make it easier to use them as prediction variables. Data availability can be another issue. Most cities or regions have a full set of environmental data which is convenient for people to use.

2.1.3. First Author's Department

To answer the question about what disciplines focus on land change studies, the first author's discipline was examined. As Figure 3 shows, 77% of the departments are from the natural and environmental sciences, 17% are from socio-economic sciences (e.g. urban planning, architecture, landscape, economics and management, and real estate), and 6% are from engineering. Environmental science and geography are ranked as the first two disciplines, and the third is urban planning with 19 articles.

When assessing driving factors by first author's discipline, natural and built environmental factors have been used across disciplines. Environmental science and geography are the disciplines that mainly use socio-economic factors for predictions, as shown in Figure 4, and are the same ranking order as seen in the total articles. Population density has been used widely in natural science (Zare et al., 2017), remote sensing (Losiri et al., 2016), geography (Han et al., 2015; Ku, 2016), civil engineering (Al-sharif & Pradhan, 2015), environmental science (Wu et al., 2015), real estate (Zheng et al., 2015) and economics (Liu et al., 2015). GDP has been a focus in environmental science in forestry (Liu et al., 2011), geo-science (Samie et al., 2017), natural science (Zhen et al., 2014) and geography (Han et al., 2015). Population was used in forestry

(Liu et al., 2011), urban planning (Hansen, 2010, 2011; Waddell, 2002), and environmental science (De Moel et al., 2011). Employment is a primary factor in urban planning (Landis & Zhang, 1998; Waddell, 2002) transportation (Amano et al., 1988), and geography (Kocabas & Dragicevic, 2007). Property value has also been used in urban planning (Munshi et al., 2014), environmental science (Fuglsang et al., 2013), and real estate (Zheng et al., 2015).

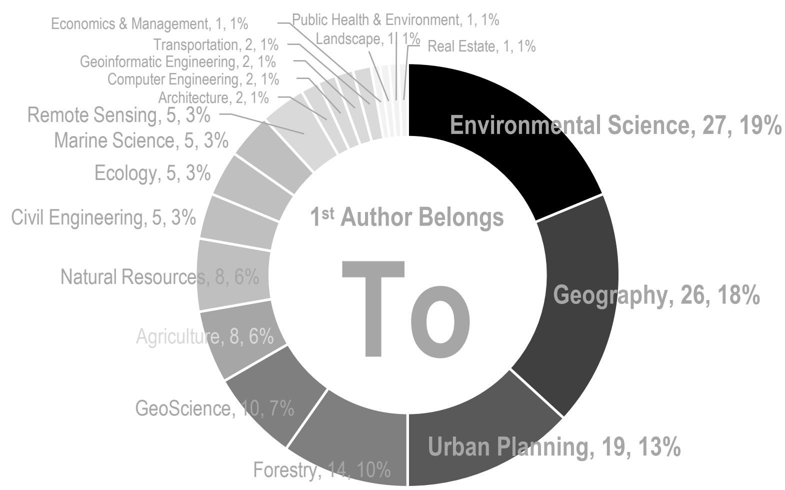


Figure 2.3. First author's department in 144 reviewed articles.

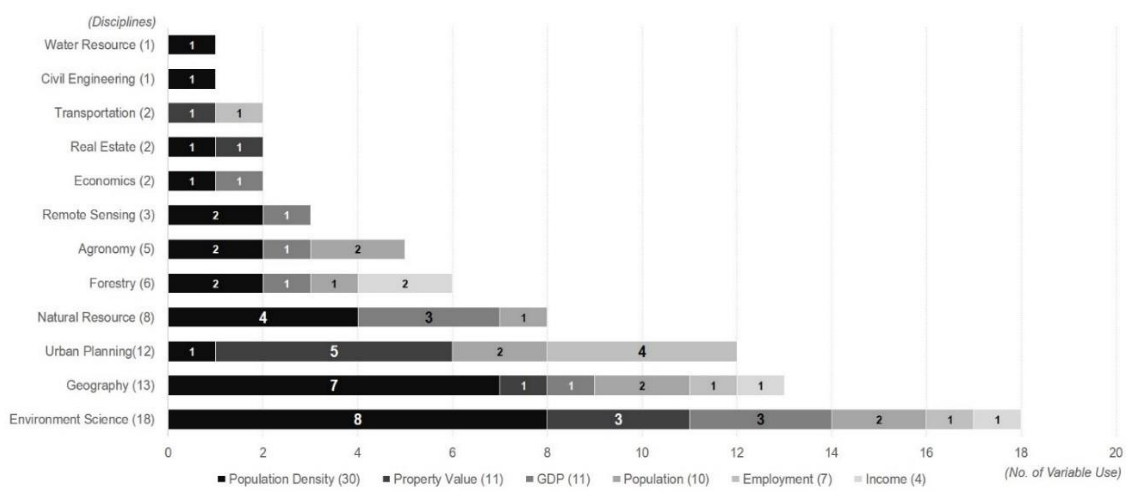


Figure 2.4. Major socio-economic variables by disciplines.

2.1.4. Study Location and Scale

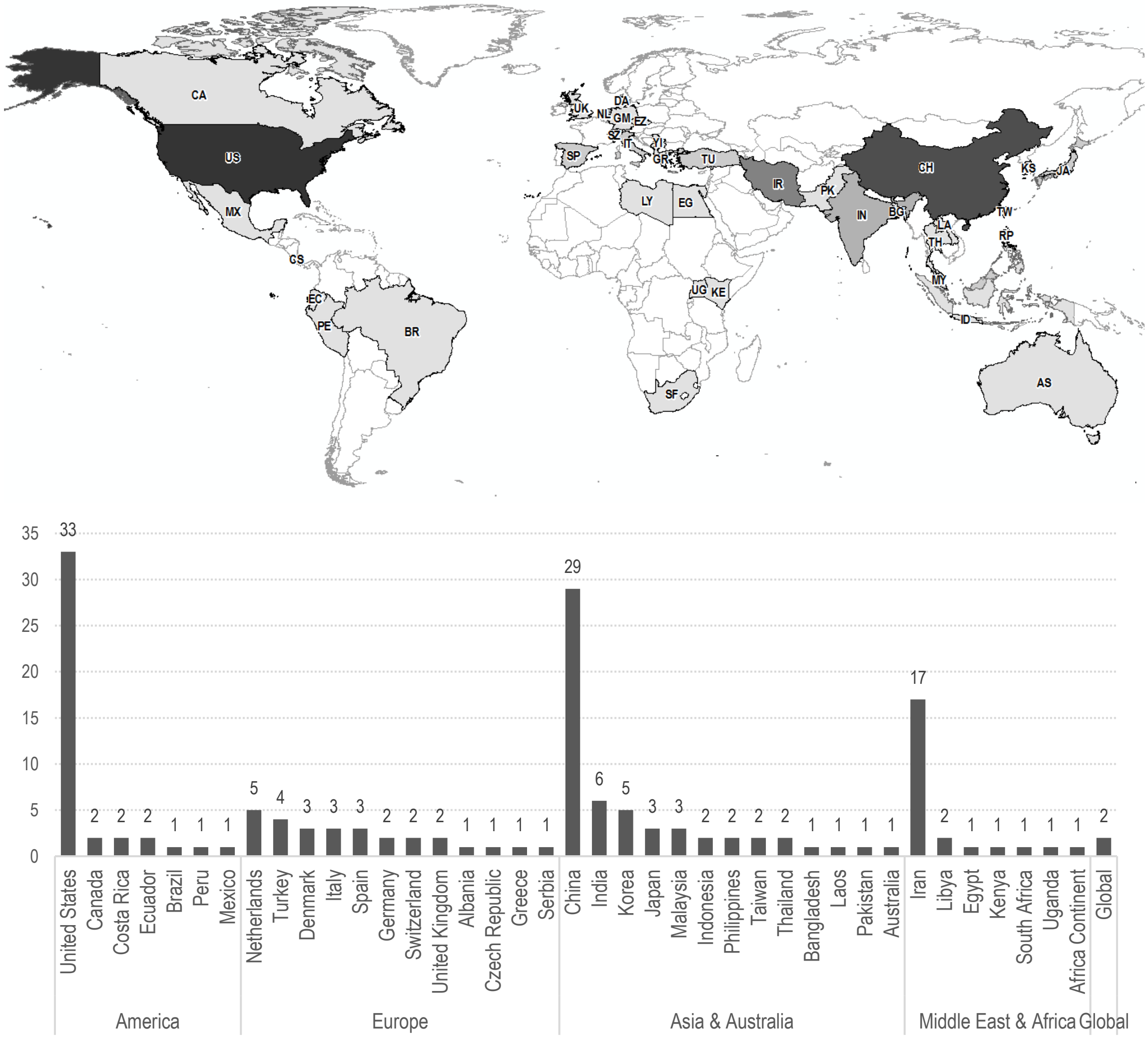


Figure 2.5. 38 countries, 1 continent, and 2 global studies in 144 reviewed articles.
(7 multi-country studies counted each country separately)

With regards to study location, the U.S. (33), China (29), and Iran (17) are the ones used the most with more than half of the total prediction articles located in these three countries. The Netherlands is the most popular location in Europe since the CLUE family prediction models were developed at Vrije University (Verburg et al., 1999).

Most studies deal with a single study area within a country: in total 38 countries have been studied. There are 17 multi-locational studies (e.g. cities, counties, regions) within a country (Amato et al., 2016; Mathioulakis & Photis, 2017; Qiang & Lam, 2016; Shafizadeh-Moghadam et al., 2017; Yuan, 2010), three multi-national studies (Nor et al., 2017; Pijanowski et al., 2005; Seto et al., 2012), one African continent scale (Linard et al., 2013) and two global scale studies (Güneralp & Seto, 2013; X. Li et al., 2017). The reasons there are few large scale (e.g. multi-national, continental, global) studies may be because of data availability and processing capability.

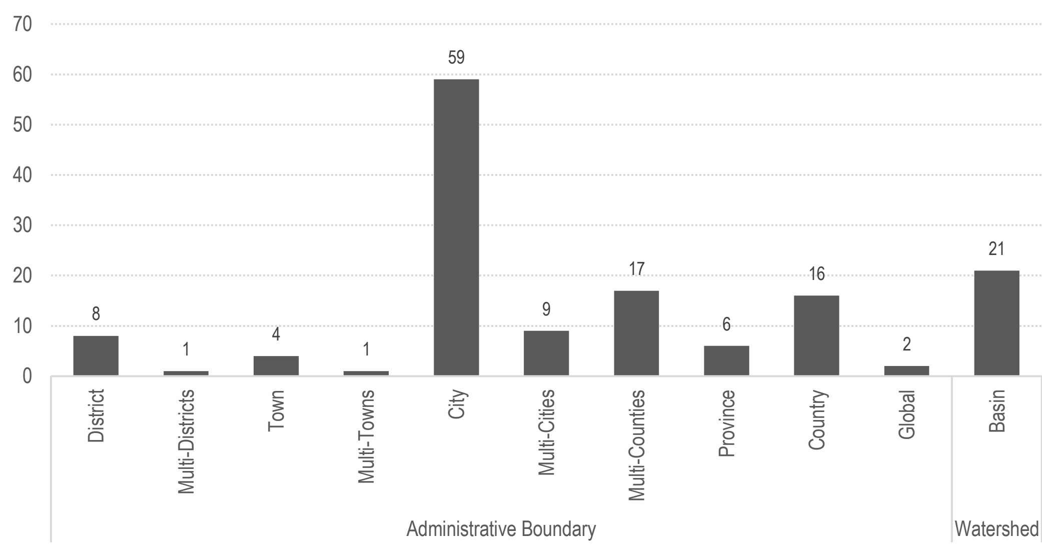


Figure 2.6. Study scales.

Depending on the research purpose, study boundaries are classified into two categories: watershed and administrative. The watershed scale is applied to calculate hydrologic impacts such as surface run-off change (Wu et al., 2015) and flood risk (Te Linde et al., 2011). Administrative boundaries vary from district (Samardžić-Petrović et al., 2016), city (Zare et al., 2017), province (Samie et al., 2017), to global scales

(Güneralp & Seto, 2013). The city scale boundary is the most popular administrative unit for various purposes: an urban growth scenario (Kocabas & Dragicevic, 2007), policy applications (Sakieh et al., 2015), and ecological impacts (Lu et al., 2016).

Depending on the study area and in pursuit of an accurate level, the use of pixel sizes vary from 25m to 5km. A 30×30m pixel size is generally applied in district, city, county and regional studies, 1×1km for the national level (Hasan et al., 2017), and 5×5 km for the global level (Güneralp & Seto, 2013). Because of data availability and processing capability, the larger the numbers of pixels, the longer the processing time. Also, pixel size influences prediction accuracy, the smaller the pixel size, the more accurate the prediction.

2.1.5. Topic and Scenario

The primary topics of urban prediction studies are to introduce a model, to forecast future urban growth, and to examine urban growth-related impacts. In the early 2000s, various prediction models (e.g. CA, CUF, CLUE, LTM) were introduced. The calibration methods developed for the models have been scrutinized, but they are used to compare performance (prediction accuracy) among different models. Pontius et al. (2008) compared the input, output, and accuracy of different prediction models across different locations, finding that the influence of raw data resolution on prediction accuracy is a highly significant factor in a model’s accuracy. Camacho et al. (2015) assessed calibration methods of land change for prediction accuracy, finding that the Land Change Model and the Cellular Automata-Markov were exemplary in regard to quantity and allocation, compared to other existing models. Lin et al. (2011) justified prediction model performance and examined previously unknown relationships between driving factors and land use change by testing the model performances among logistic regression, auto-logistic regression, and neural networks. New hybrid models, combining prediction tools and calibration methods, are still being developing to find a best-fit model.

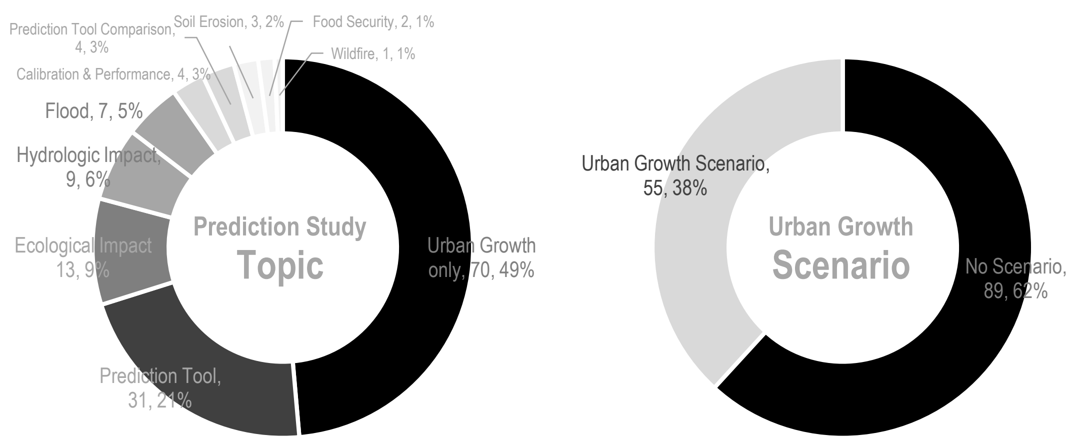


Figure 2.7. Topics and scenario use classification in the reviewed articles.

Other topics combine future urban growth with other subsequent impacts (e.g. ecologic, hydrologic, flood inundation, food production, and soil erosion). Lu et al. (2016) evaluated landscape ecological security using different spatial scenarios in Huangshan City, China. Wu et al. (2015) tested hydrologic impacts from potential land changes with the Soil and Water Assessment Tool in the Heihe River Basin, China. Lin et al. (2007) assessed the impact of land cover change on surface run-off in the Wu-Tu watershed in Taiwan. Zare et al. (2017) and Hansen (2011) delineated future urban flood risks based on the SLR in coastal areas. Zare et al. (2017) estimated a soil loss rate under future climate and land change conditions with a Revised Universal Soil Loss Equation in the Kasilian watershed in Iran. Each of these aforementioned research articles exposed the negative results of future urban expansion in ecology, flood risk, and soil loss.

Among the subsequent impact studies, there are seven articles that estimated climate change/sea-level rise (SLR) impacts. When examining flood risk, most studies used SLR scenarios in 2030, 2080 or 2100; some have also examined future river-flood probabilities (Te Linde et al., 2011) or existing flood maps as measures for flood risk increase (De Moel et al., 2011). Zhao et al. (2017) examined future urban growth with the SLR scenarios, (low/medium/high) in 2030 and 2080. Song et al. (2017) assessed total growth damage area in different urban growth locations and density scenarios. These scenarios targeted areas impacted by hurricane and accounted for SLR by 2030 and 2080, storm surge, and the 500-year floodplain. Te Linde et al. (2011) predicted economic growth scenarios for the Rhine River’s flood probability by 2050. De Moel et al. (2011) used the existing maximum flood inundation capability as a measure for future flood risk because of the Netherlands’ strong dike protection systems against current/future SLR. For analyses, all of the above articles used total flood damage areas as a measure for increased flood risk examining a single location; two articles used a monetary calculation for the impacts based on the damage areas identified by the prediction models.

In the urban growth scenario of land change prediction, 55 of the reviewed articles, or 38%, presented forecasted urban growth scenarios to identify an optimal future growth direction. Many of the studies used future growth options such as business as usual, compact development, and environmental protection. The main categories of urban growth scenarios are urban density (Song et al., 2017; Terzi, 2015), ecology (Goodarzi et al., 2017; Shi et al., 2017), economic growth (Hoymann, 2010; Te Linde et al., 2011), and planning (Liu et al., 2011; Xi et al., 2010). The methods that make scenarios different depend on prediction models and purposes, but there are three general differences: pixel number control for density (compact or loosen), location control by exclusionary layers, and driving factor influence control by using different driving factors or weighing driving factors. In the scenario for making using plans, six studies consider plans for managed/planned growth scenarios in China. Five articles use future development areas in regional development plans, and one article uses a local land use plan for a district-level study in China (Hua et al., 2014).

2.1.6. Prediction Assessment

In the review, 56 out of 144 articles did not present validation of prediction; most of them were performed before 2010. Afterward, many studies began to justify prediction accuracy with one or more measures. Popular accuracy measures are kappa coefficient with 45 times, area under curve (AUC) of receiver operating characteristic (ROC) with 31, and quantity disagreement & allocation disagreement (OA) with 12. Those are the most common methods for assessing the models' prediction performance quantitatively through an error matrix (see details in Section 2.2.3). A few studies used percent correct metric (PCM) and root mean squared error.

2.2. Artificial Neural Networks and the Land Transformation Model

The Land Transformation Model (LTM) is one of the most used land change prediction tools due to its accurate prediction performance. It is an artificial neural networks (ANN) based model. This section will explain ANNs' algorithms, history, and applications of the LTM, and its related accuracy assessment measures.

2.2.1. Artificial Neural Networks

Artificial Intelligence

Since the invention of the computer, artificial intelligence (AI) was developed by computer science to create software which tries to imitate human brain activity such as learning, reasoning, self-correcting, and problem solving in terms of methods, tools and systems (Agatonovic-Kustrin & Beresford, 2000; Boers & Kuiper, 1992). There are two categories in designing intelligent systems. The first is a traditional rule-based approach to simulate human experience and to draw conclusions based on rules and logical sequences. Due to limited knowledge in experience, these programs can only usually function in a few expert systems in narrow areas. The ANN approach is to model processing principles of the human brain, a method based on the ability to learn and generalize from experience (Agatonovic-Kustrin & Beresford, 2000; Boers & Kuiper, 1992; Zhang et al., 1998).

Brain research and modeling have been studied in psychology, biology, and computer science. The development of the ANNs started with the neural activity study by McCulloch and Pitts (1943). Rosenblatt (1958) scrutinized neurodynamics theory and how the human brain perceived and memorized information, and Minsky and Papert (1969) examined computing perception with a simple layer and its limitations. After introducing the multilayer perception by Werbos (1974) and the computation of neuron networks by Hopfield (1982), Rumelhart et al. (1985) developed a multilayer perception with feedforward networks (Jain et al., 1996).

Artificial Neural Networks

ANNs are digitized models which mimic the way biological neurons process information (Pijanowski et al., 2001; Wang, 2003); and they are simplified reproductions of the complex natural brain. Among many of neural network paradigms, the multi-layer perception (MLP) is one of the most popularly used neural nets in ANNs (Boers & Kuiper, 1992; Pijanowski et al., 2001; Pijanowski et al., 2009). In a way different from simple two-layer networks from input layer to output layer, ANNs use additional layers, hidden layers which create internal representation in the input patterns (Rumelhart et al., 1985). Neural nets consist of stratified layers with linked nodes. Each node, each artificial neuron, in a lower layer is connected to higher layer nodes with different weights, and the latter node must receive input from previous nodes (Pijanowski et al., 2005). As seen in Figure 8, the MLP consists of at least three layers: an input, hidden, and output layer. ANN algorithms calculate weights through feedforward networks and backpropagation for input, hidden, and output layer nodes (Rumelhart et al., 1985; Pijanowski et al., 2009). Feedforward networks create and modify weights for each node through layers. Backpropagation algorithms find errors (Basheer & Hajmeer, 2000) and adjust weights using the summarized mean squared error of each node between the given output and predicted output (Pijanowski et al., 2002; Rumelhart et al., 1985). Applying the adjusted weights, a new cycle starts with repeating feedforward and backpropagation. ANNs run thousands of cycles to minimize errors and to develop the best-fit result between expected output and actual output (Pijanowski et al., 2001).

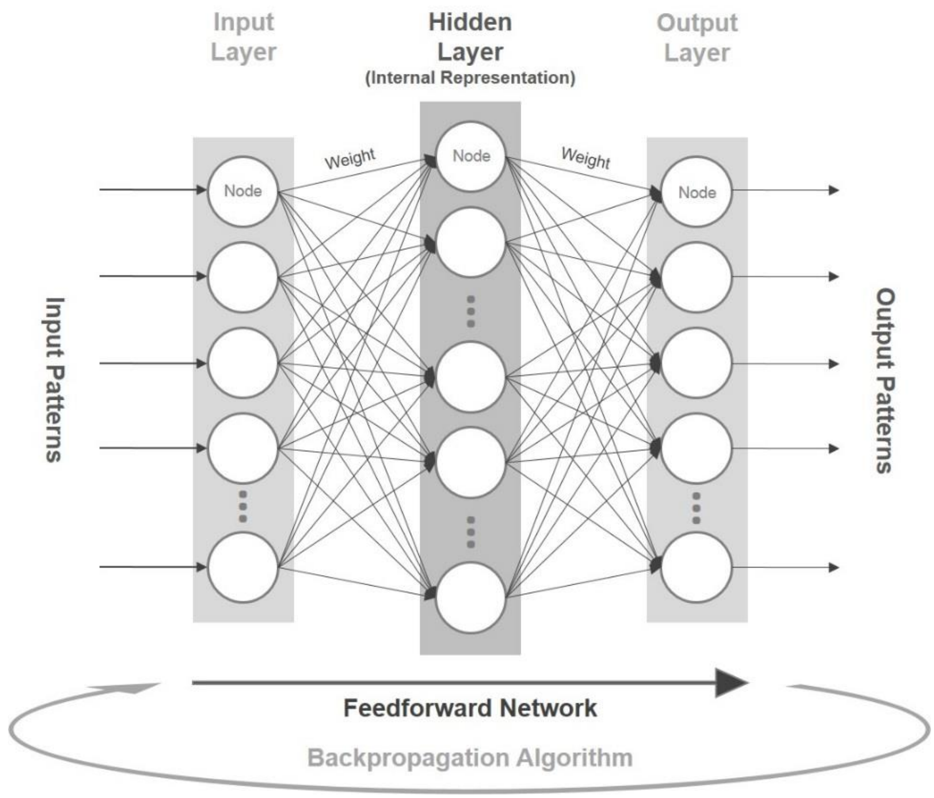


Figure 2.8. A typical multi-layer perception neural network: Feedforward and backpropagation.
Source: modified from Rumelhart et al. (1985), Pijanowski et al. (2009), and Newman et al. (2016).

Pros & Cons

ANNs are capable to recognize and classify complex behavior and patterns from examples (Pijanowski et al., 2002) so many studies use them to forecast tasks because of their distinct characteristics (Zhang et al., 1998). First, ANNs can calculate nonlinear solutions with little background knowledge. Neural networks can learn and generate rules based on examples though there is limited knowledge. Due to real world complexity, there are limitations in explaining and forecasting with linear statistics. ANNs use nonlinear data-driven approaches with little underlying assumptions (Pijanowski et al., 2001; Zhang et al., 1998). Second, ANNs can generalize results. They have an ability to achieve fault tolerance, though it includes noisy or damaged data (Swingler, 1996), with feedforward networks in hidden layers (Séquin & Clay, 1990). A model learned from a previous experiment can be applied for a new unlearned experiment when both the input and the output patterns have the same parameterization (Basheer & Hajmeer, 2000; Pijanowski et al., 2001). Third, ANNs can create various approximate results. Using known and unknown relationships, they create many options with desired accuracy. This is different from statistical approaches which usually follow direct relationships. Such features of ANNs produce more accurate better-fit results.

However, the drawback of ANNs, in a machine learning approach compared to statistical approaches is that it is hard for them to interpret internal analysis structure and variable relationships between dependent variables and independent variables. This is why they are sometimes referred to as a “black box” approach (Brown et al., 2013).

Application of ANNs

The characteristics of ANNs (their classification and forecasting capability) make them alternatives to statistical approaches, especially when there are nonlinear processes with limited data (Moody & Utans, 1994; Sharda, 1994). This is why ANNs have been popularly utilized for complicated and practical tasks in many fields: medicine, business, climatology, ecology, geography, etc.

In clinical medicine (medical science), clinical diagnoses have actively used ANNs in classification (image analysis, drug design, biochemical analysis, diagnosis), and prediction (Amato et al., 2013; Baxt, 1995). Lo et al. (1995) examined ANNs in detection of chest radiographs, and Cheng et al. (1996) developed medical image segmentation and prediction with a new type of neural networks called a competitive Hopfield neural network. ANNs are used to design drug compounding chemical elements for treatment of diabetes (Patra & Chua, 2011). Baxt (1995) applied ANNs to diagnose on myocardial infarction. It has a low incidence but a high price for misdiagnosis. Ellenius et al. (1997) used the LTM for biochemical monitoring for myocardial infarctions. Grigsby et al. (1994) used a prediction for functional outcomes, costs, and stay length. In the review of a cancer related studies using neural networks, Lisboa and Taktak (2006) reported the increasing numbers of research with ANNs on diagnosis, prognosis, and therapeutic guidance for cancer between 1994 and 2003.

In business, predictions of corporate failure and price change are important issues sustaining business (Alfaro et al., 2008). Odom and Sharda (1990) suggested a bankruptcy forecasting model and examined it with historic bankrupt firm data indicating 65 failures among 129 companies. Grudnitski and Osburn (1993) forecasted price changes in the Standard & Poor’s (S&P) Stock Index and gold with historic price and interest change. Moody and Utans (1994) predicted corporate S&P bond ratings.

Chen et al. (2003) forecasted the direction of a price movement, for profit yield in the Taiwanese stock market.

In Atmospheric Science, forecasting climate, precipitation, and river-flow are major neural network applications. Dawson and Wilby (1998) applied ANNs to flood-forecasting with historic rainfall, runoff, river flow, and catchment area because of their nonlinear function and generalizing capability. Knutti et al. (2003) used ANNs for more accurate climate change projection on surface warming and ocean heat uptake related to radiative forcing components such as greenhouse gases, stratospheric water, and others. Hydrological changes in streams (Poff et al., 1996), heat island intensity (Mihalakakou et al., 2002), and many climate related researches have been conducted with ANNs.

Ecologists, geographers, urban planners and other scientists have applied ANNs to identify patterns and forecast future developments. Manel et al. (1999) predicted Himalayan river bird distributions in India and Nepal. Park et al. (2003) used ANNs to predict aquatic insects' patterns and richness. Xia Li and Yeh (2002) used neural networks to predict future (2005) land use based on historical land covers in 1998 and 1993, and Liu and Lathrop (2002) used them for accurate land cover detection from satellite images.

2.2.2. Land Transformation Model

LTM and Application

The Land Transformation Model (LTM) is a tool to predict land use examining relationship between spatial driving factors and land use changes with the Geographic

Information System (GIS) and a machine learning process, artificial neural networks (ANNs) (Pijanowski et al., 1997). The LTM has a similar process to other regression based prediction tools to observe the relationships, however, it uses a machine learning approach with neural networks to calculate complex patterns (Pijanowski et al., 2002). Compared to other prediction models (e.g. logistic regression, SLEUTH, CLUE, etc.), the LTM performs with a higher prediction accuracy (Lin et al., 2011; Pontius et al., 2008).

Pijanowski et al. (1997) at Michigan State University (now at Purdue University) first introduced the LTM to simulate land cover change with ANNs. The LTM model forecasts increases and decreases in urban, forest, and agricultural land. It can couple to subsequent models to examine climate, hydrology, and natural habitats and the significant impacts of land use change on the environment (Pijanowski et al., 2002).

Pijanowski et al. (2001) tested the LTM in Michigan’s Grand Traverse Bay Watershed (GTBW) with growth driving factors: transportation, landscape features, and urban services. Based on 1980 and 1990 land covers as base maps, the study produced future predictions for 2020 and 2040. The prediction results were combined with the USGS’s Modular Hydrologic Model (MODFLOW) to calculate groundwater conditions and ground/surface water interactions. Then Pijanowski et al. (2002) examined the future eastern Lake Michigan watershed for urban sprawl impacts on the environment: the hydrological budget, exported nitrogen, and deforestation. Later, its calibration tools were developed (Pijanowski et al., 2005), and they enhanced the performance of application with national scale data (Pijanowski et al., 2014).

The model has been popularly applied in different locations and scales for forecasting urbanization, vacancy, deforestation (Mas et al., 2004; Müller & Mburu, 2009), and loss of agriculture (Li et al., 2012); a city scale in San Pablo City, the Philippines (Quintal et al., 2018), Chicago, the U.S. (Lee & Newman, 2017), and Fort Worth, the U.S. (Newman et al., 2016), a regional metropolitan scale in Beijing-Tianjin-Tangshan metropolitan, China (Kuang, 2011), Tehran metropolitan, Iran (Pijanowski et al., 2009), and a nation scale in the U.S (Pijanowski et al., 2014).

The forecasted results, sequential effects from urbanization, have been linked to other models: climate (Moore et al., 2012; Wiley et al., 2010), water quantity and pollution (Li & Merchant, 2013; Ray et al., 2010; Rizeei et al., 2018; Tang et al., 2005; Yan & Edwards, 2012), and soil erosion (Rizeei et al., 2016), etc.

Process

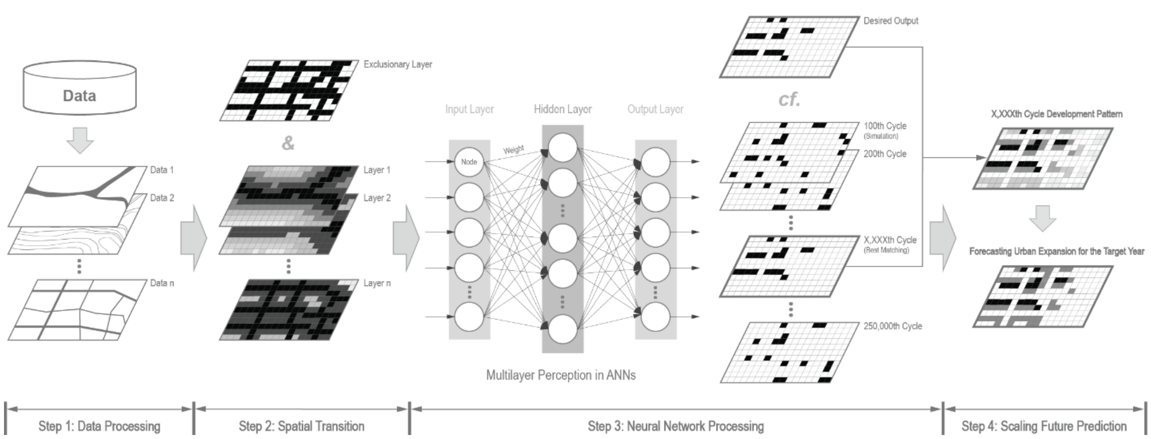


Figure 2.9. LTM process diagram.
Source: modified from Almeida et al. (2008).

As Figure 8 illustrates, the model follows four steps: 1) data processing – input layers, base maps and driving factors are processed with GIS, 2) spatial transition rules – coded grid cells represent predictors in binary or continuous variables transformed with density, patch size, site specific characteristics, and distance, 3) neural network processing – ANNs examine input layers matching with desired output through feedforward and backpropagation, and integrate predicted cell change, and 4) scaling future predictions – the amount of cell transition to decide how future predictions will be applied to the highest changing potential pattern (Newman et al., 2016; Pijanowski et al., 2002).

2.2.3. Prediction Accuracy Measures

Showing the goodness of fit with appropriate accuracy measures is important in a spatial prediction model since no best measure exists, and each measure represents different ways (Stehman, 1997). This research uses four most common types of spatial statistical measures to validate spatial patterns; percent correct metric (PCM), kappa coefficient, quantity disagreement & allocation disagreement, and area under curve (AUC) of receiver operating characteristic (ROC).

PCM is the percentage of the cells correctly predicted to change divided by the total cells actually changed during the study period (Newman et al., 2016; Pijanowski et al., 2002).

$$\mathrm{PCM} = \frac{(\text{Cells Correctly Predicted to Change})}{(\text{Cells Actually Changed})} \times 100$$

Kappa is a widely used index in accuracy assessment, and it is the proportion of agreement removing expected chance agreement (Cohen, 1960; Pontius, 2000). It is the value of observed proportion correct divided by perfect agreement with no change agreement. Kappa varies from 1 (when observed agreement matches perfectly with perfect agreement) to 0 (when observed agreement is expected agreement) (Pontius, 2002). In the evaluation of performance results, the agreements of the PCM and Kappa coefficient at 0.4-0.6 are fair, at 0.6-0.8 are good, and at more than 0.8 is excellent between prediction and real change data (Lee & Newman, 2017; Pijanowski et al., 2006; Pontius, 2002).

$$\text{Kappa} = \frac{(\text{Observed Agreement } - \text{Expected Agreement})}{(\text{Perfect Agreement } (1) \ - \text{Expected Agreement })}$$

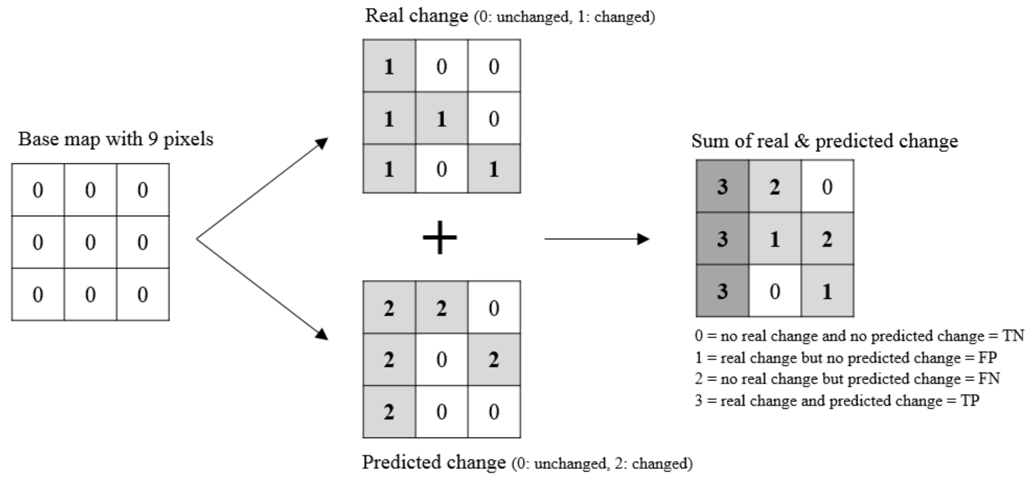
To claim a geographical limitation of the Kappa index, Pontius & Millones (2011) introduced quantity and allocation disagreement. Quantity disagreement is the difference in changed cell numbers without considering location, and allocation disagreement is the spatial difference in transition (Lee & Newman, 2017). Overall agreement can be drawn by removing the quantity disagreement and allocation disagreement. An overall agreement (OA) of more than 85% will be considered good (Lee & Newman, 2017).

$$\text{Overall Agreement } (\%) = 100 - (\text{Quantity Disgreement} + \text{Allocation Disagreement})$$

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). The Area Under the ROC Curve (AUC) shows overall fit which ranges from 0 to 1.0, where 0.5 is a chance performance and 1.0 is a perfect fit (Lee & Newman, 2017; Osborne et al., 2001). The Area under the ROC varies from 0.5 with random assignment to 1.0 with perfect probability (Alsharif & Pradhan, 2014). The AUC accuracy value means: 0.5-0.6 are weak, 0.6-0.7 are average, 0.7-0.8 are good, 0.8-0.9 are very good, and 0.9-1.0 are excellent (Zare et al., 2017).

$$\text{Sensitivity (True Positive Rate)} = \frac{(\text{True Positive})}{(\text{True Positive} + \text{False Negative})}$$

$$\text{Specificity (True Negative Rate)} = \frac{(\text{True Negative})}{(\text{True Negative} + \text{False Positive })}$$



		Real Change		
		Unchanged (0)	**Changed (1)**	**Total**
Predicted Change	**Unchanged (0)**	2 True Negative (0)	2 False Negative (1)	4 SN (0+1)
	Changed (2)	2 False Positive (2)	3 True Positive (3)	5 SP (2+3)
	Total	4 RN (0+2)	5 RP (1+3)	9 GT (0+1+2+3)

Figure 2.10. Error Matrix of real change and predicted change.
Source: modified from Lee et al. (2017) and Fawcett (2006).

2.3. Scenario Planning

The first and second subsections looked at LCM and LTM. LCM enables to predict future land changes with different scenarios. This sub-section will focus on scenario planning; definition, importance, and application in urban planning.

"It is not simply what you know that matters, but how you react what you do not know. The advantage of scenario thinking is not only a greater understanding and insight into present, and hence future, situations; it is also, and most decisively, a capacity to manage the unknown challenges of the future".

- Van der Heijden et al. (2002), p.277

2.3.1. Introduction of Scenario Planning

Why is Scenario Planning important?

As environment, society, and technology rapidly change, the future becomes more complex and unpredictable (Lincoln Institute, 2017). Such changes make practical experience and conventional judgement less reliable as guides to policy making (Kahn & Wiener, 1967). Policy choices made based on unreliable information may cause an undesirable future so policy/decision makers should navigate wide ranges of future challenges to try to alleviate the bad in advance (Kahn & Wiener, 1967).

Scenario planning is a decision making process and identifies various future options (Lincoln Institute, 2017). It helps stakeholders (e.g. agencies, local officials, developers, land owners, general public) to make a better decision for possible future conditions by comparing and assessing different and plausible stories (FHWA, 2011).

Ringland and Schwartz (1998, p.2) define scenario planning as that "part of strategic planning which relates to the tools and technologies for managing the uncertainties of the future." Van der Heijden (2011) defines scenario as external and internal: an external scenario is from mental models from the external world, internally consistent but challenging in the external world. An internal scenario is a personal anticipation of the future states of the interactional world. An internal scenario is an individual thinking process for everyday-life, and it tends to be normative with a preferred outcome. However, the external scenario is out of control, and it tends to be explorative to allow us to see the world from different perspectives beyond our experiences (Van der Heijden, 2011).

History of Scenario Planning

Scenario planning started from military war games that the RAND Corporation and the Hudson Institute developed during and after the Second World War (Van der Heijden, 2011). Then, similar game theory and decision analysis was adopted by the corporate fields (e.g. British Airways, Cable & Wireless, Shell, United Distillers, etc.) (Ringland & Schwartz, 1998). Shell Oil Company has had employed scenario planning for creating business strategies since the 1960s. The company successfully responded to the oil shock in 1973 with an oil crisis scenario and government's environmental policies in 1989 by shifting strategies according to pre-considered scenarios. Those scenarios were unpredictable based on the trends of the period. Scenario thinking is a supportive decision-making process at Shell (Bentham, 2014; Van der Heijden, 2011).

2.3.2. Scenario Planning in Urban Planning

"The beginning of scenario analysis originates from the common "predict-and-control" approach to plan with a single most likely prediction" (Van der Heijden, 2011, p.15). Similarly, Quay's (2010) "predict and plan" in urban planning is to predict future population or employment trends and calculate necessary infrastructure for future (Quay, 2010). In land use planning and transportation planning, a single preferable future state or future trend (e.g. population estimation) has been used as a standard to create future cities, and this approach works well when society and the environment are stable and predictable (Chakraborty et al., 2011; Quay, 2010). However, high uncertainty and complexity make forecasting difficult, and today's society requires a different planning approach, scenario planning relying on "qualitative causal thinking, not on probability" (Van der Heijden, 2011).

Though scenario planning has been used in urban planning, the planning practice is still in the initial stages. Quay (2010) noted that planning often fails to create/explore possible futures, to develop proper strategies by scenarios, and to achieve consensus. Chakraborty et al. (2011) and Hopkins and Zapata (2007) argued that many Metropolitan-scale plans ignore uncertainty and deal with only a single preferred scenario. Bartholomew (2007) suggested that a lack of public participation in plan making and lack of scenario assessment techniques in transportation scenario planning. Couclelis (2005) posited that there is a gap between current land-use planning methods and technical capability. Woodruff (2016) discovered that climate change adaptation plans in the U.S. fail to provide a detailed process of scenarios development and future impcats of scenarios.

Researchers have made an effort to improve the scenario development process, tools, planning process, and governance. Postma and Liebl (2005) specified a conventional scenario approach: identifying predeterminants and unknown and ranking levels of impacts and levels of uncertainties for unknowns (Van der Heijden et al., 2002). Adding to that, they suggested methodological adaptations for scenario construction such as a recombinant scenario, a context scenario, and an inconsistent scenario by considering more uncertain factors. Couclelis (2005) suggests a planning support system to create synergies with computer techniques in land-use models for scenario planning. Several land-change models and land-use forecasting tools have been created and developed since the 1970s: Markov (Bell, 1974), Land Transformation Model (Pijanowski et al., 1997), Land Use Scanner (Hilferink & Rietveld, 1999), SLEUTH (Silva and Clarke, 2002), CLUE (Verburg et al., 1999), and others. Hopkins and Zapata (2007) delineated two requests for proposals (RFP) for planning a three-county metripolitan area: current practice RFP (RFP_{CP}) and engaging the future RFP (RFP_{ETF}). RFP_{CP} follows a conventional planning approach by selecting a single prefered alternative and implementing policies. RFP_{ETF} includes contingent scenarios, a compendium of plans, and sustainable forecasting tools. Quay (2010) suggested a new planning model, anticipatory governance where anticipation and future analysis refer to exploring a range of possible scenarios, flexible adaptation strategies are meant to create flexible actions as the defined range of anticipated future, and monitoring and action are to implement anticipated strategies according to the scenario changes. Chakraborty et al. (2011) showed large-scale scenario analysis through adopting internal and external forces, applying prediction models, and identifying robust and contingent decisions. Internal options are controllable decisions, and external forces are uncertain factors. Robust plans cover future scenarios, and contingent plans support specific futures. Berke and Lyles (2013) presented new models integrating collaborative governance with Quay's (2010) anticipatory governance. "Collaborative governance is to bring diverse private and public stakeholders together in a consensus-oriented forum for decision making" (Berke & Lyles, 2013, p.191; Innes & Booher, 2010). The collaborative planning process enables educating citizens, tapping preference, to improving relationship, solving problems, and expanding partnerships among stakeholders (Berke

& Kaiser, 2006; Berke & Lyles, 2013). The suggested stages for anticipatory governance are to develop scenarios with plausible futures and impacts, to adopt flexible policies, and to create action programs for implementation and monitoring. Chakraborty and McMillan (2015) proposed the scenario planning typology, a framework that helps to make systematic decisions. The nine components of a scenario typology are organizational structure, scope, scenario type, outcome, stakeholder engagement, participation extension, engagement medium, scenario construction and analysis tools, and resources (Chakraborty et al. 2015).

Scenario planning is a valuable planning method that allows communities and decision-makers to understand the present (Van der Heijden et al., 2002) and plan for a complex and uncertain future (Holway et al., 2012). It assumes "if decision makers consider multiple plausible futures, they are more likely to make better decisions" (Chakraborty et al., 2011, p.252). Scenario planning can also be a tool for public engagement to rebuild public trust through a transparent planning process and decision making (Holway et al., 2012).

Despite the strength of scenario planning, in the Lincoln Institute and Sonoran Institute workshops, the participants identified obstacles in scenario planning, lack of trust in the process and tools (Holway et al., 2012). The distrust is due to the government's transparency, and deficient understanding of the planning process and planning tools (Holway et al., 2012). For the scenario tools, in general, tool license fee, technical staff capacity, data gathering, and a lack of interoperability between software and application to other sites are barriers. Open source data, software, and tools can be a solution, but are not yet established. In the planning process, exploring diverse and plausible scenarios, creating flexible strategies, and reaching consensus among stakeholders are other challenges.

2.4. Literature Gaps

Land use change is the result of interactions between human activity and natural resources (Agarwal et al., 2002), and land change modeling is a good planning support system (Berke & Kaiser, 2006) to assess the simulated scenarios during the planning process. Over the past few decades, urban LCMs have been developed significantly, addressing the challenges of urbanization by simulating future development and its impact assessment (Verburg et al., 2015; Güneralp, 2011). However, there are still opportunities to integrate land change models and scenario planning.

First, while if there have been many attempts to predict future urban growth with various driving factors, most of the prediction studies do not explain the relationships between urban growth and its factors. The numbers of driving factors of urban growth vary from one to seventeen depending on prediction models and study areas. Prediction articles focus more on the calibration and prediction results, but not on causal relationships. In addition, few socio-economic variables have been employed compared to natural and built environmental factors.

Second, many prediction articles have created urban growth scenarios to examine sub-sequent impacts in terms of environment, economy, disaster, and others. However, scenarios are limited, mainly in business as usual, environmental growth, and high/low density growth. Few studies have been conducted with plans to make managed/planned scenarios, but they also use the plans to define development areas from regional plans (Liu et al., 2011; Xi et al., 2010). A local comprehensive plan is the result of a community prepared plan for their future (Brody, 2001), and land use planning and policies are direct methods for growth management to control urban development where growth is proper and protecting areas where preservation is a concern for natural resources, the environment, and open space (Bengston et al., 2004; Wilmer, 2006).

Third, impact analyses of urban growth scenarios in climate-related studies are limited to the total areas exposed to flood risks. Total impact calculations such as a whole city is one important result for physical flood impacts, but impact assessment can use different scales and other evaluations. Multiple stakeholders are involved in urban issues and plans with different interests. Depending on a stakeholder's or an asset location/situation, a single regional solution cannot satisfy all the different individuals; the best regional solution can make local problems. Thus, scenario assessment in multiple scales would be necessary. Content-wise, as stated above, a local comprehensive plan can be an assessment tool for scenario planning or an assessment subject to examine possible future scenarios to determine whether a plan is robust or contingent (Chakraborty et al., 2011).

Fourth, though many LCM studies have used urban growth scenarios, the scenarios are typically about ecology, density, and economy related to urban growth. Prediction models repeatedly create similar scenarios such as same growth pattern as previous development referred as business as usual, new development outside environmental/preservation areas referred as environmental growth (Goodarzi et al., 2017; Shi et al., 2017), controlling size and location of development areas referred as sprawl/smart (Song et al., 2017; Terzi, 2015), low/high growth, (Price et al., 2015), or rapid economic growth (Hansen, 2011; Samie et al., 2017). Few studies have considered regional plans to create scenarios (Hua et al., 2014; Liu et al., 2011). In addition, no LTM studies have been conducted with scenarios. The capabilities of ANNs in non-linear modeling shows a high prediction performance with limited knowledge or data (Kocabas & Dragicevic, 2007; Li & Yeh, 2002). The existing literature on the LTM focuses on prediction accuracy and its results. Like other prediction tools, the LTM also has a potential to make scenarios by controlling pixel numbers, locations, and variables.

Last, though urban planning has used scenario planning since 1960, many plans ignore uncertainty and deal with only a single preferred scenario (Chakraborty et al., 2011, Hopkins & Zapata, 2007), and they fail to provide a detailed process of scenarios development and future impact of scenarios (Woodruff, 2016). The future become more complex and unpredictable and such changes make practical experience and conventional judgement less reliable as guides to policy making (Kahn & Wiener, 1967; Lincoln Institute, 2017). Thus, it is clear that scenario planning is a valuable planning method for communities and decision-makers to understand the present (Van der Heijden et al., 2002) and plan for a complex and uncertain future (Holway et al., 2012) dealing with such things as urban growth and changing climate conditions.

3. METHODS

3.1. Conceptual Framework

Based on the literature review, I constructed a conceptual framework for a scenario planning process for analyzing the impact of future urban growth and climate change. As Figure 11 illustrates, I divided the process into two parts: scenario making and impact analysis. Scenario making comprises urban growth scenarios, climate change scenarios, and a scenario matrix. The impact analysis is divided into two sections: the areas of urban growth of the scenarios exposed to flood risks at a city and neighborhood levels, and plan preparation for highly clustered future urban neighborhoods considering flood risks, social and physical vulnerabilities, and plan policies.

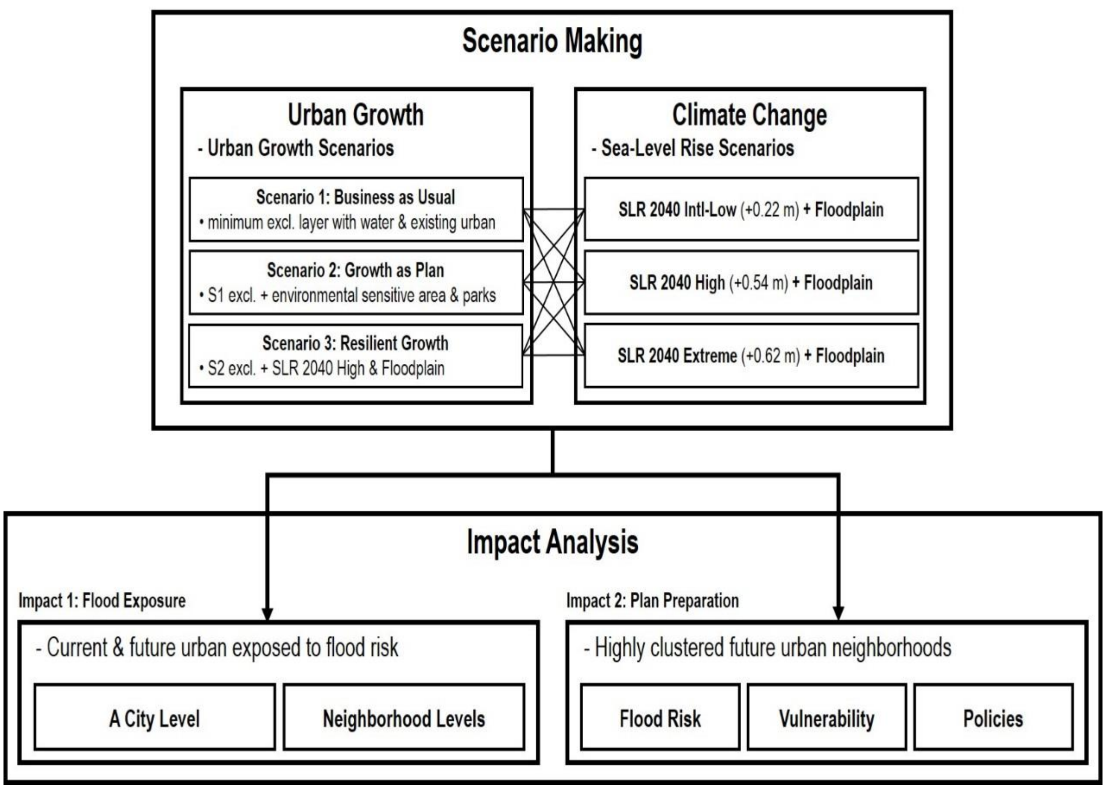


Figure 3.1. Conceptual framework for scenario planning.

3.1.1. Creating Scenarios

The urban growth scenarios in this research employ three comparable forecasts to examine future land; business as usual, growth as planned, and resilient growth. The future urban growth in scenario 1 (S1), business as usual, is natural growth without development regulations if a new development occurs according to the previous development pattern. The scenario 2 (S2), growth plan follows a land use plan reflecting how a city government and communities want to develop. Scenario 3 (S3), resilient growth, is an extreme scenario where no development occurs within future flood risk areas.

The method of creating urban growth scenarios using the LTM is to develop different exclusionary layers. It is one way to create different scenarios for controlling land development areas. An exclusionary layer intentionally includes areas where no development would occur. The S1, business as usual, uses minimum elements (e.g. existing urban area, water surfaces) as an exclusionary layer. The S2, growth as planned follows a land use plan, adding parks and environmentally sensitive areas based on the S1's exclusionary elements. The S3, resilient growth, includes flood risks (e.g. sea-level rise 2040 High, floodplains) based on the S2 growth plan.

For the sea-level scenarios, the National Oceanic and Atmospheric Administration (NOAA) provides future potential sea levels with relative sea level (RSL) projections and different heights of the sea surfaces depending on time and location, based on the historic sea level changes (Parris et al., 2012). The scenarios vary from low to high with a 90 % confidence. The low scenario is the linear estimation based on the historical sea-level rise (SLR) tide records since 1900; 1.7 mm increase per year on average. The intermediate low scenario is a standard for experts to consider as a primary risk due to ocean warming. The highest scenario calculates the maximum glacier and ice sheet loss and is a design standard for highly vulnerable facilities such as a power plant. The extreme scenario combines extreme weather and climate (Parris et al., 2012).

In this research, the RSL records in St. Petersburg, Florida were used. The NOAA's projection shows that the sea-level rise in 2040 in St. Petersburg varies from 0.18 meters (low) to 0.62 meters (extreme). As Table 1 shows, I use the intermediate low scenario (+0.22 meters) as a primary risk and the high (+0.54 meters) and the extreme (+0.62 meter) as potential highest risks in the SLR scenarios.

Table 3.1. NOAA 2017 sea-level rise scenarios in St. Petersburg.

Year	Low	Int-Low	Intermediate	Int-High	High	Extreme
2000	0.00	0.00	0.00	0.00	0.00	0.00
2020	0.09	0.11	0.15	0.19	0.22	0.23
2040	**0.18**	**<u>0.22</u>**	**0.33**	**0.43**	**<u>0.54</u>**	**<u>0.62</u>**
2060	0.28	0.35	0.57	0.80	1.06	1.25
2080	0.37	0.47	0.86	1.28	1.74	2.11
2100	0.44	0.58	1.19	1.88	2.59	3.21

Source: reprinted from USACE (2017).

I developed sea-level rise scenarios based on the National Flood Insurance Program's 100-year floodplain from the Flood Insurance Rate Map. The 100-year floodplain signifies a 1% chance of flood in any given year (FEMA, 2018); it has been used as a planning standard. SLR scenarios were delineated by using a modified bathtub method, considering sea level height and hydrologic connectivity (NOAA, 2017a), as seen in Berke et al.'s (2015) hazard mapping.

As Figure 11 and Table 2 show, the urban growth scenarios and SLR scenarios combines to make the scenario matrix with nine potential future options. The BU and IL indicates urban growth with no regulation and flood risk in 2040 (intermediate low and floodplain). The GP and HI is future urban areas following a land use plan with SLR 2040 high flood risks. The RG and EX is no future development under flood risk with an extreme SLR 2040 scenario.

Table 3.2. Scenario matrix.

		Sea-Level Rise (External / Uncontrollable Force)		
		IL (Int-Low SLR)	**HI** (High SLR)	**EX** (Extreme SLR)
Urban Growth Direction (Internal / Controllable Option)	**BU** (Business as Usual)	**BU & IL**	**BU & HI**	**BU & EX**
	GL (Growth as Plan)	**GP & IL**	**GP & HI**	**GP & EX**
	RG (Resilient Growth)	**RG & IL**	**RG & HI**	**RG & EX**

3.1.2. Impact Analysis

Impact analyses are flood exposure calculation and policy preparations.

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. The results will show how each urban growth scenario differently influences various flood risk scenarios and scales at a city and neighborhood levels.

Plan preparation examines the area of future flood risks, physical and social vulnerabilities, and plan policies focusing on highly clustered future urban neighborhoods. It will use the projected SLR 2040 high scenario as a fixed future flood risk. To select highly clustered future developing neighborhoods, I used the optimized hot spot analysis method incorporating future growth pixels in S1, S2, and S3. The hot spot analysis identifies the statistical significance of spatial clusters with high/low values (hot/cold spots) using the Getis-Ord Gi statistic, providing positive/negative z-scores (ESRI, 2018). For physical vulnerability, I used 2010 tax data from the Hillsborough Appraisal District and calculated the sum of the vulnerable structure values under the current floodplain at a tract level (Berke et al., 2015). For social vulnerability, NOAA's Social Vulnerability Index 2010 was used at the tract level. The index indicates social vulnerabilities for environmental hazards for coastal counties (NOAA, 2017b). Then, I identified and analyzed the applied policies for the neighborhoods using the resilient scorecard method (Berke et al., 2015).

3.2. Case Study Design

3.2.1. Spatial Frame

To select a case study, I used three screening filters: a planned, growing, and coastal flood-vulnerable city. Like other cities in the state of Florida, the city of Tampa has a strong community prepared local comprehensive plan (Brody, 2001). As illustrated in Figure 12, it is located on the Florida west coast in Hillsborough County, and the South Tampa region is enclosed by three Bays; Tampa Bay, Old Tampa Bay and Hillsborough Bay (Hillsborough County, 2016). The climate is humid subtropical with a large amount of summer rainfall and hot temperatures because of 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 (440 square kilometers) and the land elevations vary from sea level along the coastline to 55 feet (16.7 meters). It is the third largest city in Florida with a population of 304,200 people in 2000, and 336,800 people in 2010 (Hillsborough County, 2016). 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 shallow Tampa Bay and the city's flat land, SLR will make more residents susceptible to flood risks.

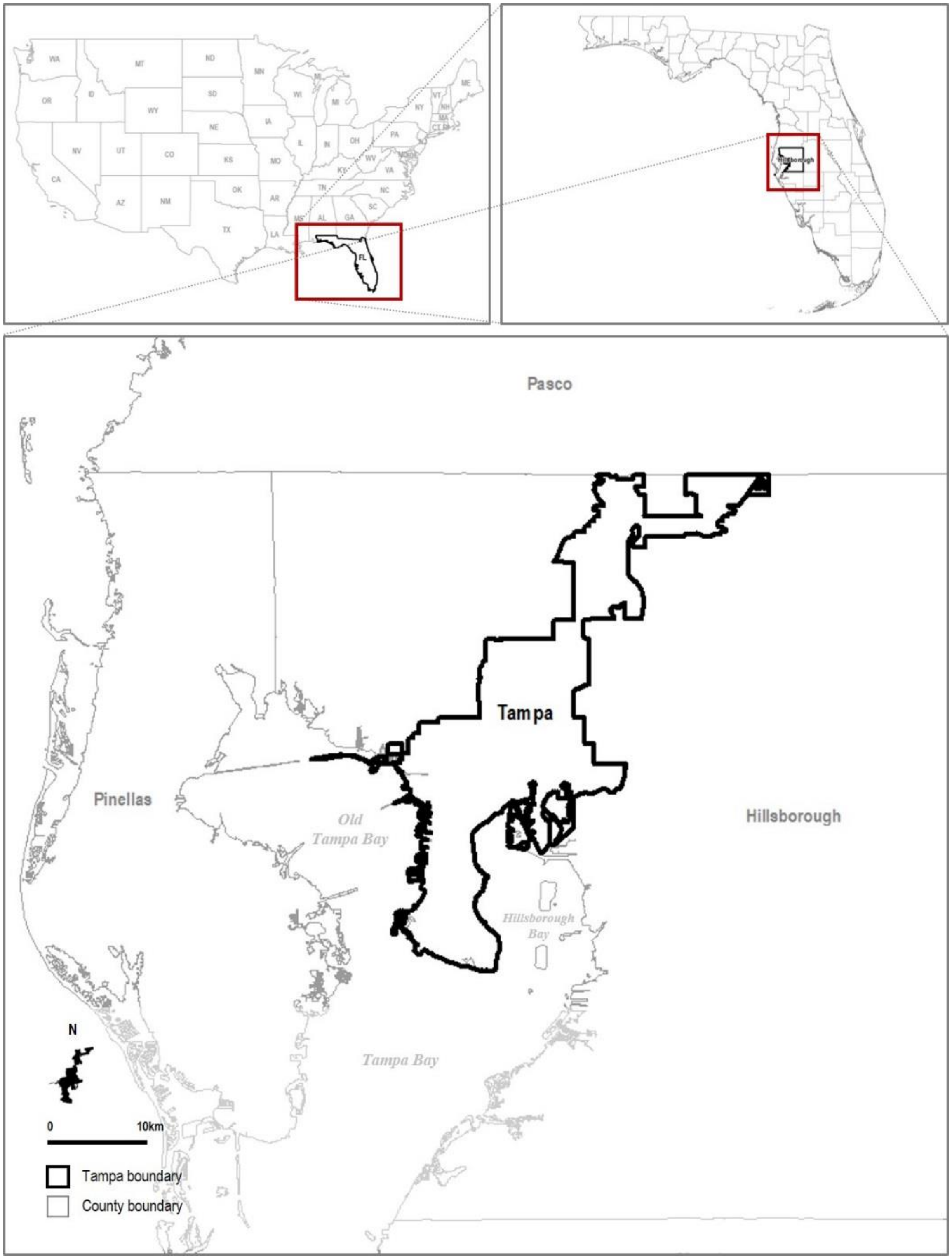


Figure 3.2. Location of Tampa, Florida.

3.2.2. Expected Data Sets and Data Source

This research requires spatiotemporal GIS datasets. The time span of the analysis is 10 years from 2001 to 2011. As Table 3 shows, the U.S. Geological Survey provides historic land cover data in raster images (30×30m pixels). I collected the 16 causal variables related to urban growth from the Tampa Geo Hub, the U.S. Census Bureau, and the Hillsborough Appraisal District. The Plan Hillsborough provides the Tampa Comprehensive Plan 2040 with future land use data in GIS shapefile format. To delineate future flood risk zones, the 100-year floodplain map from the Flood Insurance Rate Map (FEMA) and future sea-level rise projection data from NOAA (USACE, 2017) were used.

Table 3.3. Data sources and expected datasets.

Expected Data	Data Source	Operation
NLCD 2001 & 2011 Land Cover Existing urban	U.S. Geological Survey	Base map Driving factors
Slope Proximity to highway Proximity to river & lake Proximity to waterfront Proximity to park Proximity to residence Proximity to commercial Proximity to CBD Proximity to public school	Tampa Geo Hub	Driving factors
Land Value	Hillsborough Appraisal District	Driving factors
Population density Population increase Poverty Employment Race	U.S. Census Bureau	Driving factors
Land Use Inventory Future Land Use Plan	Plan Hillsborough	Scenario making
Tampa 2040 Comprehensive Plan	Plan Hillsborough	Plan evaluation
Sea Level Risk	NOAA (Sea Level Rise Inundation) US Army Corps of Engineers FEMA (Federal Emergency Management Agency)	Sea-level rise projection

3.3. Driving Factors

Sixteen growth driving factors were selected which consider Tampa's geographic location, based on the reviewed prediction literature. The determinants, as described in Table 4, to predict urban growth include proximity variables (e.g. waterfront, rivers, open space, highway, residence, commercial, CBD, existing urban areas, and public schools) and density variables (e.g. slope, population density, population increase, race, employee numbers, poverty, and land value).

Though Tampa is located on flat land, slope is a key driving factor in selection of development location so it is calculated with digital elevation model data in percentage value. Related to commuting time and cost, distance to highway (including major roads) and central business district (CBD) are calculated with Euclidean distance tool in ArcMap, and employee number is used in zip code level. Considering natural amenity regarding buyers' preference, each proximity to waterfront, water surface, and park and open space is calculated with Euclidean distance tool. Related to infrastructure and facilities, each proximity to residence, commercial, existing urban, and public schools is calculated with Euclidean distance tool. Due to the importance of land value in selecting development location, land value, population density, population increase, and poverty have been used. Considering white population moving from central to suburban areas, race variable (white population ratio) is used in a block group level.

Table 3.4. Driving factors for land change prediction model.

Type	Input Factors	Definition	Data level	Data Processing	Reference for Input Factors
Natural Environment	**Slope**	Percentage of slope	Raster	Density (DEM)	Dadashpoor et. al. (2017), Menesis et. al. (2017), Samie et. al. (2017), Shi et. al. (2017), Zare et. al. (2017a), Zhao et. al. (2017a), Chakraborty et. al. (2016), Gao et. al. (2016), Gallardo et. al. (2016), Liu et. al. (2016),
	Water Surface	Proximity to rivers and lakes	Polygon	Proximity (Euclidean Distance)	Yirsaw et. al. (2017), Zare et. al. (2017a), Zhao et. al. (2017a), Zhao et. al. (2017b), Gallardo et. al. (2016), Liu et. al. (2016), Losiri et. al. (2016), Castillo et. al. (2014), Long et. al. (2012), Pijanowska et. al. (2002)
	Waterfront	Proximity to waterfront	Polygon	Proximity (Euclidean Distance)	Al-sharif et. al. (2016), Al-sharif et. al. (2015), Zheng et. al. (2015), Mokrech et. al. (2012), Wu et. al. (2010), Pijanowskia et. al. (2002)
	Park & Open space	Proximity to parks	Polygon	Proximity (Euclidean Distance)	Nor et. al. (2017), Shafizadeh-Moghadam et. al. (2017), Losiri et. al. (2016), Samard zic´-Petrovic et. al. (2016), Achmad et. al. (2015), Zheng et. al. (2015), Tayyebi et. al. (2011), Pijanowskia et. al. (2009 & 2002)
Built Environment	**Highway**	Proximity to highways	Line	Proximity (Euclidean Distance)	Yirsaw et. al. (2017), Zhao et. al. (2017a), Zhao et. al. (2017b), Liu et. al. (2016), Castillo et. al. (2014), Ray et. al. (2010a), Pijanowskia et. al. (2002)
	Residence	Proximity to residential areas	Polygon	Proximity (Euclidean Distance)	Zhao et. al. (2017a), Munshi et. al. (2014), Long et. al. (2012)
	Commercial	Proximity to commercial areas	Polygon	Proximity (Euclidean Distance)	Zhao et. al. (2017a), Munshi et. al. (2014), Pijanowskia et. al. (2009)
	Central Business Dist.	Proximity to central business district	Polygon	Proximity (Euclidean Distance)	Gao et. al. (2016), Losiri et. al. (2016), Linard et. al. (2013)
	Existing Urban	Proximity to existing urban	Raster	Proximity (Euclidean Distance)	Ku et al. (2016), Ray et. al. (2010), Li et. al. (2002), Zare et al. (2017)
	Public School	Proximity to schools	Point	Proximity (Euclidean Distance)	Al-sharif et. al. (2015), Zheng et. al. (2015), Munshi et. al. (2014), Carreno et. al. (2011), McCloskey et. al. (2011)
Socio-Economic	**Population Density**	Population density in 2000	Block group	Density, Census	Menesis et. al. (2017), Samie et. al. (2017), Zare et. al. (2017a), Zhao et. al. (2017b), Losiri et. al. (2016), Castillo et. al. (2014), Munshi et. al. (2014), Mundia et. al. (2013)
	Population Increase	Population increase ratio from 1995 to 2000	Block group	Density, Census	Samard zic´-Petrovic et. al. (2016), Losiri et. al. (2016)
	Race	White population rate	Block group	Density, Census	-
	Employees	Employee no.	Block group	Density, Census	Mitsova (2014), Kocabas et. al. (2007), Hu et. al. (2007), Waddell (2002)
	Poverty	Poverty rate below 1.0	Block group	Density, Census	Hu et. al. (2007)
	Land Value	Land value per square meter	Parcel	Density, Land value in 2003 appraisal	Wilson (2011), Hansen (2010), Waddell (2002)

Commuting Time and Cost

Commuting time and cost to workplaces are key factors in deciding residential location. In the initial stage of city development, the Central Business District (CBD), where jobs are concentrated and its adjacent areas are developed first, and then development spreads out to the suburbs accompanying the infrastructure such as transportation and the power plant. As the urban area expands, residences and workforces move outward, new employment also decentralize, moving farther from the CBD (Mieszkowski & Mills, 1993). As highway construction leads the car-based commuting time and cost decreases, more people who can afford a car use a private car rather than public transportation because of a better environment. Finally, providing highway and road networks makes huge suburban areas accessible to metropolitan regions, and fringe development keeps expanding to keep up with population growth (Daniels, 1999). Instead of driving a car, if there are cost-efficient commuting alternatives (e.g. railways, metro, buses), the distance to public transportation will be another determinant of residence location (Mieszkowski & Mills, 1993).

Slope

Slope, the inclination of the landscape, is a fundamental rule to select a potential development area: flat and gentle-slope land are easy to develop with less cost (Landis, 1994). Optimum slope level is different for each land use, and, in general land with a slope of less than 25% (Berke & Kaiser, 2006) is regarded as developable as stable house sites because of soil erosion and run-off (Steiner et al., 2000).

Basic Infrastructure and Public Facilities

Infrastructure development (e.g. roadways, sewage, water lines, etc.) is a key implication for a future development (Daniels, 1999). Carruthers (2003) showed the relationship between public roadway and sewage investment and development patterns for counties where populations were growing, central city counties, and suburban counties in the 14 states of the U.S. where per capita spending on roadways is significant and negative to fringe development in central city counties, but not significant in suburban counties. Reducing traffic congestion helps to reduce spread development only in urbanized areas; causing people settle within the city limits. Sewage investment heavily leads to sprawl development for both counties. When developers manage development including infrastructure, the raised product cost (e.g. rent, sales) by infra construction will be a challenge for both developers and consumers (Ewing, 2008).

Public facilities providing community service and value become attractive for development and redevelopment (Berke & Kaiser, 2006). Accessibility to public facilities and institutions have been used as determinants for development (Mieszkowski & Mills, 1993; Wang et al., 2013; Zheng et al., 2015). Mieszkowski and Mills (1993) explained that high quality schools reflected the quality of neighborhoods, and they attract other households.

Buyer's Preference and Housing Price

People prefer to live close to nature and are more likely to pay additional money for the land purchase. In the real estate perspective, the land values close to waterfronts, rivers, lakes, and open spaces is higher than the value of land more distant to the amenities. (Correll et al., 1978; Darling, 1973; Ewing, 2008; Hammer et al., 1974; Hendon, 1971; McLeod, 1984). McLeod (1984) confirmed that proximity to rivers and parks were related to housing price, and a river view was a high-value determinant of housing price. Hammer et al. (1974) showed that property values close to parks were higher than the values of property at farther away. Correll et al. (1978) identified the negative relationship between housing price and greenbelt distance: the further from a greenbelt, the lower the housing price.

Land Value

Land value is a major determinant of land use (Park et al., 1967; Pendall, 1999), and it has similar aspects: both high and low value land have development potential. Land value is related to a site situation: "the sum of the money values of the situation advantages of a site" (Alonso, 1964; Marshall, 1961). In land use conversion from agricultural to urban, users (e.g. real estate developers, consumers) and landowners make bids for site values for situational advantages (Alonso, 1964). When a developer considers transitioned land value, if land is worth more as urban than as farmland, the land use is decided through a bidding process based on the economist's market logic, the "invisible hand" (Brueckner, 2000). Density and agricultural productivity influence land value: denser areas and more productive agriculture have a higher value. Density and land value are positively related to one another (Alonso, 1964; Carruthers, 2002). Farmland quality and productivity are positively related to land value. High-priced farmland is less likely to be developed into urban so the value as agricultural land works as a determinant of the urban spatial extension (Brueckner, 2000; Brueckner & Fansler, 1983; Pendall, 1999). Highly populated and high-value areas are where developers would like to develop (Carruthers, 2002) due to their current and future site advantages. High-value areas providing a denser population and more jobs draw more compact development.

On the other hand, lower land values attract more development, especially in areas of sprawl, when all other conditions are the same (Pendall, 1999). People prefer to develop inexpensive and less congested land (Ewing, 1997). Low-value land, if agricultural land has a high potential value when it changes into other uses, is more likely to be developed. Carruthers (2002) explained that urban development occurred in less dense and low property value land for the growing 283 counties in 14 states, the U.S. between 1982 and 1992. With development patterns conforming and nonconforming to land use planning in Florida, Brody et al. (2006) acknowledged that high land values in a planned area, conforming development, and low land values in sprawl development, nonconforming development, are more likely to be developed.

Race and Income

As urban areas expand due to the growing population with rising income and shortened commuting time and costs (Alonso, 1964; Brueckner, 2000), one major phenomenon is racial segregation: "chocolate city with vanilla suburbs" (Farley et al., 1978). Higher income people have more of a choice to live in a low density and rural environment (Carruthers, 2003). Paradoxically, white and higher-income people move to cheap city-fringe areas, and low-income people stay in the high-valued city areas (Alonso, 1964; Daniels et al., 2015) because rich people use private vehicles in the suburbs and poor people mainly rely on public transportation in cities (Glaeser et al., 2008). The process, called “white flight” (Massey & Denton, 1993), affects urban development patterns (Carruthers, 2003).

Land Use Planning and Policies

Land use planning and policies are direct methods for growth management to control urban development where growth is proper and protecting areas where preservation of natural resources, the environment, and open spaces in a concern (Bengston et al., 2004; Wilmer, 2006). Management methods include building permits, development rights, zoning, urban growth boundaries, tax incentives, and impact fees (Mattson, 2002; Pendall, 1999). Though a plan does not reflect future land changes perfectly, as in the Florida study comparing wetland development permits with future land use plans in the city comprehensive plan between 1993 and 2002, overall average development conformity is 79% (Brody & Highfield, 2005; Brody et al., 2006).

3.4. LTM Process

As Figure 13 shows, the LTM was ran to create scenario 1; 16 variables were used and performance results were checked. Rasterized predictor variables linked to a geographical location such as proximity and density data referred to as driving factors, and historic land covers for two different time frames, 2001 and 2011, are referred to as base maps. In the LTM process, the recommended training cycles are 250,000, and the minimum cycles are 4,000 to stabilize the error level. Larger cycles over 250,000 do not show much greater prediction accuracy, and the training process is time-consuming (Lee et al., 2017; Pijanowski et al., 2005). Thus, this study used the result up to 250,000 training cycles. After running the output of expected change between 2001 and 2011, I checked the validation with kappa, PCM, overall agreement, and AUC by comparing it to the real land use change, referred to as output scenario 1. As this stage, I identified each driver's prediction capability with the drop-one test, explained in the next sub-section. The same processes were conducted with only positively contributing input drivers. The performance was checked and each driver's prediction capability was confirmed. If every driver enhances the prediction capability, the selection of variables can be finalized and the future population growth forecast for scenario 1 can be created, referred to as forecasting.

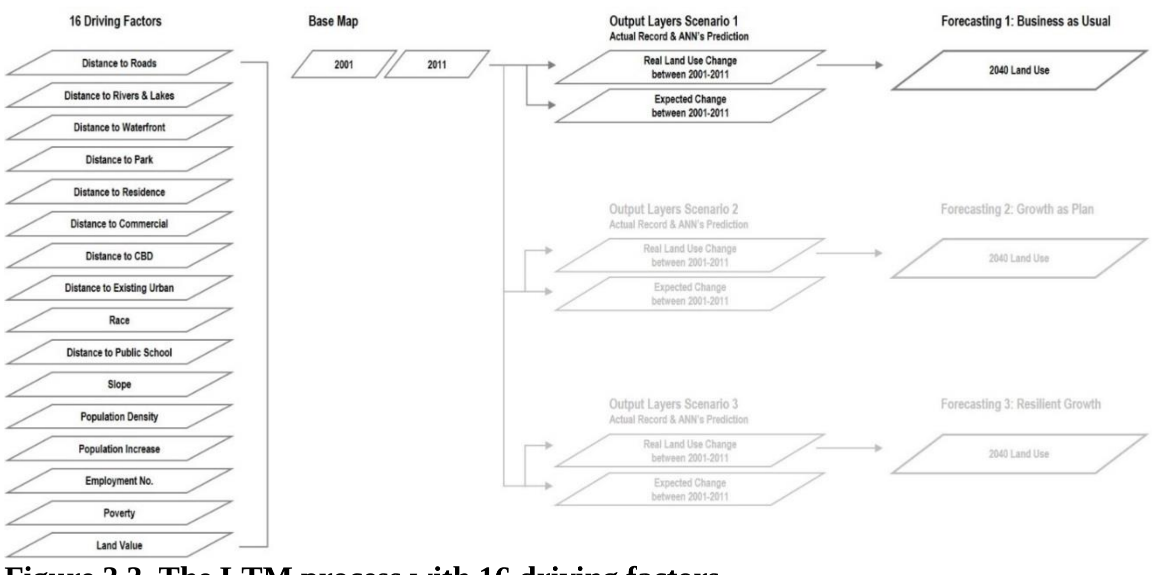


Figure 3.3. The LTM process with 16 driving factors.

4. RESULTS

This section describes scenario planning processes, scenario making, and impact analysis for Tampa. The first sub-section describes the urban growth prediction process with LTM, variable selection, urban growth prediction and validation, and urban growth scenarios for Tampa. The second sub-section delineates future flood zones considering the SLR scenarios. The third sub-section evaluates the efficacy of a land use plan comparing the growth as a planned scenario with other urban growth scenarios (business as usual and resilient growth) at city and neighborhood levels. The last shows how Tampa prepares for future urban growth and flood risks by examining plan policies and vulnerability for the highly clustered future urban neighborhoods. The first two sub-sections belong to the scenario making (urban growth and flood risk scenarios) in the research frame, and the last two sub-sections examine the impact analyses (scenario evaluation and neighborhood scaled policy analyses).

4.1. Urban Growth Scenarios

4.1.1. Driving Factors for a Tampa Urban Growth Prediction

This research employs an analytical method to identify variable relationships between driving factors for land use change called drop-one experiment (Brown et al., 2013; Pijanowski et al., 2002). It is a way to check the relative contribution of each variable in machine learning models by dropping one variable and comparing each prediction accuracy with the accuracy of the full model (Brown et al., 2013). To detect variables for the Tampa study, I first ran the LTM with 16 variables and calibrated the model. Then, I checked the influence of each variable with the drop-one test and excluded variables that reduced the total prediction capability. By selecting the variables that increased the prediction capability, I finalized the driving factors for the Tampa prediction model and created other urban growth scenarios with different exclusionary layers.

Table 4.1. Drop-one-test with 16 variables.

Excluded input factors	Highest training probability	PCM	Kappa coefficient	Model influence
Race	**200,000 th**	**52.19**	**0.48**	Least
Central Business District	**50,000 th**	**52.17**	**0.48**	
Population Density	200,000 th	51.92	0.48	
Distance to Park	80,000 th	51.71	0.48	
Distance to Commercial	250,000 th	51.53	0.48	
Distance to Public School	150,000 th	51.37	0.47	
Distance to Residence	80,000 th	51.06	0.47	
Distance to Roads	60,000 th	50.93	0.47	
Poverty	150,000 th	50.89	0.47	
Population Increase	250,000 th	50.87	0.47	
Distance to Water Surface	200,000 th	50.39	0.46	
Distance to Waterfront (sea)	250,000 th	50.23	0.46	
Employment No.	30,000 th	49.98	0.46	
Distance to Existing Urban	80,000 th	49.89	0.46	
Land Value	50,000 th	49.84	0.46	
Slope	80,000 th	49.70	0.46	Most
Full Model (16)	**50,000th**	**52.14**	**0.48**	-

The results with the 16 input factors, as illustrated in Table 4.1, show that race and distance to the central business district (CBD) variables decreased the total prediction capacity. The full model with 16 variables has 52.14 in PCM value and 0.48 in the kappa coefficient, but the PCM values after dropping race at 52.19 and CBD at 52.17 exceeded the full model capability. Thus, those variables decrease prediction capability.

Table 4.2. Drop-one-test with 15 variables without the race variable.

Excluded input factors	Highest training probability	PCM	Kappa coefficient	Model 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**	-

In the 15 variable when model excluding the race variable, as Table 4.2 shows, every variable positively contributes to the prediction capability including the distance to the CBD variable. The PCM values of each drop-one test are below 52.19, the PCM value of the full 15 variable model. For the accuracy result of the 15 variable model, the PCM is 52.19, the kappa coefficient is 0.48, the overall agreement is 92.85%, and the AUC is 0.74. All values are within acceptable and good ranges in prediction, justifying this as a proper model. The results show that distance to roads, parks, and commercial areas are the most influential factors, with population density, land value, and population increase variables the least. Then, I completed a variable selection with the 15 variables excluding race for the Tampa prediction and created other future urban growth scenarios.

4.1.2. Variable Influence

To identify the influence of each driving factor, the LTM's drop-one test is used where one variable at a time is left out and each accuracy measure (e.g. PCM and Kappa) is compared with the prediction accuracy of the full model (Brown et al., 2013).

In the result of the drop-one test with the 16 variable model, as Table 4.1 shows, the performances of two factors, race and distance to CBD, exceed the prediction accuracy of the full 16 factor model. When excluding the race factor, as shown in Table 4.2, the prediction results of the full model with 15 variables show that all factors including distance to CBD contribute to the land change prediction: each drop-one model produces a lower PCM and Kappa value than the full model. This suggests that the race variable may not have been influential in the land change of Tampa between 2001 and 2011. Literature illustrates that white and higher income people have more of a choice of living in a low density or rural environment (Carruthers, 2003) and move to cheap city fringe areas (Alonso, 1964; Daniels et al., 2015) commuting in private vehicles (Glaeser et al., 2008). However, in Tampa, high white population rated neighborhoods (with a more than 84% white population in the 2010 Census tracts) are concentrated in the South Tampa region near the waterfront, and the white population locations range from medium low (54%) to medium high (77%) in the city fringe areas in the North Tampa region.

In Table 4.2, the drop-one results with the 15 variable model show that the highest training cycle of each model varies from the 30,000th to 250,000th cycle, and each factor's influence is indicated with PCM and Kappa values. The distance to roads and distance to parks are 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 are less influential than other determinants in this land change.

4.1.3. Urban Growth Scenarios in Tampa, Florida, in 2040

With the finalized 15 driving factors, Tampa's future urban growth scenarios can be forecast. As Table 4.3 shows, forecasted model accuracy outputs are measured to validate the accuracy of the prediction model: scenario 1 (S1) has a PCM of 52%, a Kappa of 48%, an OA of 93%, and an AUC of 74%; scenario 2 (S2) has a PCM of 55%, a Kappa of 50%, an OA of 91%, and an AUC of 75%; and scenario 3 (S3) has a PCM of 68%, a Kappa of 63%, an OA of 91%, and an AUC of 82%. All measures in three scenarios show an acceptable or good level of prediction. In comparing the prediction accuracy values of each scenario, the results show that S3 is the most accurate, and S2 is more accurate than S1. In the fixed variable prediction, the total pixel numbers would influence the prediction performance: the more pixels, the less accurate, but, again, all are acceptable models.

Table 4.3. Prediction accuracy for urban growth scenarios.

	PCM	Kappa	OA	AUC
Scenario 1 in the 200,000th cycle	52.19	0.48	92.85	0.74
Scenario 2 in the 40,000th cycle	55.04	0.50	90.93	0.75
Scenario 3 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.

Following the previous land change ratio, there was a change of 8,917 pixels between 2001 and 2011 indicating a change of 32,600 people. The future urban growth scenarios project a change of 48,395 pixels 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 different exclusionary layers in each scenario. S1 excludes existing urban, rivers and lakes, highways, airports, and parks from future development areas. S2 uses environmentally sensitive areas from the future land use plan (Hillsborough County, 2016) added to S1's exclusionary layer. S3 adds future flood risk zones (2040 SLR High and 100-year floodplain) based on S2's exclusionary layer. As illustrated in Figure 4.1, the total existing urban (light gray color) in 2011 was 172.8 km^2 (57% of the total Tampa area), the increased urban area (black color) between 2011 and 2040 is 35.6 km^2 (12%), and the rest of the area (white color) within the Tampa boundary is 96.3 km^2 (31%) used for agriculture, wetlands, forests, water, and other uses.

The prediction result shows a different development pattern in each scenario. The future urban growth in S1 would mainly be in the north/New Tampa region and some development in the south and middle regions of Tampa. The urban growth in S2 would involve all the Tampa regions, the north, middle, and south. The urban growth in S3 would focus on the middle and north Tampa regions.

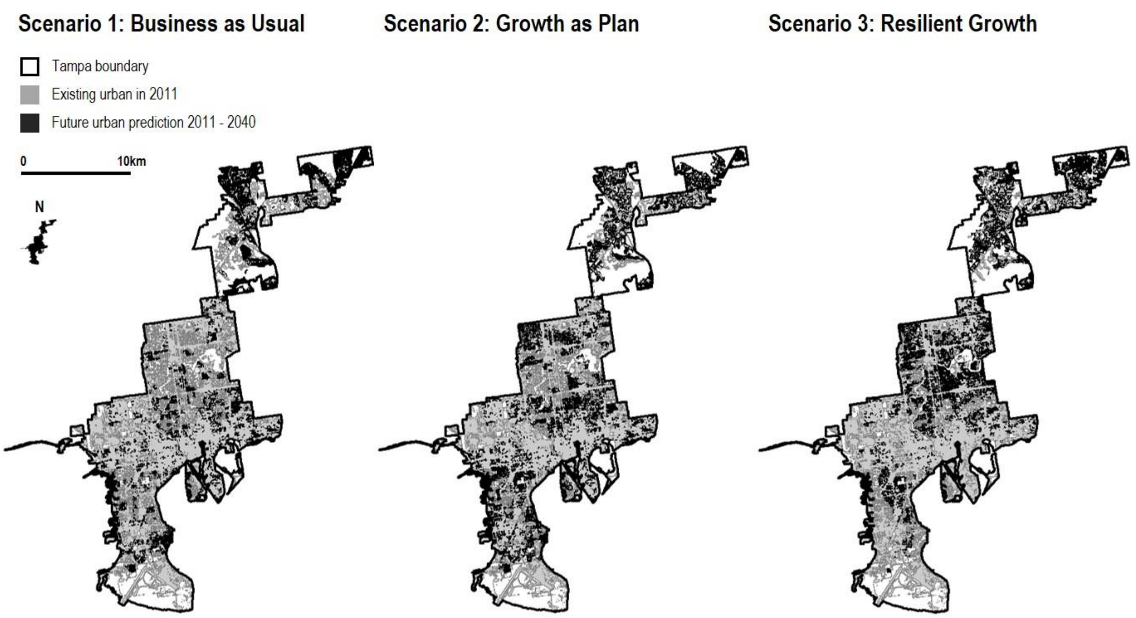


Figure 4.1. Urban growth scenarios in Tampa, 2040.

4.2. Future Flood Risk Scenarios

Future flood risks in 2040 are determined by NOAA's relative sea-level rise (SLR) scenarios (intermediate-low, high, and extreme) added to the current 100-year floodplain. In the SLR delineation, the upper Hillsborough Riverine areas are excluded due to the existing dam (Hillsborough River Dam) that controls the river water level.

As Figure 4.2 illustrates, the current 100-year floodplain covers 90.9 km^2, or 30% of Tampa areas. The 0.22m SLR intermediate-low scenario would enlarge the floodplain to 108.5 km^2 (36%), 17.6 km^2 more than the current floodplain. The 0.54m SLR (high scenario) and the 0.62m SLR (extreme scenario) would expand the floodplain to 113.4 km^2 (37%) and 114.4 km^2 (38%), respectively, which is 22.5 km^2 and 23.5 km^2 more than the current floodplain.

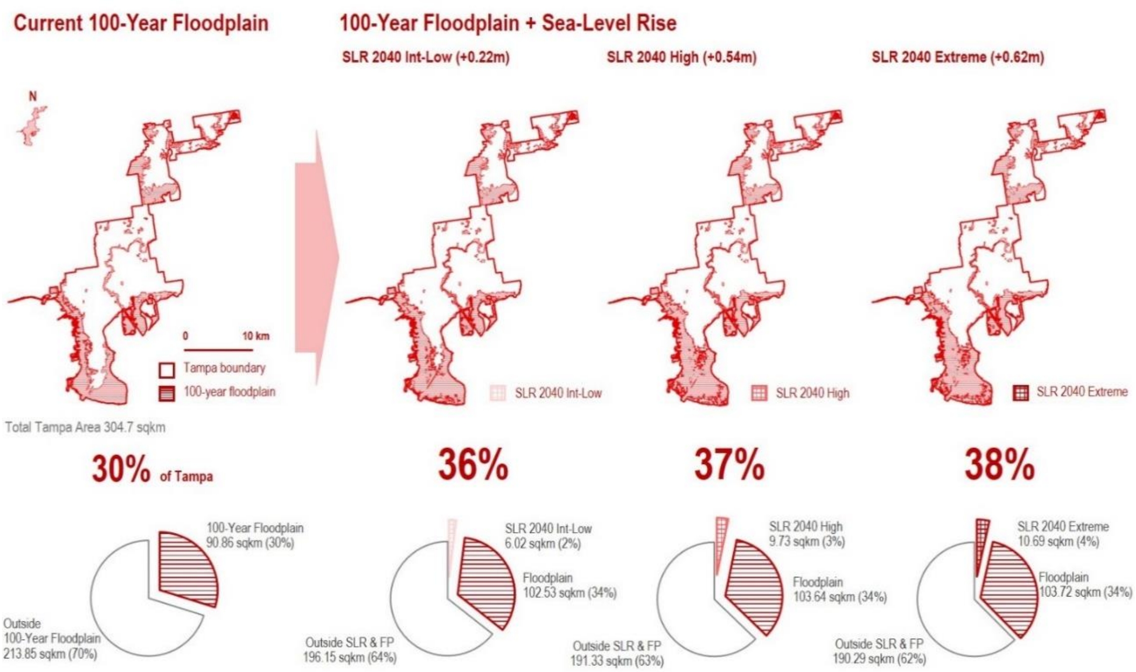


Figure 4.2. Future flood risk in 2040 (100-year floodplain and sea-level rise).

The SLR scenarios would enlarge the floodplain of the coastal South Tampa regions and downstream of the Hillsborough River. In the inter-low SLR, 6.0 km^2 or 2% of the South Tampa areas would be permanently under sea level, and the area increases as the SLR goes up: 9.7 km^2 (3%) in the high SLR and 10.7km^2 (4%) in the extreme SLR.

4.3. Scenario Evaluation

4.3.1. Scenario Evaluation at a City Level

Urban flood exposure is calculated by overlapping existing urban and projected future urban scenarios with the delineated future flood risk zones. In the existing urban exposure to future flood risk scenarios, illustrated in Figure 4.3, as the sea level rises more urban areas would be vulnerable to flood risk. In the inter-low SLR scenario at 47.4 km^2, 27% of the total existing urban area would be susceptible to flood risk. In the high and extreme SLR scenarios at 51.0 km^2 and 51.79 km^2 of existing urban areas would be vulnerable to future flood risks.

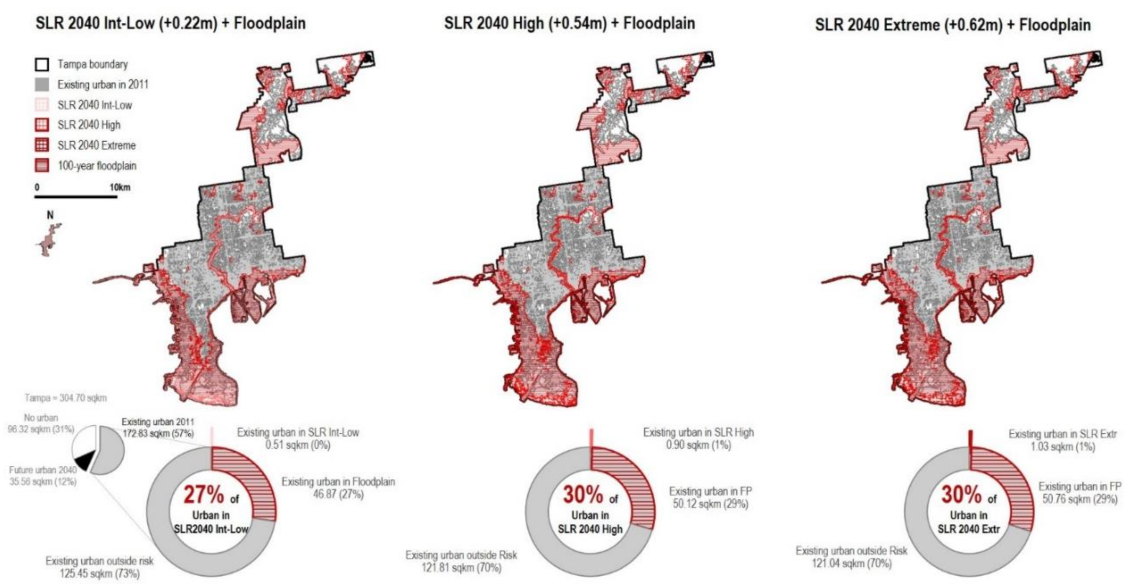


Figure 4.3. Flood exposure of existing urban areas.

Figure 4.4 shows three urban growth scenarios under different future floodplain scenarios, int-low, high, and extreme SLRs. As mentioned in 3.1.1, the intermediate low scenario is a primary SLR risk standard due to ocean warming, and the high scenario considers the maximum glacier loss with a 90% confidence. The extreme scenario combines extreme weather and climate (Parris et al., 2012). Under the int-low (+0.22m) SLR scenario, 11.9 km2 of S1 and 9.48 km2 of S2 would be endangered by flood risk, and S3 would be free from flooding due to its development setting, new development outside the floodplain. Under the high (+0.54m) and extreme (+0.62m) SLR scenarios, areas vulnerable to flooding would increase 12.4 km^2 and 12.51 km^2 in S1, and 10.0 km^2 and 10.1 km^2 in S2. In the extreme SLR case, some future urban areas would be permanently under sea level in 2040; 0.56km^2 in S1 and 0.34 km^2 in S2. In all SLR scenarios, the resilient urban growth scenario, S3 is safe 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 S3.

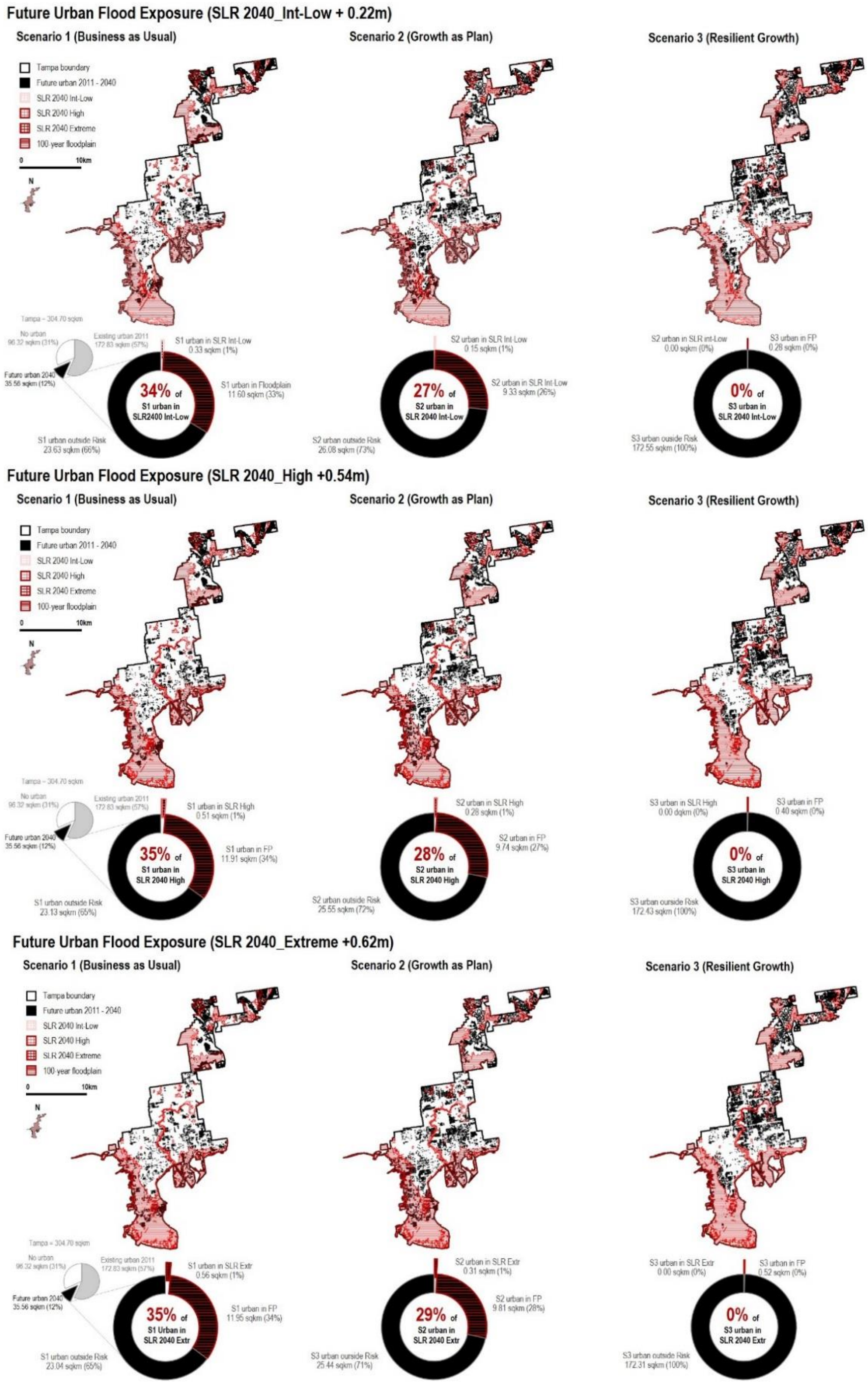


Figure 4.4. Flood exposure of future urban growth scenarios.

Table 4.4. Urban areas exposed to current/future flood risks at a city level.

		FP (Current 100-Year Floodplain)	Sea-Level Rise Scenarios		
			IL (Int.-Low SLR +0.22m)	HI (High SLR +0.54m)	EX (Extreme SLR +0.62m)
Existing Urban		EU & FP **36.5 km² (21%)**	EU & IL **47.4 km² (27%)**	EU & HI **51.0 km² (30%)**	EU & EX **51.8 km² (30%)**
Future Urban Growth Scenarios	Scenario 1: BU (Business as Usual)	BU & FP **10.7 km² (30%)**	BU & IL **11.9 km² (34%)**	BU & HI **12.4 km² (35%)**	BU & EX **12.5 km² (35%)**
	Scenario 2: GP (Growth as Planned)	GP & FP **7.9 km² (22%)**	GP & IL **9.5 km² (27%)**	GP & HI **10.0 km² (28%)**	GP & EX **10.1 km² (29%)**
	Scenario 3: RG (Resilient Growth)	RG & FP **0.00 km² (0%)**	RG & IL **0.00 km² (0%)**	RG & IL **0.00 km² (0%)**	RG & EX **0.00 km² (0%)**

Value = urban area in flood zones km^2 (percentage of flood vulnerable areas by total existing/future urban areas)

The result of urban flood exposure at the city level, as described in Table 4.4, 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 S1 and 22% in S2.

As the sea level rises, the areas vulnerable to future floods increase in both existing and future urban areas (except S3). Since Tampa's geography ranges from 0 to 55 feet above sea level (Hillsborough County, 2016), a small change in the SLR affects large areas. Existing urban areas would be impacted from 47.4 km^2 in the int-low SLR to 51.8 km^2 in the extreme. S1's flood vulnerable urban area would be enlarged from 11.9 km^2 in the int-low SLR to 12.5 km^2 in the extreme SLR. S2's would be relatively smaller, 9.5 km^2 in the int-low SLR and 10.1 km2 in the extreme SLR. S3, the resilient urban growth scenario, is safe from all the SLR impacts. In the result between the high and extreme SLR 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 these scenarios.

Overall, considering future urban areas under flood risks, the urban growth scenario as land use plan (S2) would be better than growth as business as usual (S1), but much worse than the resilient growth (S3). The number of flood vulnerable areas in S2 is less than those of S1 in all flood risk scenarios. However, the gap between the areas in S1 and S2 is not as obvious compared to that of S2 and S3 (resilient growth) in all SLR scenarios.

4.3.2. Scenario Evaluation at a Neighborhood Level

In addition to the city level analysis and comparing the total urban flood exposure among future urban growth and flood risk scenarios, this sub-section analyzes a neighborhood level urban flood exposure. It examines how many future urban areas in each neighborhood would be under future flood risks by comparing S1 and S2. Due to S3's flood free design, it is excluded from the comparison. For a flood risk, this sub-section uses a fixed high SLR scenario to compare urban flood exposure in two urban growth scenarios, business as usual (S1) and growth as planned (S2). As mentioned in 3.1.1, NOAA's high SLR scenario covers a 90% confidence interval considering the maximum glacier and ice sheet loss, and it is used as a design standard for critical facilities (Parris et al., 2012).

Table 4.5 shows potential flood impacted urban areas by neighborhood in existing urban and future urban growth scenarios 1 and 2. The results indicate that 71 out of 127 neighborhoods in existing urban areas, 55 in S1, and 58 in S2, would be vulnerable to future flood risks. In the existing urban areas, neighborhoods 103 and 86 are the most vulnerable with the largest impacted areas, 7.6 km2 in 103 and 6.3 km2 in 86. In S1, future flood risks would impact more than 1 km2 of new development in neighborhoods 13, 40, 68, and 113. In S2, future flood risks would impact more than 0.6 km2 in neighborhoods 28, 68, and 113. Neighborhood 68 would be most vulnerable to floods in both existing and future urban scenarios.

Table 4.5. Existing and future urban flood exposure under the future floodplain.

NH No.	Existing Urban Flood Exposure	S1 Urban Flood Exposure	S2 Urban Flood Exposure
1	0.000	0.000	0.000
2	0.000	0.000	0.000
3	0.000	0.000	0.000
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	0.001	0.000
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
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
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	1.176	0.014	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.

(light grey) a neighborhood where urban flood exposure in S1 is larger than in S2.

(dark grey) a neighborhood where urban flood exposure in S2 is larger than in S1.

In the urban flood exposure comparison between S1 and S2, as Figure 4.5 illustrates, 27 neighborhoods in S1 have a larger number of urban areas exposed to floods than does S2. However, 30 neighborhoods in S2 have a larger number of urban areas exposed to floods than does S1. This suggests that when future urban development follows a land use plan (S2), the 30 neighborhoods (see the right map in Figure 4.5) would have a larger amount of area under flood risk zones than urban development without a plan (S1).

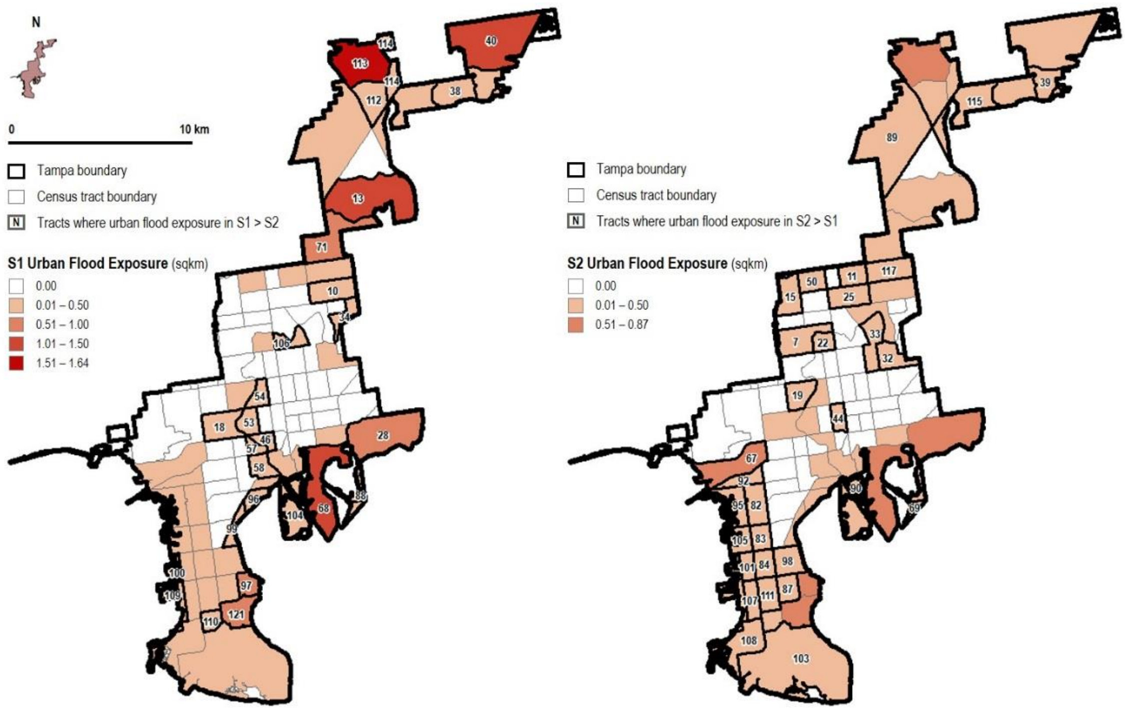


Figure 4.5. Future urban flood exposure under the future high SLR in scenarios 1 and 2.

The choropleth maps indicate urban areas exposed to flood risks in S1 (left) and S2 (right). On the maps, tracts with numbers show where urban flood exposure in S1 is larger than in S2 (left), and where S2 is larger than in S1 (right).

4.3.3. Findings: Scenario Evaluation at a City and Neighborhood Level

In the city level analysis, as the sea level rises, more urban areas in both existing and future urban areas would be endangered by future flood risks, except scenario 3. A large number of existing urban areas are under the current 100-year floodplain, 36.5km2, or 21% of the existing urban areas. It would be enlarged by up to 51.8 km2, or 30% in the extreme flood zones. Out of total future urban development, 35.6 km2 in 2040, 10.7 km2 (30% of future urban areas) in S1 and 7.9 km2 (22%) in S2 are projected to be developed in the current floodplain, and 12.5km2 (35%) in S1 and 10.1 km2 (29%) in S2 under the future extreme SLR flood risk. In the comparison of total urban flood exposure, existing urban areas are problematic, and urban growth as business as usual (S1) would cause more floodplain development than growth as planned. When examining the results of the city level analysis, S2 is better than S1 in all the SLR scenarios: the total urban area exposed to flood risks in S2 is less than in S1. However, the gap of urban flood exposure between S1 and S2 is relatively small compared with that between S2 and S3.

The neighborhood level analysis shows different results. There are 71 neighborhoods in existing urban areas, and more than 50 neighborhoods in future urban areas (55 in S1 and 58 in S2) would be impacted by future high SLR risk. More neighborhoods in S2 would be vulnerable to floods than in S1 due to floodplain development. Furthermore, in the comparison between S1 and S2, more numbers of neighborhoods in S2 would have larger areas vulnerable to flood than in S1: the 30 neighborhoods in S2 have larger developments in the flood zones than in S1, but the 27 in S1 have larger urban areas exposed to flood risks than in S2.

Thus, the findings conclude that 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.

4.4. Neighborhood Scaled Analyses

Sub-section 4.3 examined scenario evaluation by looking at city and neighborhood levels of urban flood exposure to explain the efficacy of a land use plan compared with other urban growth scenarios. However, the result is a likely possibility of flood exposure in different urban area growth and SLR scenarios. Depending on preparation for flood risks, the damage can be eliminated or minimized. Thus, this sub-section examines how prepared neighborhoods are for future urban growth and flood risk. Using Berke et al.'s (2015) resilient scorecard, future urban growth scenarios, social/physical vulnerability, and policy scores for eight highly clustered future development neighborhoods are compared (Berke et al., 2018; Berke et al. 2015). The scorecard tool enables identification of specific policies that reduce or increase flood vulnerabilities in each neighborhood.

The processes are 1) to detect highly clustered future urban neighborhoods with urban growth prediction (based on scenarios), 2) to review the characteristics of the neighborhoods, and 3) to identify neighborhood-scaled plan policies using the scorecard tool. Step 1 uses the Optimized Hot Spot Analysis with ArcGIS to find where new developments in the predicted urban growth scenarios are highly clustered. Step 2 uncovers the characteristics (e.g. current physical and social vulnerability and flood risk) of the selected neighborhoods in Step 1. Step 3 employs the resilient scorecard method to identify specific policies from plans related to urban development.

4.4.1. Highly Clustered Future Urban Neighborhoods

Based on the predicted urban growth scenarios in sub-section 4.1, eight neighborhoods were selected as highly clustered future urban growth neighborhoods using Hot Spot Analysis with ArcGIS. Hot spot analysis detects statistically significant geospatial clusters with high and low values (hot and cold spots) using the Getis-Ord Gi statistic. The Gi statistic produces each feature with a group of z-scores; a high z-score shows an intense clustering group of high values (hot spot), and vice versa (ArcGIS, 2018). The hotspot analysis has been used in spatial cluster analyses; identifying historic spatial development pattern in China (Wang et al., 2016), and analyzing potential transit oriented development location in the Arnhem and Nijmegen region, the Netherlands (Singh et al., 2014).

The results in Figure 4.6 present a different development pattern for each urban growth scenario. The growth as business as usual (S1) would mainly focus on the north Tampa areas (neighborhoods 13, 40, 41, 89, 112, 113, and 114). Some clustered development would occur in the central Tampa (4 and 28) and the south Tampa (97) neighborhoods. The planned urban growth (S2) would be distributed broadly to north, central, and south Tampa. The major difference between S1 and S2 is that S2 focuses on the central Tampa neighborhoods (3, 4, 44, 60, 61, 62, 75, and 91) and the south (82, and 5). The resilient growth pattern (S3) shows more focused development in two regions: north and central Tampa neighborhoods.

All the three scenarios commonly show a growth pattern to north Tampa, which the City Comprehensive Plan identifies as a new growth region called New Tampa (Hillsborough County, 2016). This is because of highly saturated existing urban areas in south and central Tampa and new sub-urban development in the north. The growth pattern of S1 focuses on the north, and S3's on the north and central. S2 shows a more distributed growth pattern in the whole Tampa region.

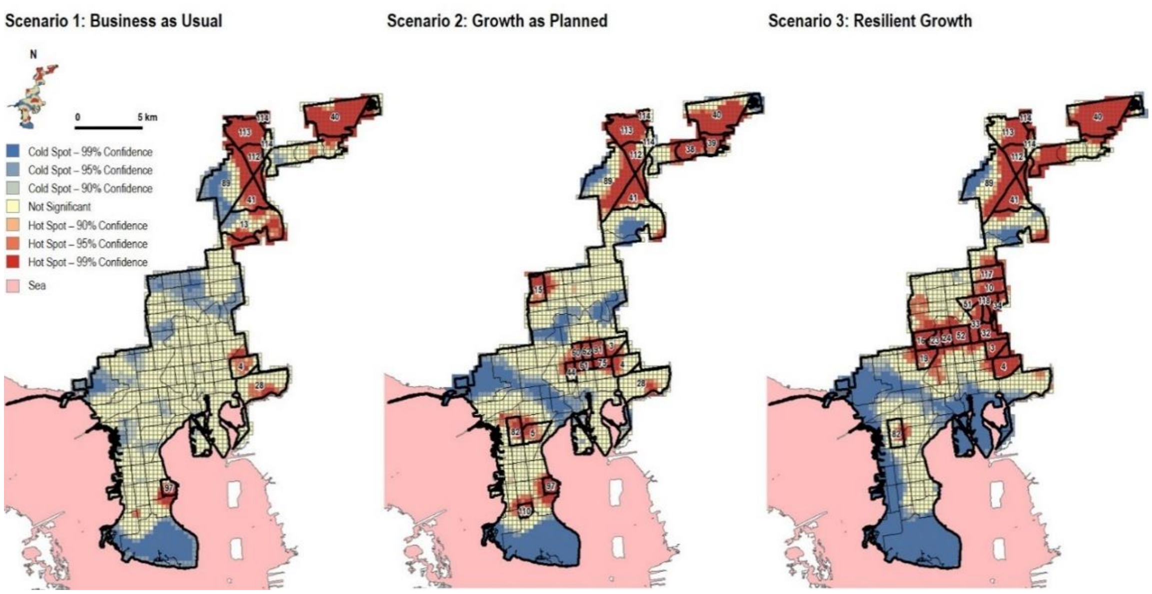


Figure 4.6. Hot/cold spot analysis for highly clustered future urban development.

4.4.2. Flood Vulnerability

"Vulnerability has a commonplace meaning: being prone to or susceptible to damage or injury … in relation to natural hazards… vulnerability means 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 (an extreme natural event or process). It involves a combination of factors that determine the degree to which someone's life, livelihood, property and other assets are put at risk by a discrete and identifiable event in nature and in society" (Wisner et al., 2004, p.11). The risk-hazard model illustrated in Figure 4.7 delineates the impact of a hazard event as exposure and dose-response (sensitivity and adaptive capacity) of the exposed item or individual (Turner et al., 2003). 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).

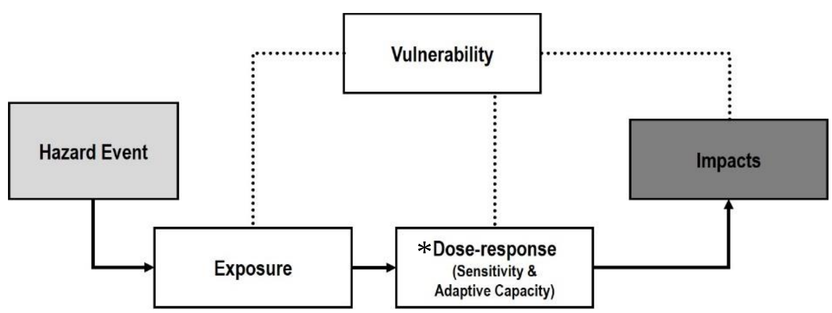


Figure 4.7. Risk-hazard framework: Chain sequence from hazard to impacts.
Source: reprinted from Turner et al. (2003). * Dose response means "range of doses over which response occurs, doses lower than the threshold produce no response while those in excess of the threshold exert no additional response," reprinted from Mosby's Medical Dictionary (2009).

For the identified highly clustered urban neighborhoods from the three urban growth scenarios, this section looks at the hazard framework of each neighborhood, future flood risk, and physical and social vulnerabilities. Future flood risk uses areas in the high SLR scenario within a neighborhood. Using a quantile method to identify the areas, 127 neighborhoods in Tampa are classified into five categories (high, medium high, medium, medium low, and low). Following the method of economic exposure to flood risk (Berke et al., 2015; Patterson & Doyle, 2009), physical vulnerability aggregates a building's value below the base flood elevation based determined by the 2010 building footprint and tax value from the Hillsborough County Property Appraiser (2011). The sum of the value of vulnerable buildings in each neighborhood is classified into five categories using a quantile method. Social vulnerability, the characteristics of certain populations in response to hazards, is obtained from NOAA's (2017b) social vulnerability index at the tract level, 2010. The social vulnerability index to environmental hazards was originally developed by Cutter et al.'s (2000, 2003) influential factors: personal wealth, age, density of built environment, employment, mobile home, race & ethnicity, occupation, and infrastructure dependence.

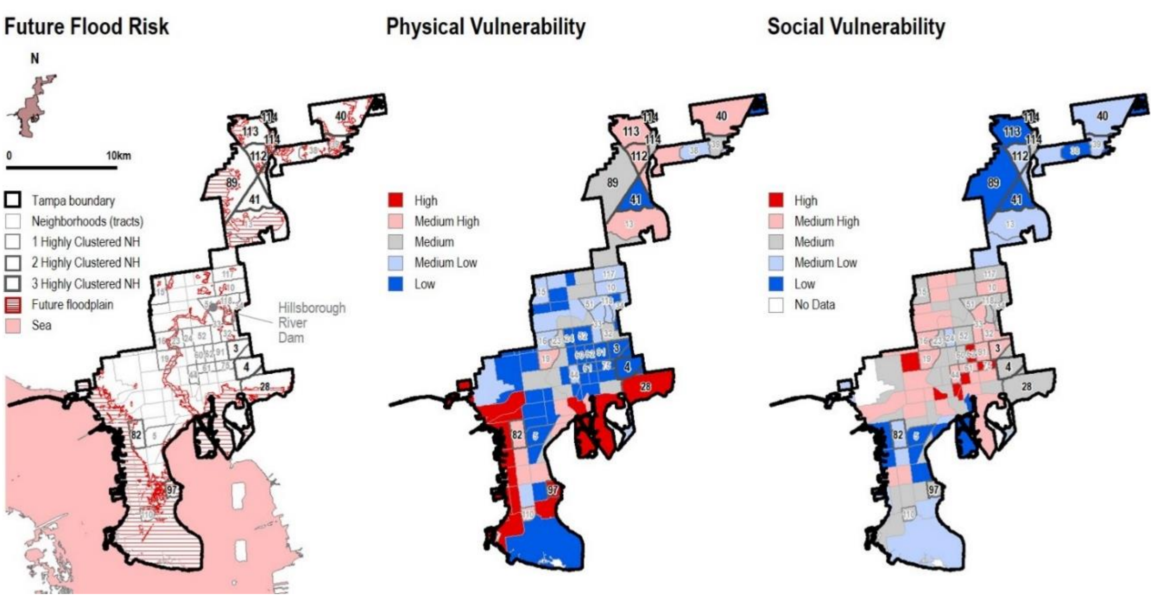


Figure 4.8. Characteristics of the highly clustered neighborhoods.

As illustrated in Figure 4.8, most coastal neighborhoods in south Tampa and riverine neighborhoods below the Hillsborough River Dam in central Tampa are influenced by an enlarged floodplain due to SLR. North Tampa is impacted only by the current 100-year floodplain. In respect to physical vulnerability, similar to the future flood risk, most coastal and north Tampa neighborhoods are physically vulnerable to current flood risk, meaning that there is a high number of existing buildings within the floodplain. In contrast to physical vulnerability, socially vulnerable neighborhoods are distributed mostly in central Tampa areas.

Table 4.6. 35 Clustered neighborhoods and their characteristics.

Neighborhood No.	Highly Clustered Future Urban Development			Future Flood Risk	Vulnerability	
	S1	S2	S3		Physical Vulnerability	Social Vulnerability
3		√	√	Low	Low	High
4	√	√	√	Low	Low	Medium
5		√		Low	Low	Low
10			√	Low	Medium Low	High
13	√			High	Medium High	Low
15		√		Low	Medium Low	Medium
16			√	Medium Low	Medium Low	High
19			√	Medium	Medium High	High
23			√	Medium Low	Medium	Medium
24			√	Low	Low	Low
28	√	√		High	High	Medium
32			√	Medium Low	Medium	High
33			√	Medium	Medium Low	High
34			√	Medium Low	Medium Low	Medium
38		√		Medium	Medium Low	Low
39		√		Medium	Medium	Low
40	√	√	√	High	Medium High	Low
41	√	√	√	Low	Low	Low
44		√		Low	Medium Low	Medium High
51			√	Medium	Medium Low	Medium
52			√	Low	Low	Medium
60		√		Low	Low	Medium
61		√		Low	Low	High
62		√		Low	Low	High
75		√		Low	Low	High
82		√	√	Medium	Medium High	Low
89	√	√	√	High	Medium	Low
91		√		Low	Low	High
97	√	√		Medium High	High	Medium
110		√		Medium High	Medium High	Medium
112	√	√	√	Medium	Medium High	Low
113	√	√	√	High	Medium High	Low
114	√	√	√	Medium High	Medium	Medium
117			√	Low	Medium Low	Medium
118			√	Low	Low	Medium

NH: Neighborhood.

a neighborhood where two urban growth scenarios have highly clustered urban areas.

a neighborhood where all three urban growth scenarios have highly clustered urban areas.

There are 35 neighborhoods where single or multiple highly clustered new development(s) would be found in one of the three urban growth scenarios. Twenty four neighborhoods have a highly clustered new development in one urban growth scenario, four neighborhoods have two highly clustered new developments in S1, S2, or S3, and seven neighborhoods are expected to be developed in all three scenarios.

In the 11 neighborhoods where future urban development would appear in more than two urban growth scenarios (the light or dark gray colored neighborhoods in Table 4.6), three neighborhoods (3, 4, and 41) are low in future flood risk, and the other eight neighborhoods are in the range of medium low to high. Neighborhoods 3, 4, and 41 are located inland so they are free from the current and future floodplain. Neighborhoods 28, 82, and 97 would be impacted by an increased floodplain due to SLR, and they range from medium to high in future flood risk depending on their coastal location. Similar to future flood risk, the physical vulnerability (building damage from the current 100-year floodplain) of eight neighborhoods range from medium to high, and three neighborhoods (3, 4, and 41) have a low physical vulnerability. Most of the neighborhoods have a medium to low social vulnerability, except neighborhood 3, which has a high social vulnerability. This means that few highly social vulnerable neighborhoods are likely to be developed in Tampa. Almost all highly clustered new development would be located in physically vulnerable neighborhoods, but not in socially vulnerable neighborhoods.

4.4.3. Plan Evaluation

To answer how prepared Tampa is for future urban growth and flood risks, this section examines specific plan policies for the eight highly clustered future urban neighborhoods. Among the 11 multiple highly clustered neighborhoods highlighted in Table 4.6, three neighborhoods, 3, 4, and 41, are excluded from this in-depth following analysis due to their lack of flood risk.

Evaluation Method

To evaluate the city's plan preparation at a neighborhood scale, this study uses Berke et al.'s (2015) "resilient scorecard," to examine the networks of plans with a policy score for each planning district (neighborhood). The evaluation method assigns a score for each policy in each plan for a hazard zone in a designated neighborhood, scoring +1 when each policy decreases physical or social vulnerability or scoring -1 for increased vulnerability (Berke et al., 2015). Then, as specified in Table 4.7, it divides the types of policies into seven categories "influencing the type, location, and amount of development" (Berke et al., 2015, p.294). The resilient scorecard has been applied in a few studies to assess plan preparation for flood vulnerability and multiple plans' alignment (e.g. local comprehensive plan, hazard mitigation plan, and open space plan). Berke et al. (2015) created the scorecard and demonstrated with the case of Washington, NC, and Berke et al. (2018) assessed six cities' policy preparation for flood vulnerability (Washington, NC, League City, TX, Fort Lauderdale, FL, Boston, MA, Tampa, FL, Asbury Park, NJ). Malacha et al. (2018) applied the scorecard in Feijenoord district, Rotterdam, the Netherlands, and Woodruff (2018) identified policy conflicts in Chester, PA.

Table 4.7. Land use policy categories.

Policy Categories	Sub Categories
Development Regulations	Permitted Land Use, Density of Land Use, Subdivision Regulations, Zoning Overlays, Setbacks or Buffer Zones, Cluster Development
Land Acquisition	Acquire Land & Property, Open Space or Easement Requirement/Purchase
Density Transfer Provisions	Transfer/Purchase of Development Rights
Financial Incentives and Penalties	Density Bonuses
Land Use Analysis and Permitting Process	Site Review, Design/Construction Guidelines/Requirements
Public Facilities	Siting
Capital Improvements	Infrastructure "Hardening" or Weatherproofing, Drainage Improvements or Flood Control, Slope/Dune/Bank Stabilization, Ecosystem Enhancement

The land use policy categories were developed based on those by Berke et al. (2015) due to Tampa's policies in plans, adding density transfer provisions and capital improvements.

Tampa's plan analysis examines four urban plans to determine the preparation for urban development and flood hazard; Imagine 2040: Tampa Comprehensive Plan, Hillsborough County Local Mitigation Strategy, Changing Tampa's Economic DNA (Consolidated Plan for Housing), and Hillsborough Long Range Transportation Plan.

The Tampa Comprehensive Plan (TCP) is a community prepared legally binding plan designing the city's future. It identifies goals, objectives, and policies based on the vision of Tampa's future urban growth, "creating an attractive and safe city that evokes pride, passion and a sense of belonging – a city where everybody cares about quality of life" (Hillsborough County, 2016, p.7). The Hillsborough County Local Mitigation Strategy (HCLMS) develops mitigation techniques and preparedness to reduce life and asset loss from potential disasters for entire communities. It assesses community vulnerabilities to hazards, identifies disaster protection plans and projects, and prioritizes the implementation (Hillsborough County, 2015). The Changing Tampa's Economic DNA (CTEDNA) is a five-year strategic plan for low and moderate income residents. It includes the city's demography, economy, and housing/job needs (City of Tampa, 2012). The Hillsborough Long Range Transportation Plan (HLRTP) aims to solve transportation issues, and is updated with the Comprehensive Plans of Hillsborough County and three major cities. It identifies goals, objectives, and policies framing transportation projects, priorities, and financing (Hillsborough County, 2014).

Neighborhood Characteristics

Among the eight study neighborhoods, five (neighborhoods 4, 89, 112, 113, 114) are located in north Tampa, one (28) in the central area, and two (82, 97) in the south. Each neighborhood's characteristics are defined by its geographic location and land use plan as seen in Figure 4.9. Looking at flood risk, due to proximity to the sea, SLR would impact three neighborhoods (28, 82, 97), and the other five neighborhoods would be influenced by SLR, but would only be endangered in the 100-year floodplain. Most areas in neighborhood 97 would be endangered by future flood risk, and neighborhood 28, even with its inland location, would be impacted by SLR. The main land use characteristics in north Tampa neighborhoods are defined by environmentally sensitive areas and mixed-use zones with suburban housing developments. As stated in the Tampa

Comprehensive Plan, state and local governments emphasize “areas of critical state concern” and define environmentally sensitive areas (ESA) for wetland and wildlife habitat preservation (Hillsborough County, 2016, p.1). The primary land use in south Tampa (82, 97), and neighborhood 28 is designated for heavy/light industrial, commercial, and residential uses. Particularly, the city of Tampa plans to provide a better transportation system with Transit Oriented Development (TOD), high-density, and mixed-use development. The Tampa Comprehensive Plan identifies transit stations and transit corridors for TOD zones in neighborhoods 28, 89, 112, and 114.

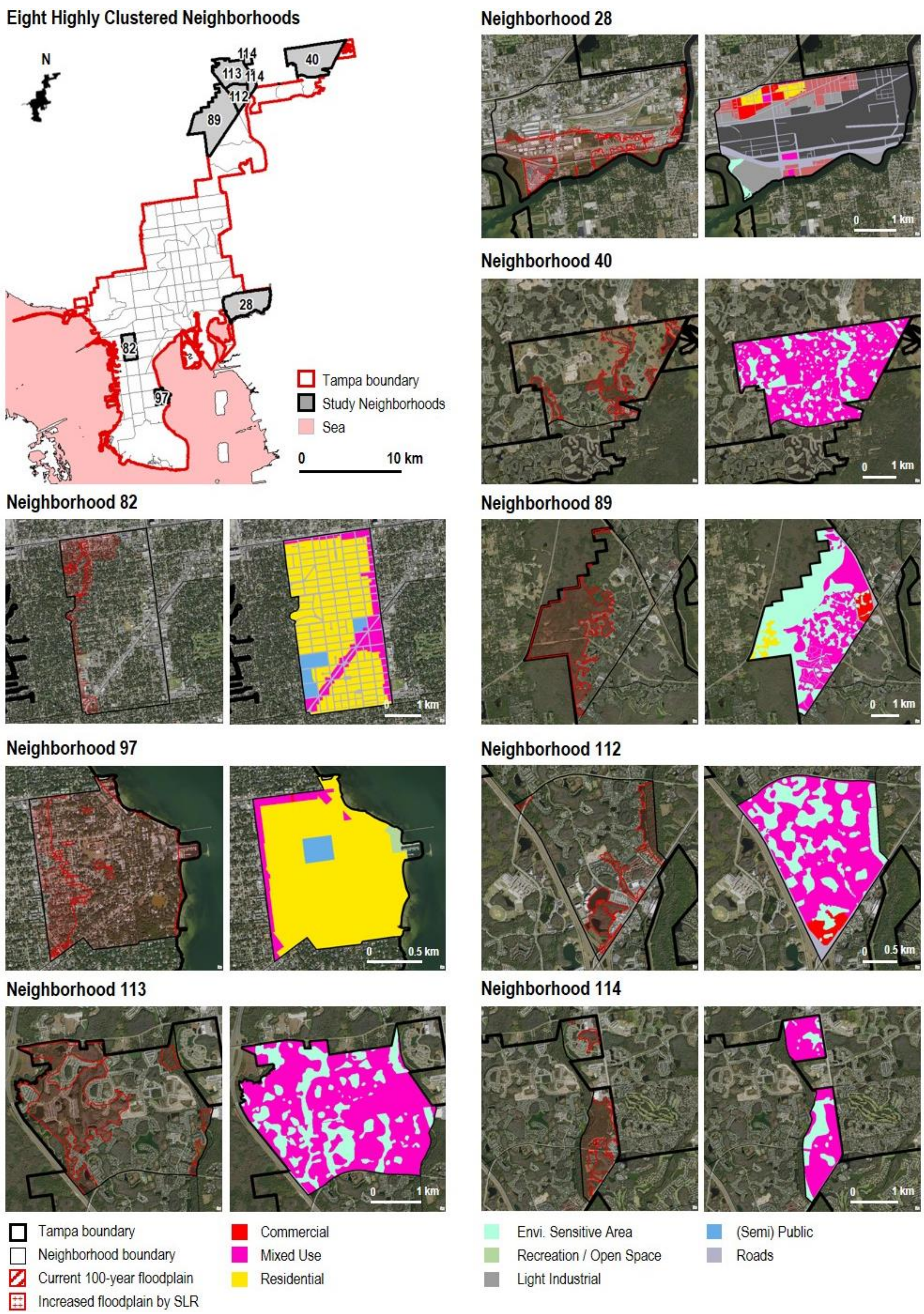


Figure 4.9. Flood risk and land use plans of study neighborhoods.

Policy Evaluation

Table 4.8. Policy scores for the eight highly clustered neighborhoods.

NH No.	Policy Preparation Score									
	TCP		HCLMS		CTEDNA		HLRTP		Total	
28	+49	40	+2	2	+1	1	+2	1	+54	44
	-9		-		-		-1		-10	
40	+32	32	-	0	-	0	+2	2	+34	34
	-		-		-		-		-	
82	+5	4	-	0	-	0	-	0	+5	4
	-1		-		-		-		-1	
89	+33	27	-	0	-	0	+2	1	+35	28
	-6		-		-		-1		-7	
97	+46	40	+3	3	-	0	+2	2	+51	45
	-6		-		-		-		-6	
112	+33	28	-	0	-	0	+2	1	+35	29
	-5		-		-		-1		-6	
113	+33	33	-	0	-	0	+2	2	+35	35
	-		-		-		-		-	
114	+31	26	-	0	-	0	+2	1	+33	27
	-5		-		-		-1		-6	

TCP: Tampa Comprehensive Plan, HCLMS: Hillsborough County Local Mitigation Strategy, CTEDNA: Changing Tampa's Economic DNA: Consolidated Plan (Housing), HLRTP: Hillsborough Long Range Transportation Plan.

Policy numbers decreasing vulnerability "+1"	Sum of policy scores decreasing and increasing vulnerability in a neighborhood
Policy numbers increasing vulnerability "-1"	

As the policy scores of the four plans for each neighborhood indicate in Table 4.8, TCP is the major plan influencing floodplain development for all study neighborhoods. HCLMS policies apply to two neighborhoods, CTEDNA to one, and HLRTP to seven. The two neighborhoods, 28 and 112, are positively scored by flood protection projects in HCLMS. Neighborhood 28, covered by the CTEDNA policy, is the only low income neighborhood and will be funded for housing development projects. The County Transportation Plan, HLRTP has positive and negative scored policies; negative in development incentives related to TOD development (Policy 5.3C), and positive in creating a transportation infrastructure that considers environmentally sensitive areas, water resources, and historic site conditions (Policies 3.1A and 3.1B).

The total scores for each plan/neighborhood are positive, and the average total score is 30.8. The total scores range from 4 to 45 points: the lowest is neighborhood 82 with 4 points, and the neighborhood with the highest score is 97 with 45 points. When interpreting the total scores, positive or higher score does not mean safe or safer from flood risk. Due to scoring system of each positive/negative policy with the same scale of ±1, the total sum means the offset amount of positive and negative policies without considering each policy's effectiveness. Thus, to know how policies work in each neighborhood, each positive/negative policy should be analyzed individually. In total, 64 policies are assigned to neighborhood 28 due to its coastal and transit locations, and environmentally sensitive areas; 54 positive policies and 10 negative policies. The neighborhood that has the fewest policy applications is 82, which is assigned six policies due to its inland location; two floodplain, three coastal planning (storm water and plantation), and one rental housing related policies. In neighborhoods 40 and 113, only positive policies are applied, meaning that those neighborhoods have no conflicting policies between decreasing and increasing vulnerability.

Policies by Land Use Categories in Each Plan

In the policies by land use categories for TCP, as indicated in Table 4.9, policies in the Development Regulations category is the most influential on development in a floodplain for most neighborhoods, more than 20 policies in the category are assigned in seven neighborhoods except neighborhood 82. The Development Regulations category is about permitted land use, density, subdivision regulations, zoning, setbacks or buffer zones, and cluster development (Berke et al., 2015). The next influential categories are Land Use Analysis and Permitting Process, Capital Improvements, and Land Acquisition. The least influential category is Financial Incentives and Penalties.

Compared to the TCP, other plans have few policies influencing development in floodplains. In HCLMS, five flood mitigation projects in Capital Improvements decrease flood vulnerability in coastal neighborhoods, two projects in neighborhood 28, and three projects in neighborhood 97. In CTEDNA, one policy in Capital Improvements is assigned in neighborhood 28 due to the plan's funding support for low/moderate income districts. In HLRTP, one policy in the Penalties category and two policies in Capital Improvements and Financial Incentives are assigned. A density bonus for major development projects implementing the TOD concept (Policy 5.3C) influences negatively (increasing vulnerability). Two policies related to new road construction considering environmentally sensitive areas, parks, and water resources (Policies 3.1A and 3.1B) are scored positively (decreasing vulnerability) for most neighborhoods.

Table 4.9. Policy scores by land use categories in four plans.

Tampa Comprehensive Plan

	28		40		82		89		97		112		113		114	
Development Regulations	+21 -8	13	+20 -	20	+1 -1	0	+20 -5	15	+21 -5	16	+20 -4	16	+22 -	22	+19 -4	15
Land Acquisition	+6 -	6	+2 -	2	+1 -	1	+2 -	2	+7 -	7	+2 -	2	+2 -	2	+2 -	2
Density Transfer Provisions	+4 -	4	+3 -	3	- -	-	+3 -	3	+4 -	4	+3 -	3	+3 -	3	+3 -	3
Financial Incentives and Penalties	- -1	-1	- -	0	- -	-	- -1	-1	- -	0	- -1	-1	- -	-	- -1	-1
Land Use Analysis & Permitting Process	+7 -	7	+4 -	4	+1 -	1	+4 -	4	+6 -	6	+4 -	4	+4 -	4	+4 -	4
Public Facilities (incl. Public Housing)	+3 -	3	+1 -	1	- -	-	+1 -	1	+3 -1	2	+1 -	1	+1 -	1	+1 -	1
Capital Improvements	+8 -	8	+2 -	2	+2 -	2	+3 -	3	+5 -	5	+3 -	3	+1 -	1	+2 -	2
Total (all policies)	**+49 -9**	**40**	**+32 -**	**32**	**+5 -1**	**4**	**+33 -6**	**27**	**+46 -6**	**40**	**+33 -5**	**28**	**+33 -**	**33**	**+31 -5**	**26**

Hillsborough County Local Mitigation Strategy

	28	40	82	89	97	112	113	114
Development Regulations	-	-	-	-	-	-	-	-
Land Acquisition	-	-	-	-	-	-	-	-
Density Transfer Provisions	-	-	-	-	-	-	-	-
Financial Inc. and Penalties	-	-	-	-	-	-	-	-
LU. Anal. and Permit Proc.	-	-	-	-	-	-	-	-
Public Facilities	-	-	-	-	-	-	-	-
Capital Improvements	+2	-	-	-	+3	-	-	-
Total (all policies)	**2**	**0**	**0**	**0**	**3**	**0**	**0**	**0**

Changing Tampa's Economic DNA

	28	40	82	89	97	112	113	114
Development Regulations	-	-	-	-	-	-	-	-
Land Acquisition	-	-	-	-	-	-	-	-
Density Transfer Provisions	-	-	-	-	-	-	-	-
Financial Inc. and Penalties	-	-	-	-	-	-	-	-
LU. Anal. and Permit Proc.	-	-	-	-	-	-	-	-
Public Facilities	-	-	-	-	-	-	-	-
Capital Improvements	+1	-	-	-	-	-	-	-
Total (all policies)	**1**	**0**	**0**	**0**	**0**	**0**	**0**	**0**

Imagine 2040: Hillsborough Long Range Transportation Plan

	28	40	82	89	97	112	113	114
Development Regulations	-	-	-	-	-	-	-	-
Land Acquisition	-	-	-	-	-	-	-	-
Density Transfer Provisions	-	-	-	-	-	-	-	-
Financial Inc. and Penalties	-1	-	-	-1	-	-1	-	-1
LU. Anal. and Permit Proc.	-	-	-	-	-	-	-	-
Public Facilities	-	-	-	-	-	-	-	-
Capital Improvements	+2	+2	-	+2	+2	+2	+2	+2
Total (all policies)	**1**	**2**	**0**	**1**	**2**	**1**	**2**	**1**

Major Policy Themes in the Tampa Comprehensive Plan

Concerning "balancing land development and protecting natural assets" (Hillsborough County, 2016, p.1), the Tampa Comprehensive Plan has prominent policy themes concerning ecology and sustainable development that increase or decrease vulnerability. The City Comprehensive Plan defines environmentally sensitive areas and coastal planning areas for natural and wildlife habitats and wetland protection. The other concern is the TOD concept, encouraging denser and mixed-use development on transit stations and corridors to provide a better transportation system and pedestrian environment (Hillsborough County, 2016).

Table 4.10. Major policy themes and assigned neighborhoods in the Tampa Comprehensive Plan.

	Major Policy Theme	Numbers of Policy	Assigned Neighborhood
'+' Policy Categories	Environmentally Sensitive Areas	24	28, 40, 89, 112, 113, 114
	Coastal Planning / High Hazard Areas	13	28, 97 (82)
	Floodplain	3	All
'-' Policy Categories	Transit Oriented Development	8	28, 89, 112, 114

The numbers of policy by theme in Table 4.10 show how much the City of Tampa cares about environmentally sensitive areas (wetland, wildlife habitats) and coastal development. Policies related to ESA, coastal high hazard areas, and floodplain limited new development, scored positively on the scorecard. Policies related to the TOD that enhance new development with additional density incentives, scored negatively. In the positively scored policy category, three floodplain policies are assigned to all eight study neighborhoods, and 24 ESA related policies are assigned to six neighborhoods. Thirteen coastal planning related policies are primarily assigned to two coastal neighborhoods. In the negative policy category, eight policies related to the TOD are assigned to four neighborhoods where transit stations and corridors are planned.

Among the 64 total applied policies from the Tampa Comprehensive Plan, several policies help to decrease vulnerability for new floodplain development, ESA (24), Coastal Planning (13), and Floodplain (3). Due to Tampa's protection efforts for wildlife habitats and wetlands, as Figure 4.10 shows, land use policies curtail new development in environmentally sensitive areas by restricting development (ENV Policy 1.2.1), infrastructure maintenance (ENV Policy 1.2.8), and transferring development rights (ENV Policy 1.2.5). In the coastal high hazard areas, there are restrictions on building healthcare related facilities (CM Policy 1.1.7). Land acquisition (CM Policy 1.3.3) and stormwater treatment improvement (ENV Policy 1.21.7) help to reduce flood vulnerability in coastal planning areas. Floodplain development is basically allowed conditionally with development regulations and building codes (ENV Policy 2.1.3 and CM Policy 1.3.4), but floodplain development within an ESA is strictly prohibited (ENV Policy 1.9.5).

On the other hand, the TOD related policies would increase vulnerability for new floodplain development. They encourage new development with density incentives within the TOD zones to provide a better pedestrian friendly environment (LU Policy 7.2.6). However, denser and more development within the floodplain could put more people and assets in danger of flood risk.

Positive Scored Policies (decreasing vulnerability)

- Environmentally Sensitive Areas

- ENV Policy 1.2.1: ***Environmentally sensitive areas shall be protected.***
- ENV Policy 1.3.7: ***Protect and conserve significant wildlife habitat, and shall prevent any further net loss of essential wildlife habitat in the City.***
- ENV Policy 1.2.8: The City may require ***the maintenance of higher levels of service for public infrastructure*** (e.g., roadways) as a means of reducing densities and clustering development intensity away from environmentally sensitive areas.
- ENV Policy 1.2.5: Use techniques, which may include ***clustering and transfer of development rights, to protect environmentally sensitive areas.***

- Coastal High Hazard Area

- CM Policy 1.1.7: ***Prohibit the location of new "special needs" facilities in the Coastal High Hazard Area***, including adult congregate living facilities, hospitals, nursing homes, homes for the aged and total care facilities.
- CM Policy 1.3.3: Give priority to ***acquiring land in the Coastal High Hazard Area*** to increase open space, recreation opportunities, public access, and ***to reduce the risk of property damage from potential disasters.***
- ENV Policy 1.21.7: Require that existing developments planned for expansion, modification or replacement in the coastal [planning] area provide or ***support stormwater treatment improvements*** within the affected drainage basin where treatment facilities are lacking. Require retrofitting of stormwater treatment facilities in coastal areas lacking such facilities.
- ENV Policy 1.22.1: Limit use of beaches and shorelines to appropriate ocean-oriented recreational and educational functions, and natural resource preservation.

- Floodplain

- ENV Policy 1.9.5: Through the land planning and development review processes, ***restrict net encroachment into the 100-year floodplain of significant wetland and riverine systems*** in accordance with the provisions of the Environmental Resource Permit Rules, administered by the Southwest Florida Water Management District and the Florida Department of Environmental Protection.
- ENV Policy 2.1.3: ***All development within the 100-year floodplain shall be in strict conformance with applicable development regulations.***
- CM Policy 1.3.4: ***Any structure within the 100-Year Floodplain that is damaged in excess of the limits established by FEMA's definition of substantial damage (50% rule) shall be rebuilt to meet or exceed all current building code requirements***, including those enacted since the construction of the structure.

Negative Scored Policies (increasing vulnerability)

- Transit Oriented Development

- LU Policy 7.2.6: In order to ***achieve additional development potential ("TOD bonus"),*** parcels within the TOD Overlay must provide transit-oriented amenities in accordance with Table TOD-4 and the methodology set forth in the City's Land Development Code. This TOD bonus provision will ensure that new development provides transit-oriented amenities that enhance the quality of life in order to achieve the desired density and intensity needed for successful Transit Oriented Development…

ENV: Environmental, CM: Construction Management, LU: Land Use.

Figure 4.10. Key policy statement in the Tampa Comprehensive Plan.

Source: reprinted from Hillsborough County (2016).

4.4.4. Urban Growth Scenarios and Policy Preparation

As stated in Chapter 3 (3.1.1), the future urban growth in scenario 1 (S1), business as usual, is natural growth without development regulations and occurs according to the previous development pattern. Scenario 2 (S2), growth as planned, follows a land use plan where new development occurs outside the designated environmentally sensitive areas (ESA) and open spaces. Scenario 3 (S3), resilient growth, has a strong development regulation assumption, no development occurs within future flood risk areas (SLR High 2040) adding to the exclusionary areas in S2. S2 would be the most likely future urban area in Tampa, S1 would be if new development does not follow the land use regulations, and S3 would be the future of if strong floodplain policies (no floodplain development) are created and assigned.

The result of urban flood exposure as shown in Table 4.11 and Figure 4.11 illustrates that predicted urban areas in S1 and S2 in all neighborhoods are exposed to flood risks except neighborhood 82 in S1. Urban flood exposure in S1 is larger than in S2 in six neighborhoods, and two neighborhoods have less urban flood exposure in S1 than in S2. For S3 (resilient growth) in all neighborhoods, all urban development would be free from current and future flood risk due to its prediction intention, restricting floodplain development.

Table 4.11. Existing and future urban exposure to flood hazards.

		NH	Existing Urban	Future Urban Growth Scenarios		
				S1	S2	S3
NH 28	Area (km²)	9.20	6.86	1.70	1.39	0.72
	Area under the current floodplain (km2)	2.35	1.34	**0.68**	**0.53**	**0.00**
	Area under future floodplain (km2)	3.26	2.04	**0.86**	**0.63**	**0.00**
NH 40	Area	12.94	1.93	4.96	2.69	4.90
	Area under the current floodplain	2.34	0.24	**1.23**	**0.43**	**0.00**
	Area under future floodplain	-	-	-	-	-
NH 82	Area	2.99	2.18	0.12	0.62	0.54
	Area under the current floodplain	0.14	0.06	**0.00**	**0.08**	**0.00**
	Area under future floodplain	0.54	0.30	**0.00**	**0.22**	**0.00**
NH 89	Area	15.36	3.34	1.36	2.19	2.59
	Area under the current floodplain	6.03	0.07	**0.08**	**0.38**	**0.00**
	Area under future floodplain	-	-	-	-	-
NH 97	Area	1.71	0.94	0.54	0.52	0.01
	Area under the current floodplain	1.30	0.64	**0.47**	**0.46**	**0.00**
	Area under future floodplain	1.65	0.89	**0.53**	**0.52**	**0.00**
NH 112	Area	3.60	1.50	1.42	0.70	0.68
	Area under the current floodplain	0.56	0.10	**0.16**	**0.13**	**0.00**
	Area under future floodplain	-	-	-	-	-
NH 113	Area	7.37	2.77	3.68	1.69	1.59
	Area under the current floodplain	2.36	0.49	**1.64**	**0.64**	**0.00**
	Area under future floodplain	-	-	-	-	-
NH 114	Area	2.16	0.44	0.41	0.10	0.32
	Area under the current floodplain	1.10	0.10	**0.10**	**0.02**	**0.00**
	Area under future floodplain	-	-	-	-	-

Neighborhood (NH) 40, 89, 112, 113, and 114 would not be impacted by a SLR so only the area under the current floodplain is used for calculations.

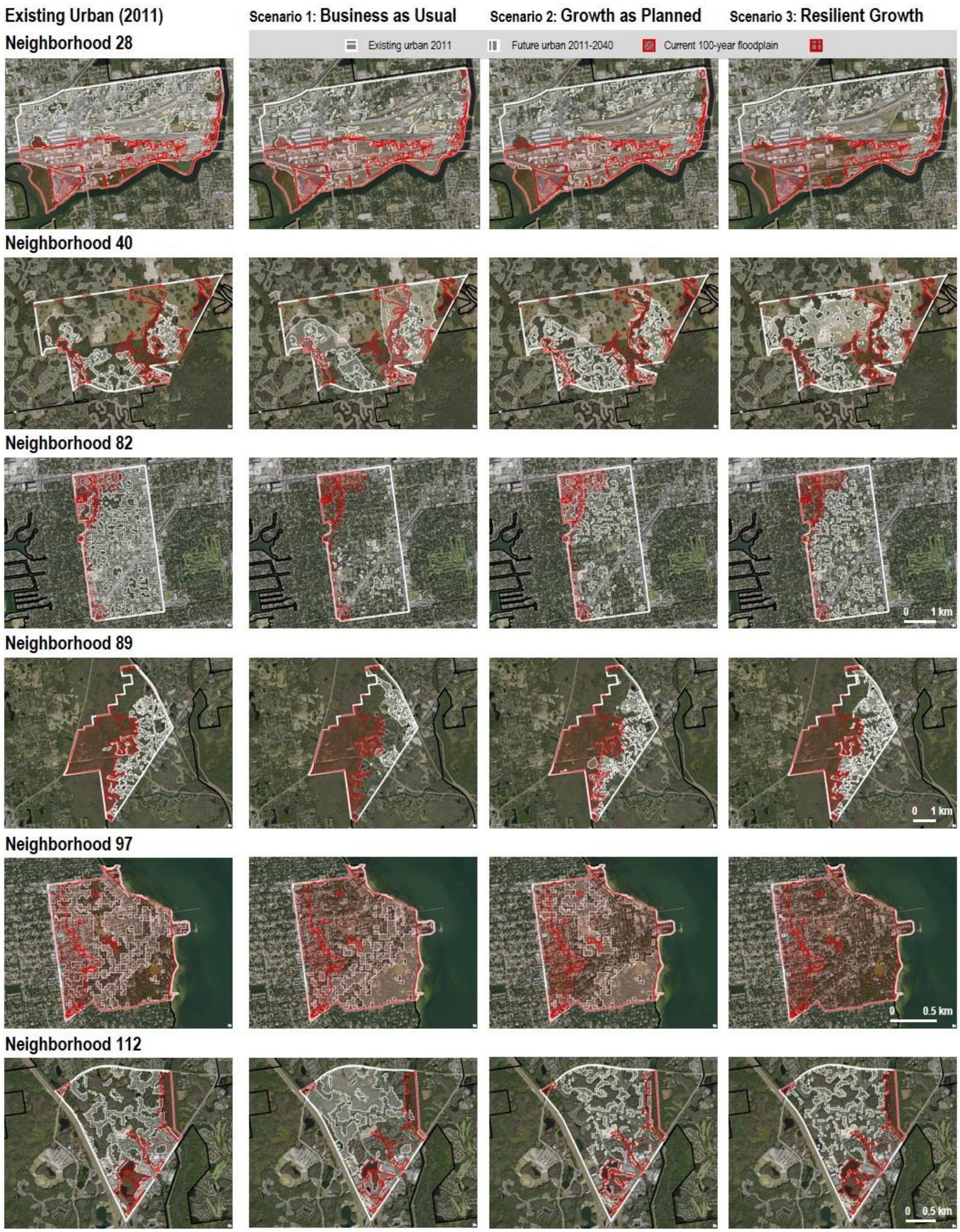


Figure 4.11. Existing and future urban exposure to future hazards.

Figure 4.11. Continued.

To assess at policy preparation on urban growth in detail, I focus on three representative neighborhoods: NH 113 impacted by the current floodplain and designated as an ESA, NH 82 located inland but impacted by SLR, and NH 28 assigned as a TOD and receiving funding for low income policies.

- **Neighborhood 113** is located in north Tampa. Land use is designated for sub-urban housing development, defined mixed-use, and ESA. Due to the long distance from the coastline, this neighborhood is not impacted by SLR so the 100-year floodplain is the flood risk. The neighborhood's physical vulnerability is medium high, and social vulnerability is low with a high median income ($101,557). The predicted future urban area in scenario 2, as shown in Figure 4.12, is 1.69km^2 and 0.64km^2 would be developed within the floodplain. The total policy score is 35 with no negative policies. The floodplain policy related to ESA (ENV 1.9.5) helps to decrease floodplain development because much of the ESA overlaps with floodplain zones.

Basically floodplain development is allowed by following building codes and controlling base flood elevation (BFE) based on the 100-year floodplain elevation (Development Regulation Ch.5 Building Code, 5-111). However, due to changing climate pattern and increasing impervious surfaces due to new development, the BFE standard may not guarantee its safety, and the false sense of security from flood risk (Tobin, 1995) would encourage more development in the floodplain.

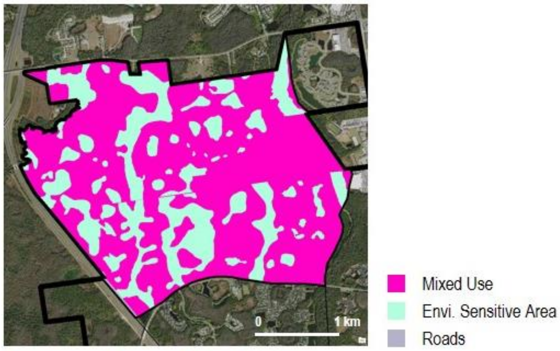
- **Neighborhood 82** is located inland in south Tampa. Though it is located inland, due to its proximity to the coastline (approximately 1 km), the neighborhood is impacted by the current and an increased floodplain due to SLR. Land use is designated for mainly residential, mixed use, and (semi) public uses. Its physical vulnerability is medium high, and social vulnerability is low with a high median household income ($69,239). The predicted urban area in S2 is 0.62 km^2, and 0.08 km^2 would be impacted by the 100-year floodplain and 0.22 km^2 by the future floodplain increased by SLR. Its inland location causes fewer policies to be assigned, mainly floodplain and coastal planning policies. The total policy score is the lowest at four and a total of six policies are assigned (five positive and one negative).

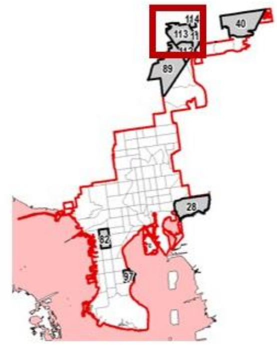
A critical issue for this neighborhood lies in the development between the current 100-year floodplain and future floodplain, because no SLR related policy exists in the Tampa Comprehensive Plan. Thus, the development between the flood zones would not be assigned any floodplain policies so it is not required to follow the floodplain building code and would be built without preparation for potential future flood risks. Scenario 2 (flood exposure) in Figure 4.13 indicates the area and location in the north part of neighborhood 82 where 0.14 km^2 would be developed within the future floodplain but outside the current floodplain where new development is not assigned floodplain policies.

- **Neighborhood 28** is located on the eastside of central Tampa and is a coastline neighborhood, meeting McKay Bay. As Figure 4.14 shows, the main land use is heavy/light industry, transportation, residential, commercial, mixed use, and ESA. The TCP designates the neighborhood as a Transit Envelope Area including transit corridors and stations. Due to its coastal location, physical vulnerability is high, and it will be impacted by an increased future floodplain due to SLR. Social vulnerability is medium, and its median household income is low ($31,932). Due to its diverse characteristics (coastal location, industrial and ESA land use, TOD zone, and low-income status), this neighborhood is assigned the highest number (64) of policies; 58 policies in TCP, two in HCLMS, one in CTEDNA, and three in HLRTP. The total score is the second highest at 44. The predicted urban area in S2 is 1.39 km^2 where 0.53 km^2 would be impacted by the 100-year floodplain and 0.63 km2 by the future floodplain increased by SLR. Much of the existing heavy industry is currently under flood risk, and predicted future industry and mixed use development would be located within the flood zones.

In contrast to other neighborhoods, its low income status and transit corridors give the neighborhood development benefits in funding and density incentives. However, the development support can work differently depending on its location, positively for development outside the floodplain and negatively for floodplain development. For example, both the development of the northern part of the residential block (located outside the floodplain) and the southern part mixed-use block (within the floodplain) can earn financial support (HSG Policy 1.1.3) and a TOD bonus in new developments (LU Policy 7.2.6). The difference is that the mixed-use development in the south will be assigned an additional floodplain policy with a building code (ENV Policy 2.1.3), which is not an enough preparation for the uncertain climate conditions. Finally, the incentives for the floodplain development would encourage denser development in a flood risk area. Though the funding support for the low income neighborhood and the TOD bonus would decrease social vulnerability in general, it could put more socially vulnerable people and assets in danger by floodplain development.

Land Use Plan





Existing and Future Urban Prediction

Current Urban 2011

	Total Area	Existing Urban	Future Urban Scenarios		
			S1	S2	S3
Area (sqkm)	7.37	2.77	3.68	1.69	1.59
%	-	37.55	49.93	22.94	21.55

Scenario 1: Business as Usual

Scenario 2: Growth as Planned

Scenario 3: Resilient Growth

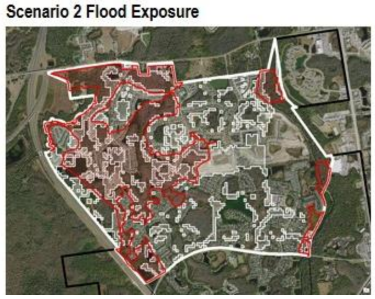
Existing and Future Urban Flood Exposure

Current Urban Flood Exposure

Urban Flood Exposure	Existing Urban	Future Urban Scenarios		
		S1	S2	S3
Urban Area (sqkm)	2.77	3.68	1.69	1.59
Area under 100-year Floodplain (sqkm)	0.49	1.64	0.64	0.00
Area under SLR (sqkm)	-	-	-	-

Scenario 1 Flood Exposure

Scenario 2 Flood Exposure



Scenario 3 Flood Exposure

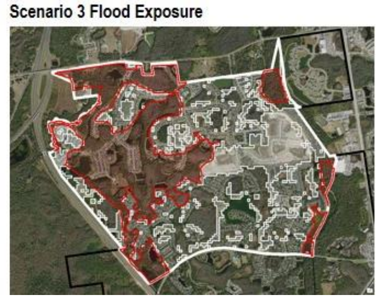
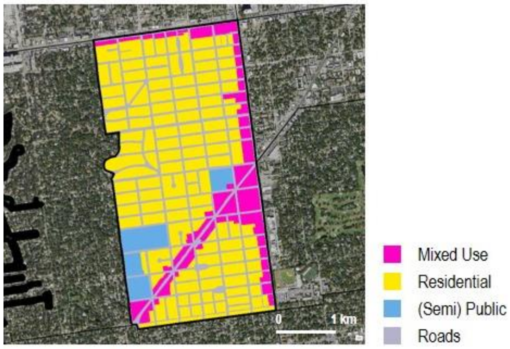
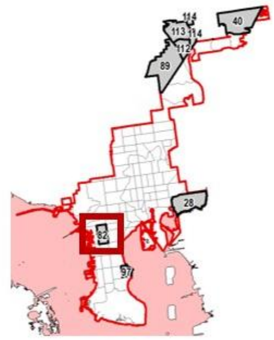


Figure 4.12. Neighborhood 113 land use, urban areas, and urban flood exposure.

Land Use Plan





Existing and Future Urban Prediction

Current Urban 2011

	Total Area	Existing Urban	Future Urban Scenarios		
			S1	S2	S3
Area (sqkm)	2.99	2.18	0.12	0.62	0.54
%	-	72.90	3.94	20.82	18.19

Scenario 1: Business as Usual

Scenario 2: Growth as Planned

Scenario 3: Resilient Growth

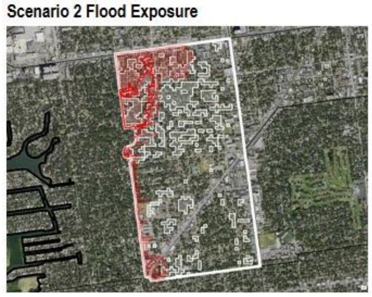
Existing and Future Urban Flood Exposure

Current Urban Flood Exposure

Urban Flood Exposure	Existing Urban	Future Urban Scenarios		
		S1	S2	S3
Urban Area (sqkm)	2.18	0.12	0.62	0.54
Area under 100-year Floodplain (sqkm)	0.06	0.00	0.08	0.00
Area under SLR (sqkm)	0.30	0.00	0.22	0.00

Scenario 1 Flood Exposure

Scenario 2 Flood Exposure



Scenario 3 Flood Exposure

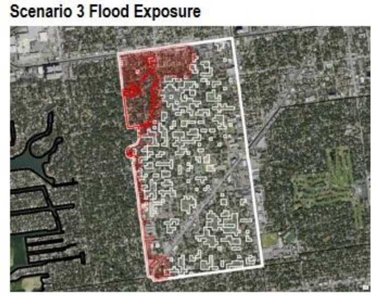
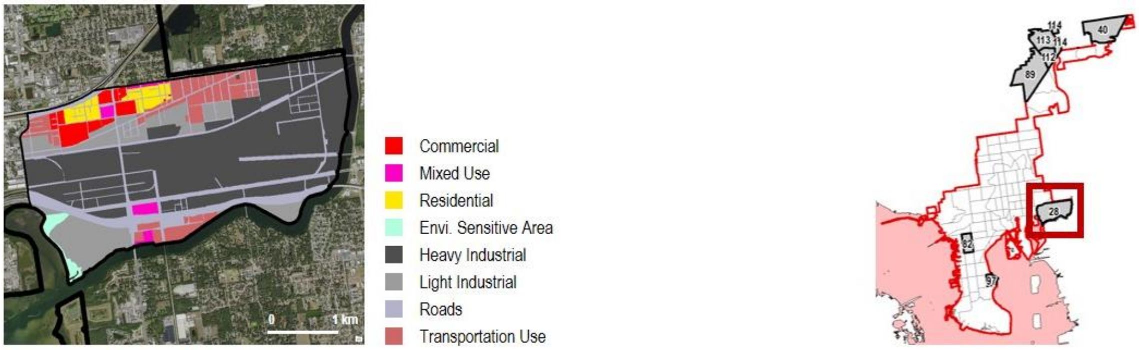


Figure 4.13. Neighborhood 82 land use, urban areas, and urban flood exposure.

Land Use Plan



Existing and Future Urban Prediction

Current Urban 2011

	Total Area	Existing Urban	Future Urban Scenarios		
			S1	S2	S3
Area (sqkm)	9.20	6.86	1.70	1.39	0.72
%	-	74.58	18.45	15.14	7.78

Scenario 1: Business as Usual

Scenario 2: Growth as Planned

Scenario 3: Resilient Growth

Existing and Future Urban Flood Exposure

Current Urban Flood Exposure

Urban Flood Exposure	Existing Urban	Future Urban Scenarios		
		S1	S2	S3
Urban Area (sqkm)	6.86	1.70	1.39	0.72
Area under 100-year Floodplain (sqkm)	1.34	0.68	0.53	0.00
Area under SLR (sqkm)	2.04	0.86	0.63	0.00

Scenario 1 Flood Exposure

Scenario 2 Flood Exposure

Scenario 3 Flood Exposure

Figure 4.14. Neighborhood 28 land use, urban areas, and urban flood exposure.

4.4.5. Findings

This sub-section examines Tampa's preparation for future urban growth using the resilient scorecard and predicted urban growth at a neighborhood scale. The scorecard method enables identification of conflicting policies in each neighborhood. The urban growth prediction illustrates potential future growth areas with specific locations in each neighborhood.

The scorecard result shows that the total plan scores in each neighborhood are all positive, ranging from 4 to 45. The average score is 30.6, meaning that each neighborhood is assigned 30 more positive policies on average than negative policies. Most scores are driven by the Tampa Comprehensive Plan. The score shows that the city prepares for urban growth and flood development with several policies related to ESA, coastal planning, floodplain, and TOD. However, a positive total score does not mean that they are totally safe from flood risks, since the resilient scorecard scores equally with a positive or negative "1" for each policy, and the total score stands for the sum of the positive and negative policies in each neighborhood. Thus, this research investigates the resilient scorecard focusing on each assigned policy in each neighborhood from the perspective of the urban growth scenarios, and there are several findings in the policies relating to flood vulnerability.

Physical Vulnerability would increase both floodplain expansion due to SLR and current TOD policies. Totally three floodplain policies are assigned positively (decreasing vulnerability) for all neighborhoods. Floodplain development is currently allowed by controlling the base floor elevation with consideration of the 100-year floodplain. In the previous climate (rainfall) pattern, the floodplain policy may have worked well with the building code regulations based on the floodplain. However, in today's climate changing pattern with heavy rainfall and increased surface runoff due to urban expansion, the same policy can work negatively, increasing flood vulnerability. Allowing floodplain development can give people a false sense of security (Tobin, 1995), encourage increased development in flood-prone areas, and put more people at risk. Moreover, no SLR related policy exists in any of the city's related plan.

SLR will enlarge current floodplains, but the current floodplain policies in Tampa are based on the 100-year floodplain without considering the impact of an SLR. As an example, neighborhood 82 (applicable to all coastline neighborhoods including NH 28 and NH 47), new development within the future increased floodplain due to SLR (but outside the current 100-year floodplain) is not assigned any floodplain policies, which will impact all coastal neighborhoods without preparing for flood protection resulting in extensive damage.

TOD is intended to develop a transit system to create a better livable environment by enhancing the use of public transportation (Hillsborough County, 2016), but it may encourage more development in flood risk areas. TOD zones (e.g. transit stations and transit corridors) are designated in neighborhoods 28, 89, 112, and 114. New development within the TOD zones will earn density bonuses. However, for floodplain development within TOD zones, the incentive would put more life and assets at risk, especially a socially vulnerable population as in neighborhood 28.

Compared with the policies dealing with physical conditions, few policies are related to social status and they focus on development. Two policies are in TCP and one is in CTEDNA: funding for new multi-family housing (HSG Policy 1.1.3), and restricting critical infrastructure in the coastal areas (CM Policy 1.1.7) in TCP, and funding for public infrastructure in CTEDNA. In general, these policies are beneficial in providing a better pedestrian and living environment for low income people, and improve their social and physical conditions. However, in the case of neighborhood 28, funding for new development would encourage more floodplain development and increase the flood risk for socially vulnerable people. Encouraging floodplain development with funding and density bonuses that ends up with more damage would do them a greater detriment.

The aforementioned policies in floodplains, TOD, and funding for low income people have positive intentions in each purpose. However, depending on how or where a policy is applied, a good policy in the wrong place can work negatively. Thus, a more careful and conservative approach is necessary for future floodplain development.

4.4.6. Policy Implications

Though Tampa is making an effort to prepare for sustainable future urban growth, some policies should be updated to make a community more resilient. Based on the policy review related to physical and social vulnerability, future urban growth, and flood risks, my suggestions are:

- The best way to minimize flood damage is to restrict floodplain development with land use and policies. As a strong flood mitigation tool, land use can guide future development locations outside current and future flood risk areas (Berke et al., 2015; Burdy et al., 1999). Floodplain policies should be strengthened with active techniques such as development restrictions, land acquisition, and transfer of development rights. ESA policies and its land use in TCP strongly restrict development within the zone. No current development has occurred within the ESA, and the restriction even helps to reduce floodplain development due to its overlap with the 100-year floodplain. Through a consensus between planners and stakeholders, as in the ESA case, floodplain development could be restricted.
- Adding to reinforcing floodplain policies, regulations for building on floodplains should be updated due to climate change and urban expansion. Changing climate patterns with severe rainfall and additional surface run off because of more impervious surfaces in future urban areas will increase floodplain areas and base flood elevations. Building codes, controlling construction BFE above the current 100-year floodplain elevation are not enough to guarantee safety from uncertain or obvious future flood risks. Also, allowing floodplain development will give citizens a false sense of safety (Tobin, 1995) and promote more development in flood hazard areas.
- Furthermore, TCP should consider the SLR impacts on floodplains, currently no SLR policy exists. TCP only indicates the current 100-year floodplain and

the Coastal High Hazard Zones, but not SLR zones, the increased floodplain areas due to SLR. Neighborhoods 28, 82, and 97 will be directly impacted by the increased floodplain, but, under the current policies, new development within the zone but outside the 100-year floodplain will not be protected by proper building regulations. Finally, the development would be impacted without any preparation for future flood risks. Thus, updated flood risks and construction standards considering SLR should be considered for floodplain development.

- TCP should re-designate TOD zones to achieve its sustainable development goal considering flood hazard zones, otherwise unexpected results could occur, placing more people at risk. TOD, encouraging development with density incentives, may cause more and denser floodplain development as in neighborhood 82, a denser mixed-use development in a floodplain.

More policies should address socially vulnerable communities since people in these communities have less adaptive capacity, are easily impacted by natural disasters (Zahran et al., 2008), and take more time to recover than higher income people due to limited financial sources (Peacock et al., 2014). In the Tampa Comprehensive Plan, most policies deal with physical vulnerability, and only three social policies exist focusing on development incentives. Policies on low income population should be prepared based on their needs.

- Funding for new housing in low income neighborhoods (HSG Policy 1.1.3 in TCP) should exclude floodplain development or support for a flood preparation (e.g. mounding, base elevation). Misused incentives, especially in a low income neighborhood, would exacerbate physical as well as social conditions, in the same way as in the TOD policy case.

- Green Infrastructure (GI) and Low Impact Development (LID) related policy should be prepared for existing and future urban development. Prioritized funding in GI/LID for low-income neighborhoods can help to decrease their social vulnerability. GI (e.g. parkland, forests, and floodways) helps to slow runoff, filter water, and cool urban heats effects, and is also beneficial to raise land value, quality of life, and public health (Foster et al., 2011). LID is a lot-level stormwater management and land design strategy by mimicking a natural hydrologic system, and it minimizes development impact to hydrology and natural resources (Ahiablame et al., 2012; Coffman & France, 2002). It also saves more natural areas and reduces infrastructure cost in stromwater management and roadway (Coffman & France, 2002).
- Adding to the mitigating policies in the development stage, adaptation strategies for during or post-disaster should be prepared. For example, among various strategies, establishing neighborhood warning system and early warning in multiple languages will help individuals with less English proficiency and old population (Yuen et al., 2017). Also, quick financial support in recovery stage can help low-income people to bounce back their normal life quickly (Peacock et al., 2014).

“Low-income populations and communities of color often have less access to transportation, health infrastructure, or information. Equity is about fairness, ensuring that people have access to the same opportunities and have what they need to thrive and succeed” (Yuen et al., 2017, p.16). To be more effective policies, social vulnerability should be addressed based on their needs, and should be reflected on plan policies. NOAA’s Social Vulnerability Index (NOAA, 2017b) and equity checklist (Resilient Communities Initiative, 2015) can help planners/funders to identify socially vulnerable population during planning making processes.

5. CONCLUSIONS AND LIMITATIONS

5.1. Research Question Assessment

This research examined future urbanization using prediction modeling coupled with scenario planning to advance conditions for uncertain future climate change. It used the city of Tampa as an example to demonstrate a scenario matrix using urban growth and flood risk with SLR scenarios and impact analysis with scenario evaluation and policy analyses. Scenarios were made using the LTM for urban growth prediction and GIS for delineating future flood risks. The impact analysis used scenario evaluations and neighborhood scaled policy analyses. Scenario evaluations compared the urban flood exposure of each urban growth and SLR scenarios at city and neighborhood levels. Policy analyses investigated each policy and flood vulnerability with an urban growth prediction in each highly clustered neighborhood.

The LTM is a planning support tool to illustrate potential future urban growth. The forecasted urban growth and flood risks determined with the plan evaluation enable people to understand how prepared Tampa is for future urban growth and flood risks. Tampa plans (e.g. land use and plan policies) help to achieve the city's vision, an attractive and safe city with sustainable growth (Hillsborough County, 2016). However, land use and policies should be updated to enable Tampa to become a more resilient city by taking into consideration potential urban growth and uncertain climate change.

This scenario planning process is one application of the growth prediction model and SLR scenarios, and it can be applied to make/update/evaluate a city plan with planners and stakeholders by providing locations for tangible future urban areas at a neighborhood level. It will finally help to develop robust and contingent strategies to prepare for future uncertain climate change.

5.1.1. Subsidiary Research Questions

The overarching research question for this study is “How prepared are U.S. coastal cities for future urban growth and flood risk?” This main research question consists of the following sub-questions.

(Subsidiary Question 1) “How well-suited is the LTM in predicting future urban growth related to flood risk?”

The LTM is a capable model for creating future urban growth scenarios to examine flood risk. This research identified driving factors through a review of 144 prediction articles, and selected 15 variables with which to perform a drop-one test to determine Tampa’s future urban growth. The test result showed that all 15 variables contributed to the prediction capability. The three urban growth scenarios that were created were validated through four measures; all results proved fair/high prediction accuracy. Each urban growth scenario showed a different pattern of urban growth. However, the drop-one test is limited to show the relationship between driving factors and urban land change, and the performance results are relatively low.

(Subsidiary Question 2) “How effective is the current comprehensive plan in adapting urban growth to climate change?”

The current future land use plan for Tampa may not be the best plan, in terms of urban flood exposure. The city scale comparison of urban flood exposure, the future urban area developed with a land use plan (S2) would have fewer impacted urban areas by all future risk scenarios than the growth without development regulations (S1), but much more urban flood exposure than the scenario with strong floodplain regulation (S3). Moreover, in the neighborhood level analysis, the number of neighborhoods exposed to flood risk in planned growth (S2) is larger than in growth as business as usual (S1), and more neighborhoods have larger urban areas of flood vulnerability in S2 than in S1. Thus, the current land use plan (S2) is not well-prepared enough to achieve resilient communities by comparing other urban growth simulations; the growth without development regulation (S1) and the resilient growth (S3). It underscores the idea that one regional solution can be worse at a local scale, "planning as a wicked problem" (Rittel & Webber, 1973).

(Subsidiary Question 3) "How well-suited are neighborhoods to absorbing predicted growth based on current policy and vulnerability?"

Tampa is a well-prepared city in land use and plan policies under the previous climate conditions. Policies related to ESA, coastal planning, floodplains, and TOD policies help to accomplish its sustainable growth. However, most policies consider physical condition, but not citizens' social status. Among the policies considering physical vulnerability, floodplain policies and floodplain development regulations have to be updated based on the changing climate patterns (e.g. heavy rainfall and SLR) and the increase in impervious surfaces. Moreover, the TOD and development funding for low-income populations should re-designate their locations considering hydrologic impacts. The incentives would make the social condition worse by encouraging more development in flood risk zones, and placing more people in danger: a good policy in an improper location can cause unexpected results. To accomplish the city's vision, "a city where everybody cares about quality of life" (Hillsborough County, 2016, p.7), more policies for socially vulnerable families need to be created based on their needs such as funding for recovery, buy outs, etc. Under the current floodplain and development incentive related policies, floodplain development will be encouraged without proper preparation, and physical/social vulnerability will be increased.

In sum, this research showed a scenario planning process with an application in urban planning, scenario making with urban growth and flood risk scenarios and impact analyses in scenario evaluation and neighborhood scale policy analysis. The results of the impact analyses confirm dilemmas in urban planning: a regional solution can be worse in a neighborhood, and a good policy in the wrong place can work negatively. When making/updating plans, planners and stakeholders together can make a better decision by examining plausible scenarios and identifying their impacts through scenario planning as a planning support tool.

5.2. Study Limitations and Future Research

5.2.1. Study Limitations

While this study contributes to developing a scenario planning process for urban growth and climate change through scenario making and impact analyses, it is only a first step. There are some limitations in prediction accuracy in urban growth and flood risks that can be improved upon in future studies and advancements in prediction capabilities/technologies.

First, the prediction accuracy is relative low with 52.19 of PCM value; fairly acceptable range. This study used a one time-frame between 2001 and 2011 with 15 variables for an urban growth prediction. To evaluate prediction accuracy, four measures were employed for each prediction resulting in a validated forecast. While it might be impossible to predict the future perfectly, to raise prediction performance, a multi-timeline analysis and a proper driver selection would enable the creation of a better confiding and highly accurate future urban forecast.

Second, variable influence is limited in explaining its relationship to land change, and is hard to generalize. The LTM's drop-one test showed the relative influence of each variable in the urban growth model, but failed to explain the relationships and significance between driving factors and land change. The result could be only applied to Tampa between 2001 and 2011 or for a city of similar geographic, social, and urban development status.

Third, density was not considered in the urban growth prediction since the LTM is not designed for predicting density control. This study created three urban growth scenarios by controlling for future development locations with the same development areas and the same number of pixels for all development scenarios. With location, density can change the results, the development patterns, and create a new development scenario, being a more realistic prediction. The SLEUTH model is capable to create density scenarios by controlling its parameters (e.g. dispersion, spread, and road gravity) (Song et al., 2017).

Fourth, future flood risks were limitedly represented with SLR scenarios adding to the current 100-year floodplain. To be a more plausible risk scenario, it should consider the increase in impervious surfaces impacting hydrology and a new floodplain considering future run-off and peak flows (Gori et al., 2019; Muñoz et al., 2018). Moreover, as climate is changing, rainfall patterns become severe, exceeding a 100-year rainfall. It would be necessary to consider other flood risk standards such as the 500-year floodplain.

5.2.2. Future Research

To further advance LCM and scenario planning, future research needs to improve prediction accuracy in urban growth and flood risk, to provide a convenient prediction tool for future forecasts, and to integrate scenario planning into the plan making process.

First, prediction accuracy matters. Variable inventory on urban growth and hydrologic modeling for future floodplains enable the representation of a more realistic future condition. Though LCM has advanced in the last few decades, growth driving factors are still unclear. This study reviewed driving factors from 144 prediction articles, but the reviewed result explained variable types and accumulated numbers of each variable application in the study. Among the total 52 variables in the review, the most prominent driving factors, which are applicable to all prediction models, need to be identified. Future studies can focus on standardizing variables by examining multiple cities or regions with variable relationships using regression models (Bishop, 1995; Chu & Chang, 2009; Pijanowski et al., 2002). In future floodplain estimations, as mentioned in 5.2.1, extreme climate conditions and a new floodplain modeling based on future increases in impervious surfaces should be considered.

Second, researchers and engineers need to provide a more convenient prediction tool. Though people agreed on the efficacy of scenario planning, its complexity in prediction tools, data collection, calibration, and scenario making and assessment causes fewer people to use it (Holway et al., 2012). While planners popularly use the CommunityViz program due to its ease of use (Lincoln Institute, 2017), the modeling approach and accuracy are unknown and it is a commercial product. To more actively apply scenario planning to real world planning, an easy-to-use and accurate prediction model needs to be developed.

Last, integrating scenario planning into the planning process needs to be done to create better decision making among planners and diverse stakeholders. “Collaborative governance is to bring diverse private/public stakeholders together in a consensus-oriented forum for decision making” (Berke & Lyles, 2013, p.191; Innes & Booher, 2010), and the process enables educating citizens, tapping preference, improving relationship, and solving problems among stakeholders (Berke & Kaiser, 2006; Berke & Lyles, 2013). Figure 5.1 illustrates the general planning process (Governor's Office of Planning and Research, 2017) integrated with the collaborative planning process (Berke & Kaiser, 2006) and scenario planning process (Bood & Postma, 1997; Postma & Liebl, 2005; Ringland & Schwartz, 1998). To utilize scenario planning in the plan making process, researchers need to develop scenario analysis (scenario decision, making, and evaluation) and efficient communication methods.

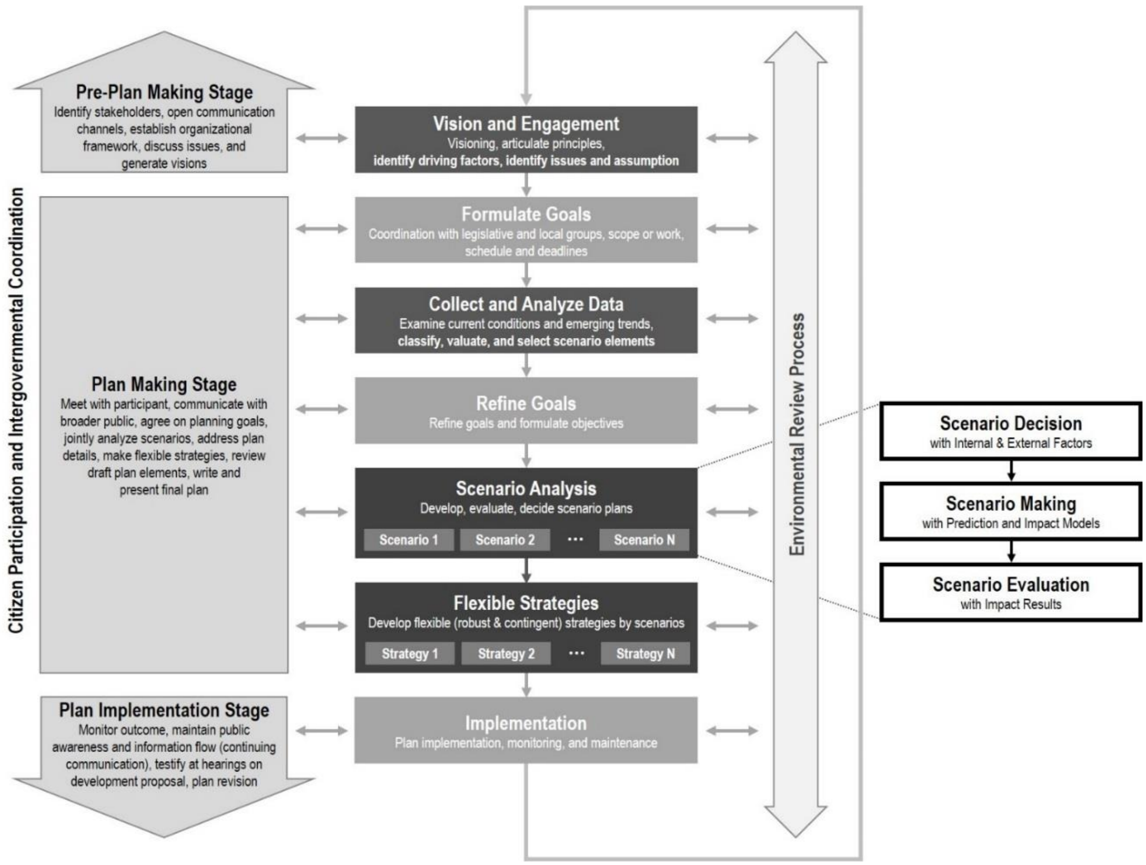


Figure 5.1. Anticipatory and collaborative planning process in a general local planning process.

Source: modified and adapted from the Governor's Office of Planning and Research (2017), Chakraborty et al. (2011), Berke & Kaiser (2006), Postma & Liebl (2005), Ringland & Schwartz (1998), and Bood & Postma (1997).

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APPENDIX A

RASTER DATA FOR URBAN GROWTH PREDICTION

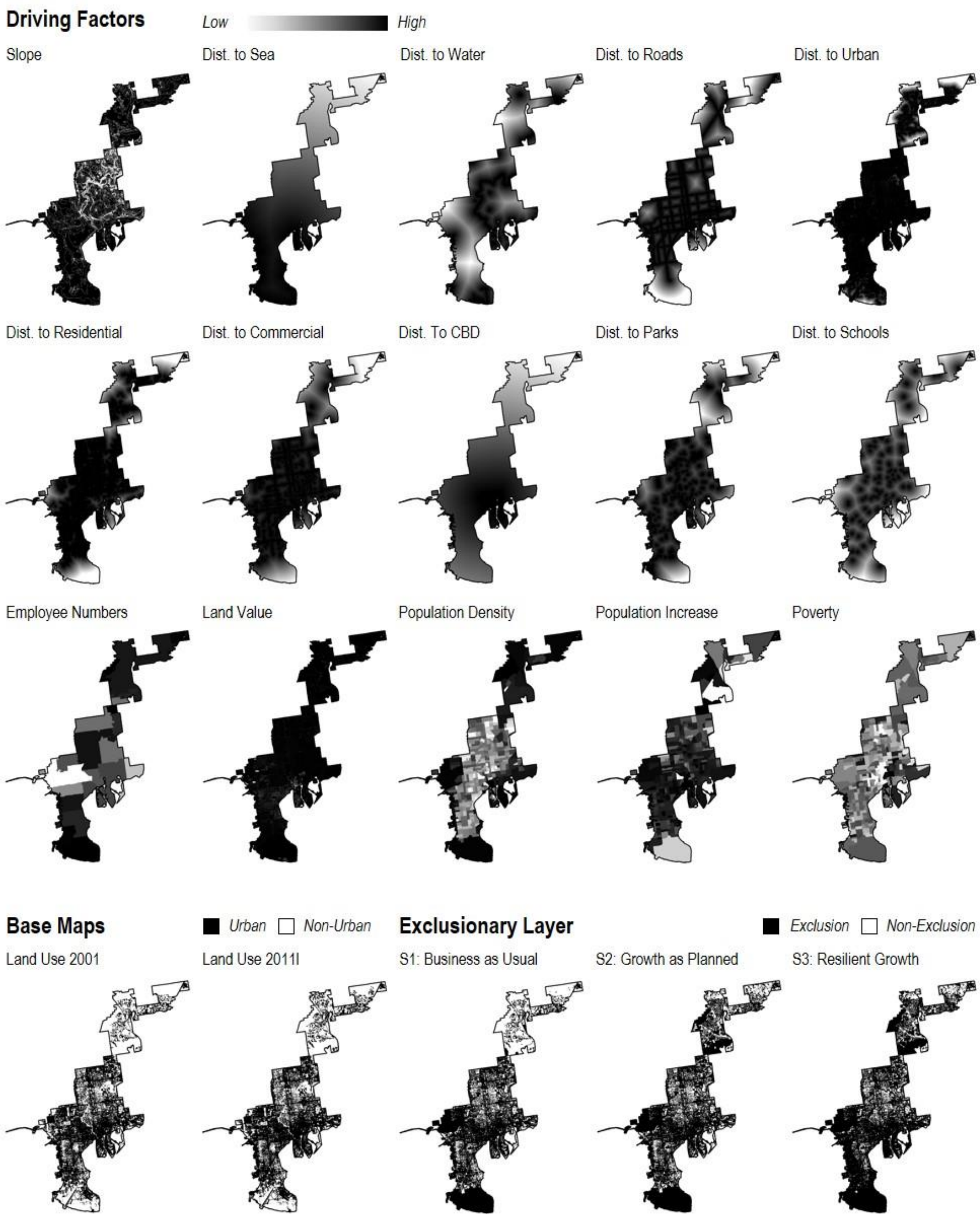
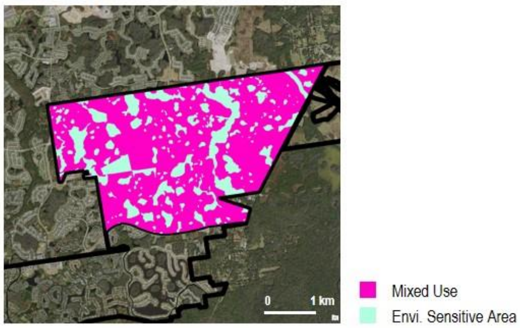


Figure A.1. Driving factors, base maps, and exclusionary layers for urban growth prediction.

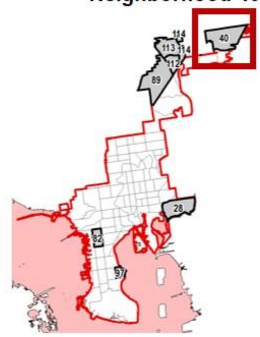
APPENDIX B

NEIGHBORHOOD LAND USE, URBAN AREAS, AND FLOOD EXPOSURE

Land Use Plan



Neighborhood 40



Existing and Future Urban Prediction

Current Urban 2011

	Total Area	Existing Urban	Future Urban Scenarios		
			S1	S2	S3
Area (sqkm)	12.94	1.93	4.96	2.69	4.90
%	-	14.90	38.34	20.79	37.89

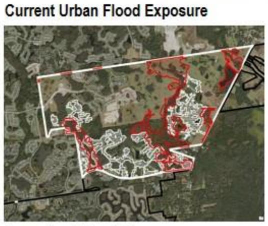
Scenario 1: Business as Usual

Scenario 2: Growth as Planned

Scenario 3: Resilient Growth

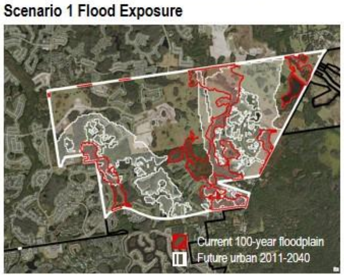
Existing and Future Urban Flood Exposure

Current Urban Flood Exposure

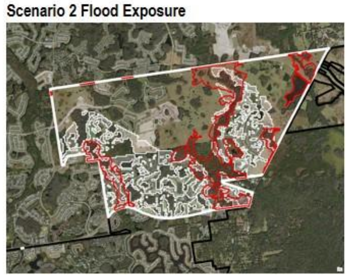


Urban Flood Exposure	Existing Urban	Future Urban Scenarios		
		S1	S2	S3
Urban Area (sqkm)	1.93	4.96	2.69	4.90
Area under 100-year Floodplain (sqkm)	0.24	1.23	0.43	0.00
Area under SLR (sqkm)	-	-	-	-

Scenario 1 Flood Exposure



Scenario 2 Flood Exposure



Scenario 3 Flood Exposure

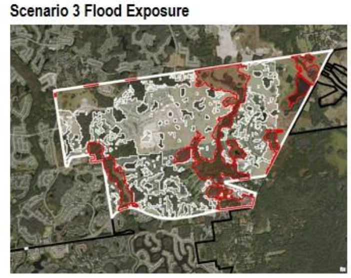
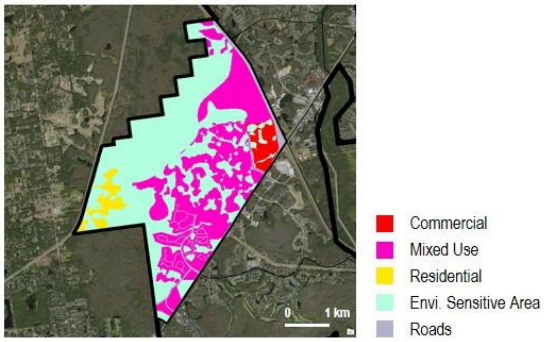
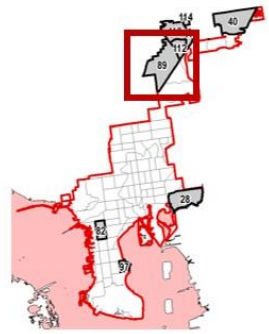


Figure B.1. Neighborhood 40 land use, urban areas, and urban flood exposure.

Land Use Plan

Neighborhood 89





Existing and Future Urban Prediction

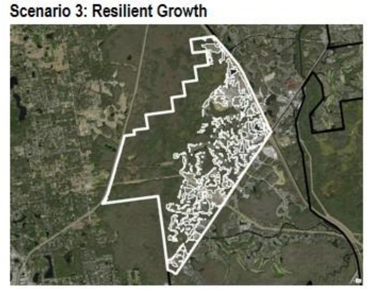
Current Urban 2011

	Total Area	Existing Urban	Future Urban Scenarios		
			S1	S2	S3
Area (sqkm)	15.36	3.34	1.36	2.19	2.59
%	-	21.73	8.85	14.25	16.85

Scenario 1: Business as Usual

Scenario 2: Growth as Planned

Scenario 3: Resilient Growth

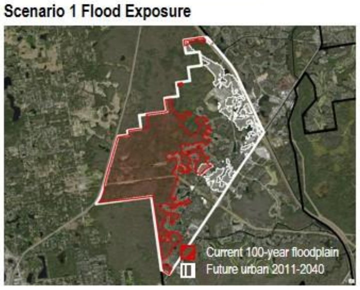


Existing and Future Urban Flood Exposure

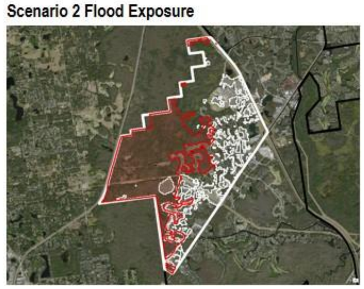
Current Urban Flood Exposure

Urban Flood Exposure	Existing Urban	Future Urban Scenarios		
		S1	S2	S3
Urban Area (sqkm)	3.34	1.36	2.19	2.59
Area under 100-year Floodplain (sqkm)	0.07	0.08	0.38	0.00
Area under SLR (sqkm)	-	-	-	-

Scenario 1 Flood Exposure



Scenario 2 Flood Exposure



Scenario 3 Flood Exposure

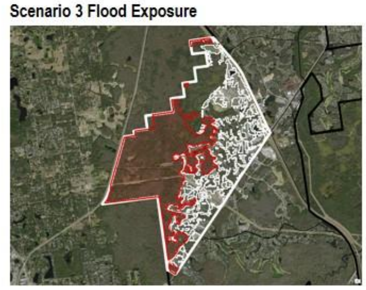
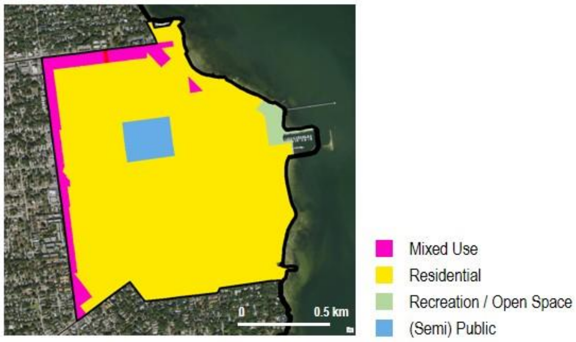
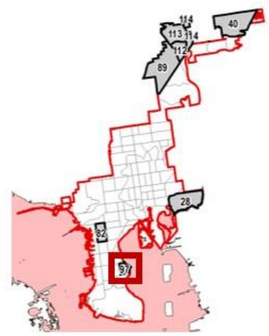


Figure B.2. Neighborhood 89 land use, urban areas, and urban flood exposure.

Neighborhood 97

Land Use Plan





Existing and Future Urban Prediction

Current Urban 2011

	Total Area	Existing Urban	Future Urban Scenarios		
			S1	S2	S3
Area (sqkm)	1.71	0.94	0.54	0.52	0.01
%	-	55.15	31.36	30.42	0.30

Scenario 1: Business as Usual

Scenario 2: Growth as Planned

Scenario 3: Resilient Growth

Existing and Future Urban Flood Exposure

Current Urban Flood Exposure

Urban Flood Exposure	Existing Urban	Future Urban Scenarios		
		S1	S2	S3
Urban Area (sqkm)	0.94	0.54	0.52	0.01
Area under 100-year Floodplain (sqkm)	0.64	0.47	0.46	0.00
Area under SLR (sqkm)	0.89	0.53	0.52	0.00

Scenario 1 Flood Exposure

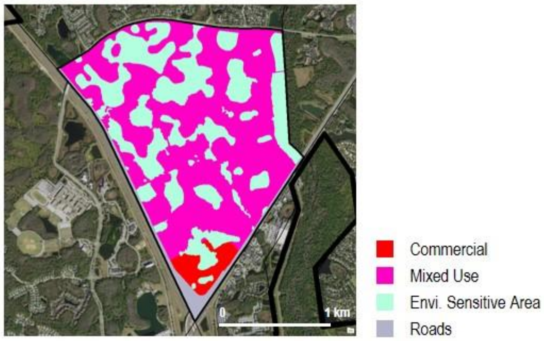
Scenario 2 Flood Exposure

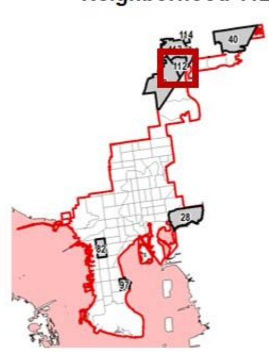
Scenario 3 Flood Exposure

Figure B.3. Neighborhood 97 land use, urban areas, and urban flood exposure.

Land Use Plan

Neighborhood 112





Existing and Future Urban Prediction

Current Urban 2011

	Total Area	Existing Urban	Future Urban Scenarios		
			S1	S2	S3
Area (sqkm)	3.60	1.50	1.42	0.70	0.68
%	-	41.57	39.35	19.54	18.91

Scenario 1: Business as Usual

Scenario 2: Growth as Planned

Scenario 3: Resilient Growth

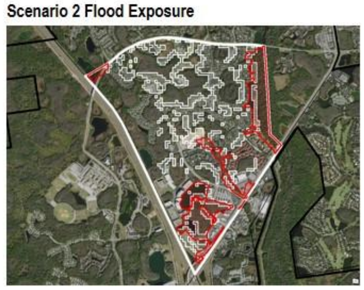
Existing and Future Urban Flood Exposure

Current Urban Flood Exposure

Urban Flood Exposure	Existing Urban	Future Urban Scenarios		
		S1	S2	S3
Urban Area (sqkm)	1.50	1.42	0.70	0.68
Area under 100-year Floodplain (sqkm)	0.10	0.16	0.13	0.00
Area under SLR (sqkm)	-	-	-	-

Scenario 1 Flood Exposure

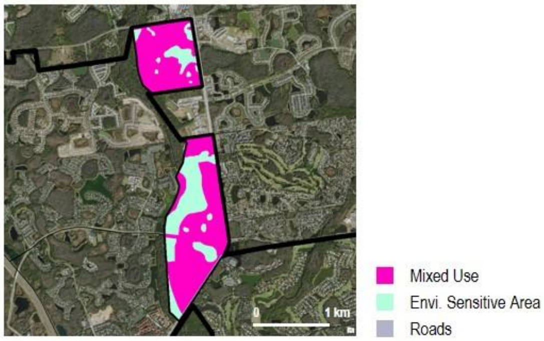
Scenario 2 Flood Exposure



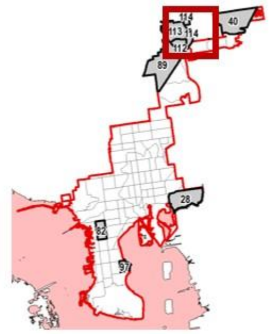
Scenario 3 Flood Exposure

Figure B.4. Neighborhood 112 land use, urban areas, and urban flood exposure.

Land Use Plan



Neighborhood 114



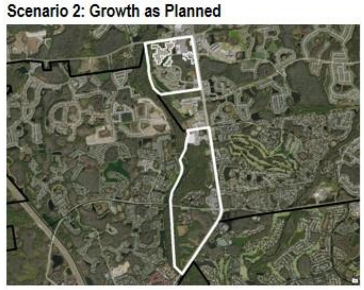
Existing and Future Urban Prediction

Current Urban 2011

	Total Area	Existing Urban	Future Urban Scenarios		
			S1	S2	S3
Area (sqkm)	2.16	0.44	0.41	0.10	0.32
%	-	20.46	18.99	4.76	14.70

Scenario 1: Business as Usual

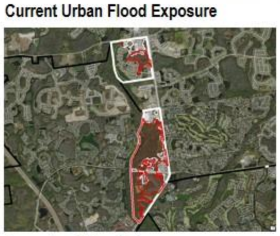
Scenario 2: Growth as Planned



Scenario 3: Resilient Growth

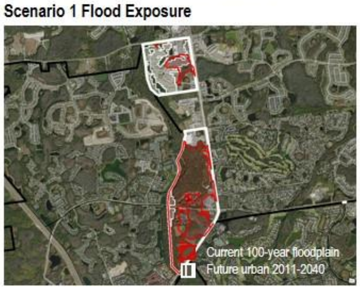
Existing and Future Urban Flood Exposure

Current Urban Flood Exposure

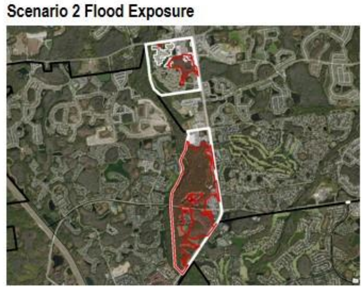


Urban Flood Exposure	Existing Urban	Future Urban Scenarios		
		S1	S2	S3
Urban Area (sqkm)	0.44	0.41	0.10	0.32
Area under 100-year Floodplain (sqkm)	0.10	0.10	0.02	0.00
Area under SLR (sqkm)	-	-	-	-

Scenario 1 Flood Exposure



Scenario 2 Flood Exposure



Scenario 3 Flood Exposure

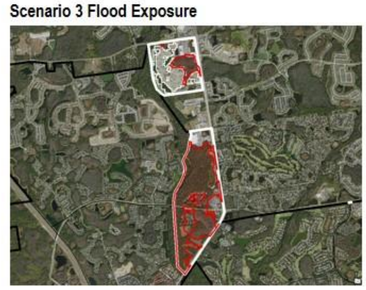


Figure B.5. Neighborhood 114 land use, urban areas, and urban flood exposure.