Integrating Prediction and Performance Models into Scenario-based Resilient Community Design

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Abstract: Urban expansion can worsen climate change conditions and enlarge hazard zones. Sea level rise due to climate change makes coastal populations more susceptible to flood risks. The use of land change prediction modelling to inform scenario-based planning has been shown to help increase capabilities when dealing with uncertainties in urbanization such as urban growth and flood risk, when compared to singular comprehensive plans. This research uses the Land Transformation model to predict three different urban growth scenarios for Tampa, FL to determine how effective the current comprehensive plan is in adapting urban growth to decreasing flood risk and pollutant load. To achieve this, the research develops master plans according to each scenario then assesses their probable impact using the Long-Term Hydrologic Impact Analysis Low Impact Development Spreadsheet as a performance model. Findings show that the current future land use plan for Tampa, while it appears to be better than current patterns of development, has higher flood exposure, stormwater runoff, and pollutant discharge that current conditions but more than a purely resilient approach to future growth.

Keywords: Land transformation model, urban prediction, resilience, geodesign, scenario planning

1 Introduction

Globally, more than 600 million people live in coastal regions lower than 10 meters above sea level, and almost 2.4 billion people live within 100 km of a coastline (UNITED NATIONS 2017). In the U.S., 254 counties (8%) out of 3,142 are located on the coast. 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). Shoreline county populations have grown steadily since 1970 and are projected to continue to grow (CROSSETT et al. 2013). Sea level rise due to climate change makes coastal populations more susceptible to flood risks. Urban expansion due to population growth can worsen climate change conditions and enlarge hazard zones. As urban population accrue, impervious surfaces increase, resulting in increases in stormwater runoff and urban heat reflection. Both urban heart, stormwater runoff, and flood event frequency are increasing due to climate change. When open space land uses are converted to urban land uses, flood risk can increase due to increases in floodplain area and impervious surfaces. The capability to accurately predict both future floodplain changes and future urban growth allows for the capacity to better prepare coastal communities for the effects of future climate change and helps support urban planning for better potential future flood risk mitigation.

Tampa, Florida, USA, is ranked in the top five of U.S. cities most vulnerable to flooding and is expected to grow by over 100,000 people by 2040 (CLIMATE CENTRAL 2012). Flood risks are expected to worsen due to the effects of climate change and anticipated sea level rise. Scenario planning has been shown to be a more effective approach to prepare for unknown futures than singular comprehensive plans (WOODRUFF 2016). Spatial relationships involving the process of urbanization and flood risk are still not fully integrated with scenario plan-

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ning-based studies (BATTY 2008). Programs such as Geographic Information Systems (GIS) have developed software to help predict future flood plains and urban conditions.

The use of innovative digital tools with GIS to help analyse, predict for, and design geographic space has been referred to as Geodesign. WILSON (2014) suggests that Geodesign processes can be used for a visioning purposes and/or representing futures-to-come, on multiple scales. STENINITZ (2012) references Geodesign's ability to integrate fields of research and describes it as a set of concepts and methods derived from geography and spatial sciences which seeks to create a symbiotic collaboration between both geographic sciences and design based professions. In this research, Geodesign is refers to a method of applying systems thinking in an effort to provide a framework which provides alternatives to geographic contexts which can then be altered through new design strategies/programs (GOODCHILD 2012).

In this research, a series of tools are used on multi-scalar spatial datasets with a purpose of increasing resiliency in a flood prone neighborhood. The Land Transformation Model (LTM), a GIS-based neural network for Land Change Modelling (LCM), is used to predict potential future urban growth of Tampa according to three different scenarios: 1) Business as usual – predicted urban growth based on current growth patterns; 2) Growth as planned – predicted urban growth based on the current land use plan; and 3) Resilient growth – predicted urban growth based on all future development occurring outside of the floodplain.

This research asks, how effective is the current comprehensive plan in adapting urban growth to decreasing flood risk and pollutant load? The site under investigation is a coastal neighborhood on the east Tampa, FL, and one of the most socially and physically vulnerable neighborhoods. It is both heavily effected by flooding and characterized by industrial land uses, brown fields, and sites listed by the US Environmental Protection Agency's Toxic Release Inventory (TRI). TRI sites are those that can cause cancer or other chronic human health effects, significant adverse acute human health effects, and/or significant adverse environmental effects. The site's numerous sources of pollution are resulting in severe contamination and related effects from runoff containing industrial by-products. To answer the research question, three different urban design master plans are developed based on each scenario's prediction outputs. Then, resilience analytics and landscape performance models are ran on each design scenario to project impact. Resilience performance quantifies the effectiveness with which a neighbourhood's existing conditions impact flood risk levels or designed/planned solutions fulfil their intended purpose to reduce flood risk (NEWMAN et al. 2019). To conduct the design impact analysis, the Long-Term Hydrologic Impact Assessment (L-THIA) Low Impact Development Spreadsheet was applied to each scenario's master plan to gauge the performance of each plan in decreasing runoff and industrial pollution. The L-THIA estimates long-term average annual runoff (e. g. volume, depth), and nonpoint source pollution resulting from future land changes. By developing and operationalizing measures to evaluate the performance of the built environment, baseline data is used to compare new urban growth schemes against to determine design/plan benefits.

2 Literature Review

2.1 Flood Resilience

Floods are the costliest natural hazard globally. Flood vulnerability is compounded by land use conversion and increased impervious surfaces, amplifying the harmful social and economic impacts of recent and future floods. Given the far-reaching impacts of recent major US storms, such as Hurricanes Katrina (2008), Ike (2005), Sandy (2012), and Harvey (2017), it is clear that the increased frequency and damage costs of flooding is not an issue solved through only engineering. The way humans settle and build upon the physical landscape is a major factor contributing to flood risk. Since flood disasters are a human-induced phenomenon, changing the way we shape communities through their development patterns may be the most effective way to mitigate repetitive and costly flood events. Urbanization and the proliferation of impervious surfaces across watershed units have long been considered a major contributor to adverse impacts associated with flood events (BERKE et al. 2015). Conversion of natural landscapes to urban or suburban developments can reduce the functionality of hydrological systems leading to reduced soil infiltration and increased surface runoff and peak discharge in nearby streams (BHADURI et al. 2000). In an observational study of 37 coastal counties in Texas, BRODY et al. (2008) found that each square meter of impervious surface added to the landscape translated into approximately $3,602 of added property damage caused by floods per year from 1997-2001. More recent research indicates that flood impacts are driven not solely by the amount of impervious surface, but by its pattern and intensity across a given landscape. The specific form of the built environment is an important contributor to flood losses. BRODY et al. (2012) found that the intensity of development within counties/parishes along the Gulf of Mexico coast significantly impacted the amount of reported property damage from floods. Jurisdictions with large amounts of high-intensity development patterns experienced, on average, lower amounts of property damage from floods. Socioeconomic characteristics and household composition can also be significant factors predicting the likelihood and extent of flood disasters (CUTTER et al. 2003).

2.2 Land Change Modelling (LCM) and Scenario Planning

LCM is a planning support system which applies future land predictions to land use planning processes (BERKE & KAISER 2006). Over the past few decades, LCM has been developed significantly, addressing urbanization issues and their related impacts in many fields (VERBURG et al. 2015). The use of LCM has created the opportunity to mold uncertain futures into more determined conditions via scenario planning. LCM has been increasingly used in flood resilience and climate change research and is an effective tool to evaluate future urban growth scenarios (BROWN et al. 2013). Scenario planning is strategic planning which links technologies into the management of uncertain futures through the creation of alternative forms of growth (RINGLAND & SCHWARTZ 1998). In urban planning, scenarios have been widely utilized for land use, transportation, economic development, environmental systems, and resilience (GOODSPEED 2017). Many LCM studies have forecasted urban growth scenarios and projected their impacts to identify optimal urban growth directions. Some have estimated climate change impacts on future urban growth, but such approaches are rare (SONG et al. 2017)

The LTM is a GIS-based tool used to predict land use to examine relationships between spatial driving factors and land use changes (PIJANOWSKI et al. 1997). The LTM has a similar process to other regression-based prediction tools, however, it uses machine learning to calculate complex patterns (PIJANOWSKI et al. 2002). Compared to other prediction models (e. g. logistic regression, SLEUTH, CLUE, etc.), the LTM has reported relatively higher prediction accuracies (LIN et al. 2011, PONTIUS et al. 2008). The LTM is an Artificial Neural Network (ANN) prediction model. ANNs recognize and classify complex behaviours and patterns (PI-

JANOWSKI et al. 2002) and have been popularly utilized for complicated and practical tasks in many fields including medicine, business, climatology, ecology, and geography. PIJANOWSKI et al. (1997) first introduced the LTM to simulate land cover change. The model has been 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). It has been applied in places such as Amsterdam, the Netherlands, Houston, TX, (KIM & NEWMAN 2019), Chicago, IL (LEE & NEWMAN 2017), Fort Worth, TX (NEWMAN et al. 2016), Beijing-Tianjin-Tangshan, China (KUANG 2011), and Tehran, Iran (PIJANOWSKI et al. 2009; PIJANOWSKI et al. 2014). Though it is considered highly accurate, the LTM's prediction process is time-consuming and its internal analytic structure and variable relationships can be difficult to interpret (BROWN et al. 2013).

3 Methods

The LTM synthesizes input drivers (factors contributing urban growth mapped as raster data) and input patterns (historic land cover raster images also mapped as raster data) by analysing the change between input patterns and linking the drivers of urbanization to this change (Fig. 1). Up to 250,000 training cycles are then ran to determine the best model fit. Using 15 proven input drivers (nine proximity variables including distance to waterfront, rivers, open space, highway, residence, commercial, central business district, existing urban areas, and public schools, and six density variables including slope, population density, population increase, employee numbers, poverty, and land value) contributing to urban growth, the LTM was used to predict urban growth by 2040 for the business and usual, growth as planned, and resilient growth scenarios. Three exclusionary layers were across each urban growth scenario. Exclusionary layers prohibit predicted growth in specific areas based on selected criteria and predicted future urban growth is only allowed outside of any exclusionary layer. The U.S. Geological Survey provided historic land cover data in raster images (30 × 30 m pixels). Hillsborough County provides the Tampa Comprehensive Plan 2040 with future land use data. To delineate future flood risk zones, the 100-year floodplain map from the Flood Insurance Rate Map (FEMA 2018) and future sea-level rise projection data from NOAA (USACE 2017) were used.

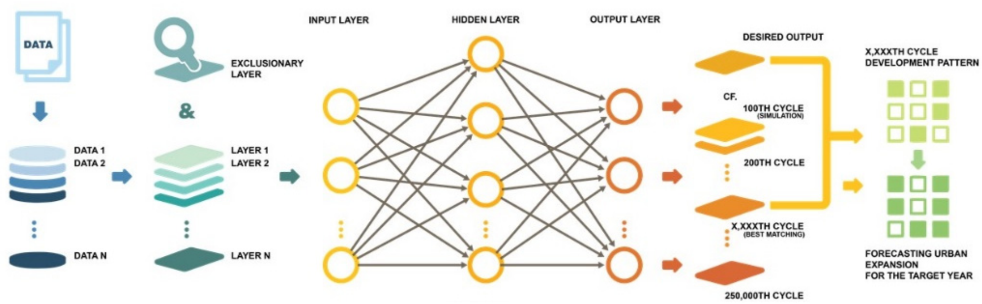

Fig. 1: LTM process for predicting urban growth

The four most common types of spatial statistical measures were used to validate predictions and calibrate the model to test its accuracy: percent correct metric (PCM), kappa coefficient, quantity disagreement & allocation disagreement, and area under curve (AUC) of receiver operating characteristic (ROC) (NEWMAN et al. 2016). All calibration outputs showed the model as acceptable or better according to the standards used in the literature (PONTIUS et al. 2008), with a 52.19 PCM reading, a 0.48 Kappa statistic, a 92.85 % for OA, and 0.74 in the AUC output. Urban growth predictions by 2040 per scenario were analysed according to the flood plain with sea level rise as dictated by the NOAA intermediate-high projection. Masterplans based on each scenario's predicted urban growth were then developed and different land use schemes were utilized to achieve each growth projection.

The Long-Term Hydrologic Impact Analysis (L-THIA) Low Impact Development Spreadsheet was used as a performance tool to measure impacts across each predicted/design scenario. The L-THIA is an urban growth analysis tool that is applied to estimate long-term runoff and nonpoint source pollution impacts of different land use development scenarios. It generates estimates of 14 types of non-point sources pollution loadings to waterbodies based on land use changes. The model has been used to track land-use change in watersheds for historical land-use scenarios (TANG et al. 2005), identify non-point source pollution areas and evaluate land use development for pollution management (BHADURI et al. 2000).

4 Results

4.1 LTM Output

Flood exposure calculations compare existing urban area with predicted future urban area through urban growth scenarios at city and neighbourhood levels. Urban flood exposure is calculated by overlapping existing urban and projected future urban scenarios with the delineated future flood risk zones. The current 100-year floodplain covers 90.9 km^2, or 30 % of Tampa's area. 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. Business as usual excludes existing urban areas, rivers and lakes, highways, airports, and parks from future development areas; growth as planned also excludes environmentally sensitive areas from the future land use (according to the comprehensive plan's policy); and resilient growth also excludes development within future flood risk zones (2040 SLR High and 100-year floodplain).

The result of urban flood exposure at the city level, shows that a large amount of current urban area (more than 20 %) is under the current 100-year floodplain. Future predicted urban development projects 30 % development of in the business and usual and 22 % in the growth as planned scenario within the current flood zone. NOAA's projection shows that the sea-level rise by 2040 in the study site varies from 0.18 m (low) to 0.62 m (extreme). Considering an intermediate-high sea level rise, 35 % of the predicted urban growth in the business as usual, 28 % in growth as planned, and 0 % in the resilient growth scenario would be within the 100-year flood plain (See Fig. 2). At the neighbourhood scale, within the design site, nearly 90% of the new growth would be in the floodplain, 83 % with the currently planned growth and only 5% in the resilient growth scenario (See Fig. 3).

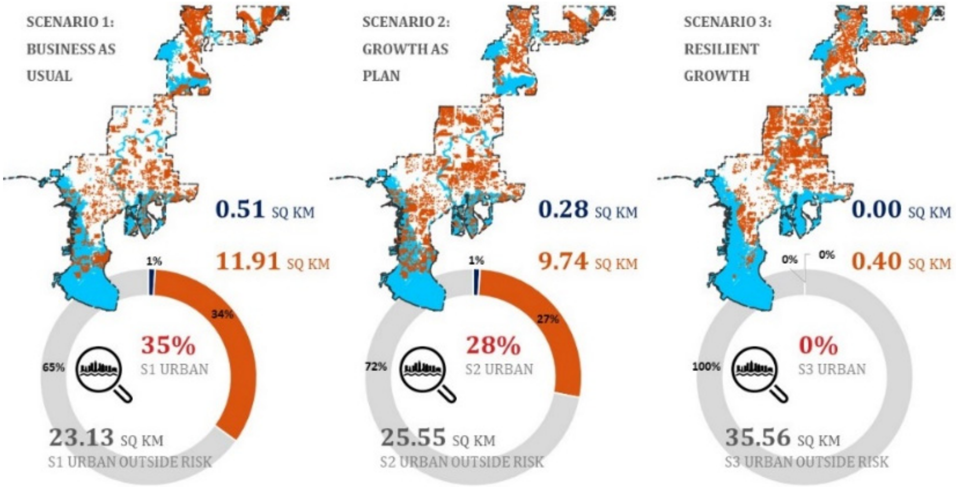

Fig. 2: Urban growth predictions and flood risk at the Tampa scale

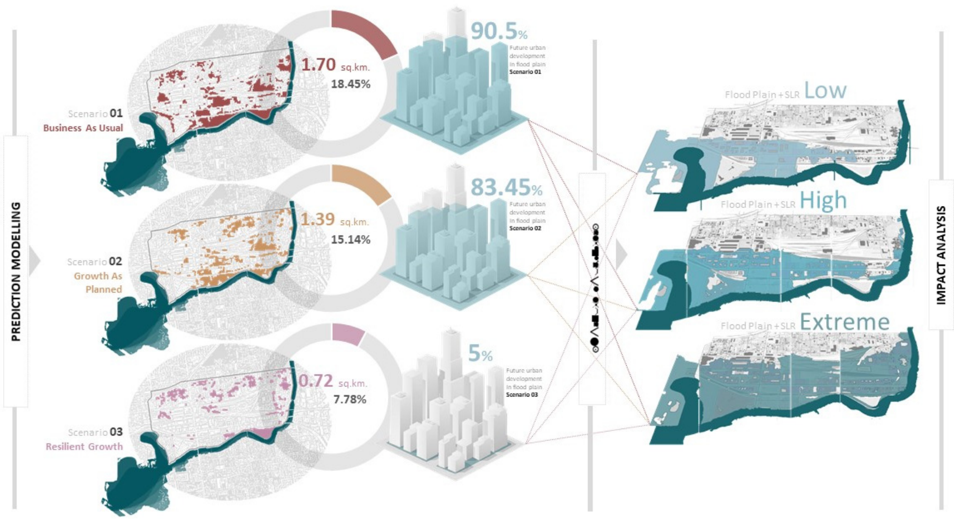

Fig. 3: Urban growth predictions and flood risk at the site scale

4.2 Neighbourhood Masterplans

The designs within the neighbourhood used the relative locations and amounts of the prediction outputs to inform development locations and land use arrangement. The transportation hierarchy remained the same across all design sites but densities and land use arrangements had to alter since the location of new development was restricted in certain areas in the growth as planned and resilient growth scenarios. Figure 4 shows the differences in land use percentages per scenario while Figure 5 show the master plan layouts.

Fig. 4: Land use breakdowns per design scenario

4.3 Design Impacts

The performance model outputs for the current conditions suggest that the business as usual scenario increases impervious surfaces, decreases green infrastructure area, increases area within high flood risk, and increases public exposure to contaminants/pollutants in surface runoff, compared to the other two scenarios. The L-THIA model outputs show an average of around 70 acre-feet of stromwater runoff decrease per scenario, with business as usual having the most runoff and resident growth having the least (Fig. 6). A similar trend is found when examining average runoff depth, with resilient growth decreasing the amount nearly by half when compared to business as usual. Compared to the current situation only resilient growth reduces runoff depth and volume, with all other scenarios increasing the rate. All 14 pollutants decrease significantly in the resilient growth scenario, compared to other scenarios. This reduction is nearly 30 % lower than the current situation. While growth as planned reduced pollutants compared to business as usual, both scenarios increase pollutant load in runoff compared to the current land use arrangement. While the resilient growth scenario appears to be a more optimal approach, construction/maintenance costs for low impact facilities and the increased densities to achieve the desired land use regulations can increase upfront costs. These costs are, however, lessened over time due to indirect benefits such as increased groundwater, increased carbon sequestration, decreased runoff, and decreased energy costs.

Fig. 5: Master plan for business as usual, planned growth, and resilient growth scenarios

L-THIA* LID Spreadsheet Result Table:

RUNOFF RESULTS		Current	S1	S2	S3
Avg. Annual Runoff Volume (acre-ft)		292.51	354.99	293.94	214.83
Avg. Annual Runoff Depth (in)		5.21	6.32	5.24	3.82
NONPOINT SOURCE POLLUTANT RESULTS		Current	S1	S2	S3
1	Nitrogen (lbs)	1218	1466	1222	886
2	Phosphorous (lbs)	334	398	334	240
3	Suspended Solids (lbs)	39296	48185	39053	26463
4	Lead (lbs)	8.586	9.022	7.057	5.17
5	Copper (lbs)	8.613	10.045	8.115	6.367
6	Zinc (lbs)	109.032	136.027	107.069	70.235
7	Cadmium (lbs)	0.739	0.85	0.698	0.506
8	Chromium (lbs)	5.059	6.793	4.775	2.855
9	Nickel (lbs)	7.356	10	8	5
10	BOD (lbs)	18640	23046	18980	13245
11	COD (lbs)	66336	87606	69713	45547
12	Oil & Grease (lbs)	4404	6021	4704	2960
13	Fecal Coliform (millions of coliform)	45378	51739	44328	33089
14	Fecal Strep (millions of coliform)	120272	141257	121329	90883
	Total Pollutant	296017.39	359890.74	299798.71	213403.13
			+21.58%	+1.28%	-27.91%

*L-THIA estimates changes in recharge, runoff, and nonpoint source pollution resulting from past or proposed development. In this basic model of L-THIA, users only need to input: their location (state and county); the type of soil in the area; and the type and size of land use change that will occur.

Source: https://engineering.purdue.edu/mapserve/LTHIA7/lthianew/tool2.php

Fig. 6: L-THIA outputs by scenario

5 Conclusions

This research asks, how effective is the current comprehensive plan in adapting urban growth to decreasing flood risk and pollutant load? It examined future urbanization using prediction modelling coupled with scenario planning to advance conditions for uncertain future climate change. The research used the city of Tampa, FL as an example to demonstrate a scenario matrix using urban growth and flood risk with SLR scenarios and impact analysis with scenario evaluation. Our findings show that the current future land use plan for Tampa may not be the best approach for dealing with climate change, in terms of urban flood exposure, stormwater runoff increase, and pollutant discharge. In the city scaled comparison of urban flood exposure, the future urban area according to the current plan would have fewer impacted urban areas by all future risk scenarios than the growth without development regulations, but much more urban flood exposure than the scenario with strong floodplain regulations. Moreover, at the neighbourhood level, the amount of runoff and pollutant load in the design site exposed to flood risk in planned growth is larger than in resident growth and higher than the current status. Thus, the current land use plan may be not well-prepared enough to achieve resilient communities, when compared to other urban growth simulations.

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