

Article

# Climate Change Preparedness: Comparing Future Urban Growth and Flood Risk in Amsterdam and Houston

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**Abstract:** Rising sea levels and coastal population growth will increase flood risk of more people and assets if land use changes are not planned adequately. This research examines the efficacy of flood protection systems and land use planning by comparing Amsterdam in the Netherlands (renown for resilience planning methods), with the city of Houston, Texas in the US (seeking ways of increasing resilience due to extreme recent flooding). It assesses flood risk of future urban growth in lieu of sea level rise using the Land Transformation Model, a Geographic Information Systems (GIS)-based Artificial Neural Network (ANN) land use prediction tool. Findings show that Houston has currently developed much more urban area within high-risk flood-prone zones compared to Amsterdam. When comparing predicted urban areas under risk, flood-prone future urban areas in Amsterdam are also relatively smaller than Houston. Finally, the increased floodplain when accounting for sea level rise will impact existing and future urban areas in Houston, but do not increase risk significantly in Amsterdam. The results suggest that the protective infrastructure used in the Netherlands has protected its future urban growth from sea level rise more adequately than has Houston.

**Keywords:** urban growth; flood risk; land use change model; land transformation model

## 1. Introduction

“Observed temperature increases due to climate change since the 1950s are unprecedented; the atmosphere and ocean have warmed, the amounts of snow and ice have diminished, and sea level has risen” [1]. The National Oceanic and Atmospheric Administration (NOAA) reports that regarding future sea level rise (SLR) scenarios, global mean sea level will rise between 0.2 meters and 2.0 meters by 2100 [2]. Simultaneously, global populations project to grow from 7.6 billion in 2017 to 9.8 billion by 2050 with 68% of the world population living in urban areas by 2050 [3]. Currently, more than 600 million people live in coastal areas, less than 10 meters above sea level, and nearly 2.4 billion people live within 100 km of the coast [4]. Rising sea levels due to climate change will make global coastal cities more vulnerable to floods. Growing populations and urban expansion can worsen climate change conditions and enlarge hazard impacted areas, if land use changes are not planned adequately.

As computer systems and technological capabilities have advanced, many scientists/planners use land change modeling (LCM) to help account for uncertain future land use modifications. LCM is system that supports land use prediction capabilities and integrates them into the planning process [5]. Understanding historic land development processes to better predict future circumstances helps support urban planning for potential future flood risk mitigation. Over the past few decades, LCM has been used to significantly contribute to addressing the challenges of urbanization and estimating its potential impacts [6–8]. However, few studies have integrated urbanization research with both climate

change and flood risk [9,10]. Of the rare studies that have, these studies are also limited to single locations and single growth prediction scenarios.

This research fills this research gap by examining two coastal cities and estimating the efficacy of their land use planning methods regarding future flood risk and urban growth projection using the Land Transformation Model (LTM). The study areas under investigation, Amsterdam in the Netherlands and Houston in the US, confront both SLR and population growth. The Netherlands is well-known for their flood protection strategies (though much of its land is below sea level) and consistently lead the charge in urban resiliency with plans to upgrade their flood control infrastructure to combat SLR [11]. Contrarily, Houston has suffered from flood events periodically (most recently, the historic flood in 2017 by Hurricane Harvey), and is in need of more comprehensive resilience planning to help counteract flooding from future hurricanes and other flood hazards. Using these two case sites, this research assesses and compares the flood risk of predicted future urban growth in lieu of SLR.

## 2. Literature Review

### 2.1. LCM

#### 2.1.1. Urban Prediction Models

Urban prediction modeling began in 1974 with the Markov model using a stochastic process for characterizing previous land use change patterns [12]. Many new prediction models were introduced by the 1990s and early 2000s including: CUF [13], Cellular Automaton [14], Land Use Scanner [15], What IF [16], CLUE (Conversion of Land Use and its Effects) [17], LTM [18], Slope, Land use, Exclusion, Urban extent, Transportation and Hillshade (SLEUTH) [19], and Urban Sim [20]. Afterwards, performance and calibration methods were developed to assist in increasing prediction accuracy. By 2010, many hybrid tools were created by combining each various technique including statistical regressions, machine learning, cellular automata, exogenous quantity, and pure pixels [21].

The four most current popular prediction models are SLEUTH, artificial neural network (ANN), Markov, and CLUE. The SLEUTH model (formerly the Clarke Urban Growth model), uses a cellular automaton procedure on a gridded map to analyze and forecast change [14]. The SLEUTH model reveals four types of urban growth patterns: spontaneous, diffusive, organic, or road-influenced [19]. The LTM is an ANN-based land change prediction model using Geographic Information Systems (GIS) [18]. Due to ANN's capabilities in non-linear models, the LTM can be applied to natural, social, economic, and political factors. However, its primary limitation is that the LTM does not reveal the causal relationships between each factor used regarding their effect on urban growth [22]. The Markov model uses a stochastic process [12] to describe the probability of change from non-urban to urban land within a given time [23], following continual historic trends [22]. A transition matrix summarizes the probability results, and a cellular automaton simulates the matrix into a spatial map. The CLUE model predicts land use change based on empirical relationships between land uses 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 [24]. CLUE was initially developed for national scale land use predictions [17], and CLUE-S was developed for land change at small scales such as watersheds and provinces [25]. Dyna-CLUE (dynamic) and CLUE-Scanner are also both more advanced versions of the CLUE model.

#### 2.1.2. Urban Growth Scenarios

Many prediction model-based studies deal with a single study area using multiple scales: a district, a town, a city, a watershed, a country, and/or the world. Research examining multiple cities has primarily only predicted urban growth patterns or tested prediction capabilities. Few studies have estimated urbanization's impact comparing more than one or multiple cities. Yirsaw et al. (2017)

estimated future urban impacts on ecological value [26], and He et al. (2015) assessed climate change impacts on future urban areas [27]. Both articles were based on Chinese contexts and considered multiple adjacent cities within a region, but their results were presented at a regional scale. However, Nor et al. (2017) examined the effect of master planning on urban expansion and green space in Kuala Lumpur, Malaysia, Jakarta, Indonesia, and the Metro Manila, Philippines [28]. They evaluated development policies of three city's plans by comparing different growth patterns and influence on green infrastructure. The reason there is little multiple-location research is typically due to data availability.

Many studies have forecasted urban growth scenarios to identify optimal future growth directions for cities. Most of these studies used future growth scenarios such as “business as usual”, “compact development”, and “environmental protection”. Each scenario is defined below:

- “business as usual:” same growth pattern as previous growth pattern [29,30]
- “compact development:” controlling development density [29]
- “environmental protection:” restricting development location beyond environmentally sensitive areas [31]

Most urban growth scenarios considered measures such as urban density [29,31] and economic growth [9,32] when developing “compact development”. Inversely, “environmental protection” scenarios are typically based on the amount of ecological areas preserved or species richness [30,31,33]. Most studies use the “business as usual” scenario approach in that they assume current land use patterns will continue along their present trajectories. Few studies integrated comprehensive plans for managed/planned growth into their scenario analyses; from the few that have, most have used future development areas in regional development plans [34,35]. To create different scenarios using LCMs, there are three general approaches: pixel number control for density (compact or loosen), location control by exclusionary layers, and driving factor influence control by using different driving factors or weighting driving factors. Those methods are applied differently depending on prediction models, driving factors, and purposes.

### 2.1.3. Increasing LCM Accuracy

The primary topics in the literature about urban prediction studies are related to the introduction of new models, forecasting future urban growth, and examining urban growth-related impacts. As noted, in the early 2000s, a series of new prediction models (e.g., CA, CUF, CLUE, LTM) were introduced. Calibration methods for each model were also developed (although some have been scrutinized) to help comparing prediction accuracy among each different model. 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 [21]. 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 regarding quantity and allocation, compared to other existing models [36]. Lin et al. (2011) justified prediction model performance and examined previously unknown relationships between driving factors and land use change by testing the model performance among logistic regression, auto-logistic regression, and neural networks [37]. New hybrid models, combining prediction tools and calibration methods, are still being developing to find a best-fit model.

### 2.1.4. The LTM

The LTM is a spatial tool used to predict land use relationships between spatial driving factors and land use changes with GIS and a machine learning process known as an ANN [38]. The LTM has a similar process to other regression-based prediction tools to observe relationships; however, it uses a machine learning approach with neural networks to calculate complex patterns [14]. Compared to other prediction models (e.g., logistic regression, SLEUTH, CLUE, etc.), the LTM performs with a

higher prediction accuracy [21,37]. Pijanowski et al. (2001) tested the LTM in Michigan's Grand Traverse Bay Watershed with growth driving factors: transportation, landscape features, and urban services [39]. 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 Modular Hydrologic Model to calculate groundwater conditions and ground/surface water interactions. Then Pijanowski et al. (2005) examined the future eastern Lake Michigan watershed for urban sprawl impacts on the environment: the hydrological budget, exported nitrogen, and deforestation [40]. Later, its calibration tools were developed [41], and they enhanced the performance of application with national scale data [42].

The model has been popularly applied in different locations, scales, and scenarios for forecasting urbanization, vacancy [43–45], deforestation [46,47], and loss of agriculture [48]; a city scale in San Pablo City, the Philippines [49], Chicago, the US [44], and Fort Worth, the US [45]; a regional metropolitan scale in the Beijing-Tianjin-Tangshan metropolitan, China [50], and the Tehran metropolitan, Iran [51]; and a nation scale in the US [42]. The forecasted results, sequential effects from urbanization, have been linked to other models: climate [52,53], water quantity and pollution [54–58], and soil erosion [59].

### 2.1.5. LCM and Flood Risk

Some research has combined future urban growth with other subsequent impacts (e.g., ecologic, hydrologic, flood inundation, food production, and soil erosion), but only a small amount. The LTM, although thought to be one of the most accurate models due to its ANN capabilities, has not been used to assess urban growth regarding future flood risk and SLR. Lu et al. (2016) evaluated landscape ecological security using different spatial scenarios in Huangshan City, China [6]. Wu et al. (2015) tested hydrologic impacts from potential land changes with the Soil and Water Assessment Tool in the Heihe River Basin, China [7]. Lin et al. (2007) assessed the impact of land cover change on surface run-off in the Wu-Tu watershed in Taiwan [60]. Zare et al. (2017) and Hansen (2011) delineated future urban flood risks based on the SLR in coastal areas [8,61]. 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 [8]. Each of these aforementioned research articles exposed the negative results of future urban expansion in high flood risk zones.

Some flood related research has calculated the future urban growth area impacted by future flood risks as a measure for possible climate change impacts. When examining flood risk, most studies used SLR scenarios in 2030, 2080, or 2100; some have also examined future river-flood probabilities [9] or existing flood maps as measures for flood risk increase [10]. Zhao et al. (2017) examined future urban growth with the SLR scenarios, (low/medium/high) in 2030 and 2080 [62]. 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 [29]. Te Linde et al. (2011) predicted economic growth scenarios for the Rhine River's flood probability by 2050 [9]. 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 [10]. For analyses, all the above articles used total flood damage areas as a measure for increased flood risk examining a single location; two articles [9,10] used a monetary calculation for the impacts based on the damage areas identified by the prediction models.

## 3. Literature Gaps and Research Questions

Over the past few decades, LCMs have significantly developed prediction models and their capabilities. This has allowed them to be applied to diverse fields to address different challenges posed by urbanization. Most LCM studies present models' prediction capabilities or examine subsequent impacts of urban growth on ecology, hydrology, flood, soil, food security, or wildfire. However, these studies are limited in that prediction models repeatedly create similar scenarios in a single location rather than being compared across cases [30,33]. Although land use planning and planning policies are influential determinants for future land change, few studies have considered regional or

comprehensive plans to create prediction scenarios [63,64], and no flood related studies examined multi-city comparison.

To fill these gaps, this research will examine the efficacy of flood protection systems and land use planning with future urban growth prediction and flood risks in Amsterdam, the Netherlands compared to the city of Houston, US. It assesses flood risk of future urban growth in lieu of SLR to determine how the future of each city would be impacted by climate change. It answers the questions; (1) how much urban land will be endangered by future flood risk in each city by the year 2040 when considering SLR? and (2) how will the flood-vulnerable area differ in each city from 2010 to 2040?

## 4. Methods

### 4.1. Study Areas

To justify the efficacy of land use plan and flood protection for future flood risks, this study examines coastal cities whose population is increasing. Amsterdam in the Netherlands with a legally binding land use plan prepared by the local government [65] and Houston in the US with no city comprehensive plan are used for comparative purposes. Amsterdam is the capital city of the Netherlands, located in the province of North-Holland. The area is 196.9 km<sup>2</sup>. The city population is predicted to grow from 790,110 in 2012 to 869,808 in 2040 [66]. Houston is located on the Gulf of Mexico coastline, and the land area is 1733.3 km<sup>2</sup>. The Texas Water Development Board [67] forecasts that the Houston population will catapult from 2,240,974 in 2010 to 3,073,268 by 2040.

In the Netherlands, safety from flood disasters is a national issue [68]. Responding to flooding in 1953, the Delta Plan was created to divide the Netherlands into a series of dike rings [69], or geographical units enclosed by flood protection structures (e.g., dikes, and natural/artificial dunes) [10]. Thousands of dikes have now been constructed to control water levels, and they are designed with different safety standards, flood probabilities, and in-levee capacities according to population density. These capacities include high-density areas with 10,000-year flood probabilities, and less dense areas with 4000 year or 2000-year flood probabilities [69]. After the flooding due to high water discharge in 1993, 1995, and 1998 [70], the government developed a “room-for-the-river” policy, enlarging river capacity, and allowing them to hold more water [71,72]. Since 2010, the National Delta Plan Program has used a new strategy, called a “multi-layer safety approach”. This approach requires (1) protection by dikes and dams, (2) sustainable spatial design, and (3) disaster management [69]. For Amsterdam, the City Vision Plan 2040 [66] requires green infrastructure to control future preservation areas and to limit new construction areas [66]. As shown in Figure 1, though the city meets the North Sea, the regional dikes (e.g., Afsluitdijk and Houtribdijk), dike rings, dike upgrade plan, and the vision plan enable the city to be virtually free from SLR impacts.

In contrast, Houston does not have zoning and is the only major city in the US which does not regulate land use in such a manner [73,74]. Development is governed by city codes without addressing land use [75]. The public minimally restricts development, and private sectors (e.g., investors, developer, planners) and business organizations such as the Chamber of Commerce have driven urban development in Houston [74]. This “laissez-faire” context has limited initial infrastructure provisions by the public sector such as sewers, roads, health, education, and parks [74]. The Harris County Flood Control District (HCFCD) has been in charge of flood damage reduction since 1935 [76]. The district’s mission is to devise flood damage reduction plans, to implement these plans, and to maintain their infrastructure. The HCFCD has been implementing structural (e.g., channel modification, stormwater detention, bypass modification, levee) and non-structural (e.g., buyout) flood reduction tools as well as conducting infrastructure maintenance. However, Houston has been negatively impacted by many flood events periodically, and SLR from the Gulf of Mexico and its feeder riverine systems creates an additional challenge.

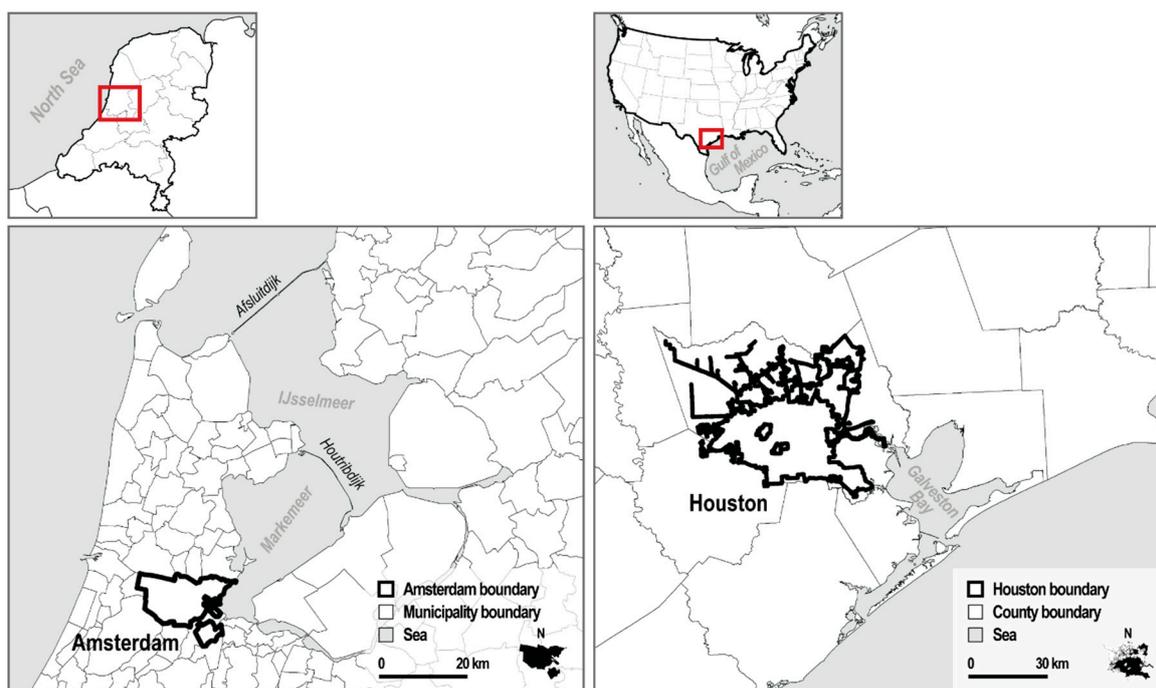


Figure 1. Location of study areas.

Both countries use flood risk maps in different ways. The Netherlands adopted provincial risk maps which are based on extent of flooding, maximum water depth, and maximum flow rate; these maps were developed by the European Union Directive on Flood Risks in 2007. The extent of flood risk is classified into three flood probability types: likely chance (1/10 per year), medium chance (1/100 per year), and small chance (1/1000 per year) [77]. The risk maps are combinations of numerous scenarios on coastal and riverine flood including dike breach [70,77]. In the US, the Flood Insurance Act of 1968 established the US National Flood Insurance Program to reduce the impact of flooding on the private and the public [78,79]. The 100-year floodplain, one percent flood probability in any given year, was adopted as a regulatory threshold [78], and has been a planners' standard for identifying flood risk zones in the US.

#### 4.2. Process

To answer these research questions, this research follows a specific process; (i) forecasting future land use changes in Amsterdam and Houston, (ii) geo-processing the SLR floodplain by 2040 for Houston, and (iii) identifying impacted areas of the predicted urban growth in the 2040 floodplain.

Future land use change by 2040 is forecasted using the LTM; it uses relationships between spatial predictor drivers (such as natural, built environmental, and socio-economic factors) and predicted cell change to analyze how much each factor influences future land use change [18,45]. The land use is predicted based on historic growth patterns. Due to existing land cover data availability, the Amsterdam LTM uses 2006 and 2012 land cover maps while the Houston LTM uses maps from 2001 and 2011 (see Figure A1). For future development areas in Amsterdam, current open spaces are excluded according to the land use plan in the City Vision Plan 2040. This is done to ensure that the forecast follows the city's land use plan. In Houston, state parks and current parks are excluded for future urban forecast, meaning the forecast follows the business as usual approach. The future flood risk in 2040 is spatialized with 3ft and 6ft SLR scenarios from NOAA by adding projected SLR increases to the base elevation of the 100-year floodplain [79,80] for Houston. The current 1/100 flood extent [77] is used for Amsterdam since there are no sea level risk impacts on Amsterdam because of the dike system in place. Due to Amsterdam's strong flood protection systems, the current flood risks will remain as future flood risks, but Houston's flood zones will enlarge as the SLRs. As flood

hazard zones enlarge, they are more likely to impact larger urban areas. However, this depends on the location of current and future urban areas as well as the infrastructure in place to help mitigate flood risks. The inability to decrease flood risk area will put both more of the population at risk as well as increase damages to homes during times of flood. In this research, therefore, future flood impacted areas are calculated from the forecasted land use change and the future flood risks.

#### 4.2.1. Model Reliability and Accuracy (Calibration)

Calibration is the statistical difference between the observation and the prediction [110,111]. It is important to show the goodness of fit with appropriate accuracy measures in a spatial prediction model since no best measure exists, and each represents different ways [112]. However, it does not exist a universal calibration tool, so this research uses four types of accuracy measures; percent correct metric (PCM), kappa coefficient, quantity disagreement and allocation disagreement, and area under curve (AUC) of receiver operating characteristic (ROC). Each are equally important in the literature and help measure different aspects of model accuracy.

PCM is the percentage of the cells correctly predicted to change divided by the total cells actually changed during the study period [18,45]. Kappa is a widely used index in accuracy assessment, and it is the proportion of agreement after removing chance agreement [113,114]. It is the value of observed proportion correct divided by perfect agreement with no change agreement. It varies from 1, when observed agreement is perfect agreement, to 0, when observed agreement is expected agreement [115]. In the evaluation of calibration 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 [44,115,116].

Due to claims of a geographical limitation of the Kappa index, quantity disagreement and allocation disagreement were introduced [117]. Quantity disagreement is the difference in changed cell numbers without considering location, and allocation disagreement is the spatial difference in transition [44]. Overall agreement can be drawn by removing the quantity disagreement and allocation disagreement. An overall agreement (OA) of more than 85% is considered good [44]. 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 [118,119]. 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 [44,120]. The area under the ROC varies from 0.5 with random assignment to 1.0 with perfect probability [121]. 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 [122].

#### 4.2.2. Drivers and Prediction Process

This study employs drivers of urban growth, including natural, built environment, and socio-economic drivers based on the literature as shown in Table 1. Due to data availability and different site contexts, the two cities use different driving factors to forecast future urban growth; in total, there are 12 driving factors used, with five common factors and seven differing between two models. Previous prediction literature shows that there is a numerous and broad amount of driving factors in land use change prediction, varying up to 20 or more factors [83]. Also, previous research used different driving factors depending on factorial influence, geographic location, prediction models, and data availability. Thus, this research uses major prediction variables used in previous literature for each city under investigation, and different site-specific variables in each city according to condition and data availability. This research uses all proven drivers identified in previous research; the references for each variable used to assist in prediction are listed in Table 1.

**Table 1.** Driving Factors of Urban Growth Prediction and Related Literature for the Data Collection.

Input Factors	Input Patterns		Explanation	Reference for Input Factors	
	Amsterdam	Houston			
Natural Environment	Water	✓	✓	Proximity to water surface Yirsaw et al. (2017) [26], Liu et al. (2016) [81]	
	Sea	✓		Proximity to sea Jafari et al. (2016) [82], Allen and Lu (2003) [83]	
	Floodplain		✓	Proximity to 100-year floodplain Nourqolipour et al. (2016) [84], Nourqolipour et al. (2015) [85], Conway (2005) [86], Bright (1992) [87]	
Built Environment	Highway	✓	✓	Proximity to highways Yao et al. (2017) [88], Samie et al. (2017) [89], Ke et al. (2017) [90], Hansen et al. (2017) [91], Samardžić-Petrović et al. (2016) [92], Lu et al. (2016) [6], Han et al. (2015) [93]	
	Roads		✓	Proximity to roads Yirsaw et al. (2017) [26], Losiri et al. (2016) [94], Liu et al. (2016) [81], Jafari et al. (2016) [82]	
	Bus Routes		✓	Proximity to bus routes Nourqolipour et al. (2016) [84], Zheng et al. (2015) [95], Fuglsang et al. (2013) [96], Yuan (2010) [97]	
	Railway	✓		Proximity to railways Lu et al. (2016) [6], Gallardo (2016) [98], He et al. (2015) [27], Han et al. (2015) [93]	
	Dike	✓		Proximity to dikes Nourqolipour et al. (2016) [84], Nourqolipour et al. (2015) [85]	
	Park	✓	✓	Proximity to parks Loonen and Koomen (2009) [99], Pettit and Pullar (2004) [100]	
	Business	✓	✓	Proximity to business Nourqolipour et al. (2016) [84], Nourqolipour et al. (2015) [85]	
	Recreation	✓		Proximity to recreational space Nourqolipour et al. (2016) [84], Nourqolipour et al. (2015) [85], Tang et al. (2005) [55]	
	Commercial	✓		Proximity to commercial Feng et al. (2016) [101], Munshi et al. (2014) [102], Plata-Rocha et al. (2011) [103]	
	Residential	✓		Proximity to residential Zhao et al. (2017) [62], Kavian et al. (2017) [104], Pijanowski et al. (2002) [18], Schotten et al. (2001) [105]	
	Urban		✓	Proximity to existing urban Jafari et al. (2016) [82], Allen and Lu (2003) [83]	
	Hospitals		✓	Proximity to hospitals Zheng et al. (2015) [95], Plata-Rocha et al. (2011) [103]	
	Schools		✓	Proximity to schools Ku (2016) [106], Zheng et al. (2015) [95]	
	Socio-Economy	Population Density	✓	✓	Population density in 2000 Samie et al. (2017) [89], Hansen et al. (2017) [91], Losiri et al. (2016) [94], Zhen et al. (2014) [107]
		Household	✓		Household numbers Losiri et al. (2016) [94], Landis (1995) [108]
Race			✓	White population ratio Hu and Lo (2007) [109]	

As Figure 2 and Table 1 show, distance to highways, water, parks, business, and population density are the common variables used in both cities’ prediction models. For Amsterdam, distance to railway, sea, dike, recreation, commercial, residential, and household numbers in a neighborhood are employed. Most proximity variables for Amsterdam are from the land use data in 2006 from the Central Statistics Office [123]. The GIS shapefile for the Amsterdam dike is from the Risk Data [77]. Population density and household numbers are from the Census [123]. For Houston, distance to roads, existing urban, public transportation routes, race, hospitals, public schools, and floodplain are used. Proximity variables are from the Houston Galveston Area Council and the City of Houston GIS Open Data Portal [124], and socio-economic data is from the Census Bureau [125].

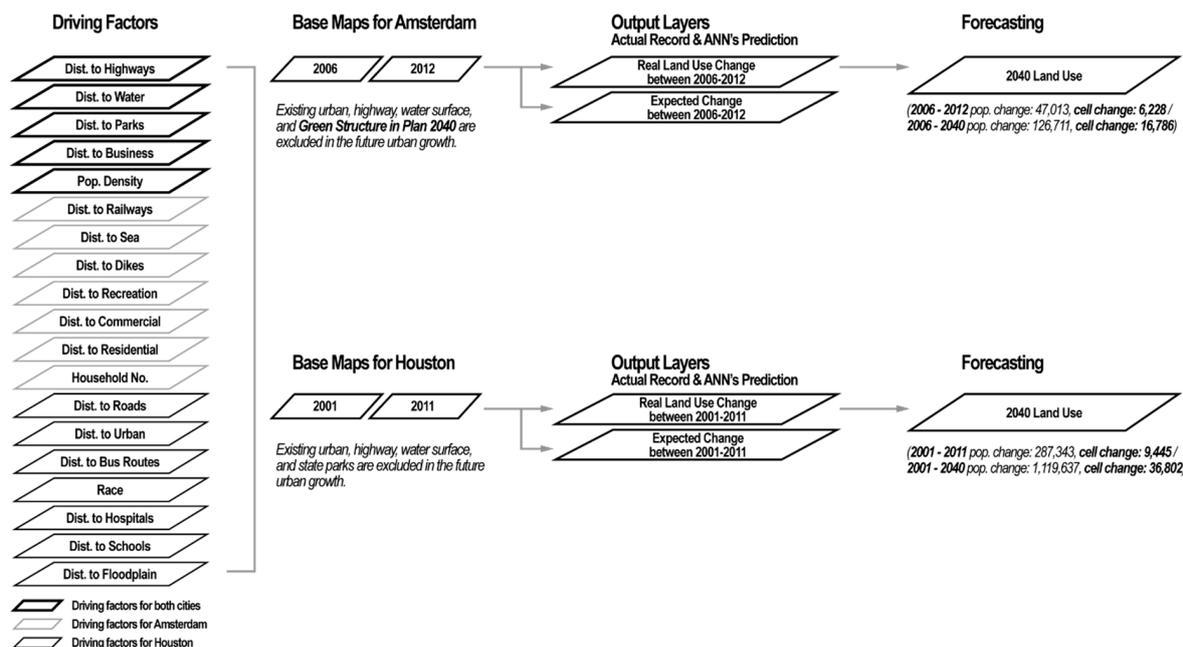


Figure 2. Driving factors, base map, output comparison, and forecasting for Amsterdam and Houston.

For base maps, Amsterdam uses 2006 and 2010 land use shapefile data, and Houston uses 2001 and 2011 land cover raster data from the US Geographical Survey, due to data availability. After running the LTM prediction for 2011, the expected changes are compared to the real land use changes in the output layers stages. Then, the highest matching cycle is selected to predict future land use 2040 according to the ratio of pixels to the estimated population referred as forecasting.

#### 4.2.3. Variable Justification

Commuting time and cost to work space are key factors which influence residential location. Providing highway and road networks ensures suburban areas access to metropolitan regions. Repeatedly, fringe development expands according to population growth [126]. Infrastructure development (e.g., roadways, sewage, water line, etc.) is also a key implication for a future development [126]. Cost-efficient commuting alternatives (e.g., railway, metro, bus), distance to public transportation options are also determinants of urbanization [127]. Despite these factors, urban area increases primarily due to growing populations. Rising income and shortened commuting time and cost can also influence urbanization patterns [128,129]. Another major phenomena is racial segregation [130], as the separation of racial classes within the built environment [131] has been shown to affect urban development patterns [132].

Public facilities, providing community service and value become attractive for development and redevelopment [5]. Accessibility to public facilities and institutions have been used as determinants

(or anchors) for development [95,127,133]. Mieszkowski and Mills explained that high quality of schools reflected quality of neighborhood, and they can attract other households [127].

People also prefer to live close to nature and are willing to pay more money for purchasing land nearer to open space. From a real estate perspective, land values closer to waterfront, river, lake, and open space is higher than the values in further distances to such amenities [134–139]. Land value is a major determinant of land use [140,141]. Neighborhoods with both high and low land values can have some development potential. Density and agriculture productivity have been shown to influence land value. Denser areas and more productive agriculture have typically higher land values and increased density and high land value have been shown to be positively related to one another [128,142].

Finally, land use planning and policies are direct methods for growth management. Urban development should be controlled to channel growth where development is proper and protect critical green space where preservation is necessary for natural resource [143,144]. Management methods can include building permits, development rights, zoning, urban growth boundaries, tax incentives, and impact fees [141,145].

## 5. Results

### 5.1. Predicted Urban Areas

As shown in Figure 3, forecasted model calibration outputs are measured to validate the accuracy of the prediction model; PCM: 82%, Kappa Statistic: 75%, OA: 89%, and Area Under the ROC Curve: 87%. All calibration levels show a very good level of prediction in Amsterdam. Houston calibration outputs show PCM: 52%, Kappa: 41%, OA: 82%, and Area under the ROC Curve: 71% with all an acceptable or good level of prediction. The reason for the slightly lower calibration outputs in Houston, may be due to the fit of driving factors and the prediction scale. There, of course, could exist other factors contributing to future urban growth that may not have been available spatially. However, the differences are minimal in both models and each model proved to be fit for predicting according to the series of proven calibration methods used. The prediction scale closely relates to the ratio between predicting pixel and population pixel numbers; Amsterdam predicts 6228 urban pixels out of 126,711 population pixels between 2006 and 2012, and Houston predicts 9445 urban pixels out of 1,119,637 population between 2001 and 2011. The 90,000-person projected population increase [66] in Amsterdam would cause urban growth primarily the western periphery of the city. The increased urban areas between 2012 and 2040 would be 9.6 km<sup>2</sup>, 5% of the total Amsterdam area. The over 832,000-person population increase [67] between 2010 and 2040 in Houston would expand urban area mainly in the south-east portion of the city and the suburban areas closer to the urban edge. The increase in urban areas projects to be 273.6 km<sup>2</sup>, 16% of the total Houston area.

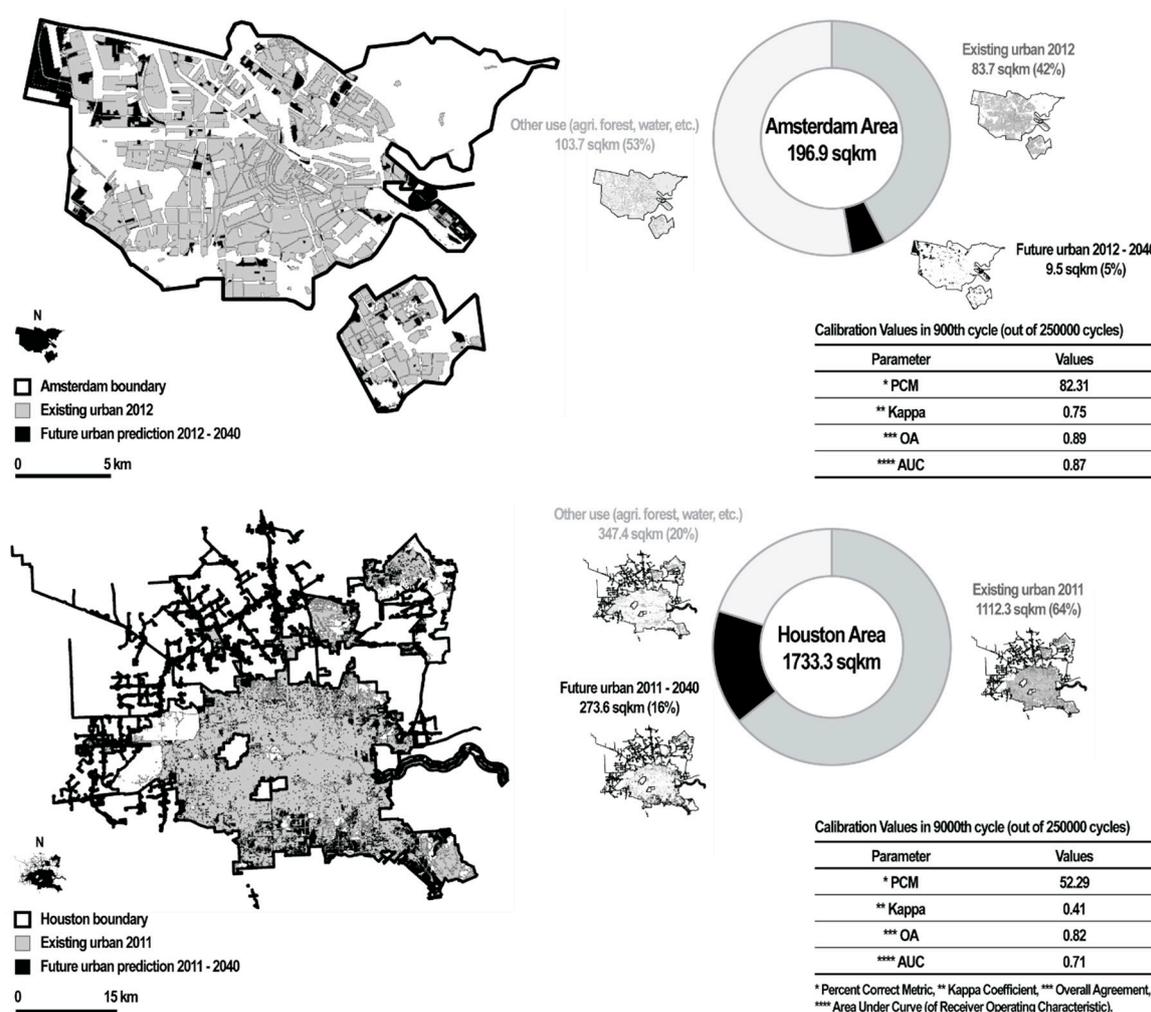


Figure 3. Existing and future land use change in 2040.

### 5.2. Future Flood Risk

In Amsterdam, the 1/10 flood probabilities (likely chance) occupies less than 1 km<sup>2</sup> of area, but the 1/100 and 1/1000 flood risk areas occupy 16.5 km<sup>2</sup> (9%) and 114.9 km<sup>2</sup> (48%) of Amsterdam, respectively. In Houston, the 100-year floodplain occupies 443.27 km<sup>2</sup>, which is 25.6% of the total Houston area. A 3ft SLR would enlarge the floodplain 457.20 km<sup>2</sup> (26.4%), 10 km<sup>2</sup> more than the current floodplain, and a 6ft SLR would expand the floodplain into 489.05 km<sup>2</sup> (28.2%), 46 km<sup>2</sup> more its current size (see Figure A4). As noted, the future flood risk areas in Amsterdam remains 9% of the city with SLR, but Houston’s flood risks would enlarge from 25.6% (the current 100-year floodplain) to 26.4% with a 3ft SLR and 28.2% of a 6ft SLR scenario. Due to Houston’s relatively flat terrain, SLR through the connected bayous would enlarge 2.6% (46 km<sup>2</sup>) more floodplain in an extreme SLR scenario.

### 5.3. Current/Future Urban under Flood Risk

The difference in calculation methods of flood probability in the Netherlands and the 100-year floodplain in the US makes it difficult to compare both cities flood risk directly. Therefore, this study compares the 1/100 flood probability for Amsterdam to the 100-year floodplain in Houston and its increase due to climate change projections. This similarity of risk in comparison increases the generalizability of findings.

The results (see Figures 4 and 5) show that existing and future urban areas of both cities are impacted by increased flood risk. However, the 100-year floodplain in Houston effected by future SLR so depending on SLR scenarios the flood risk areas would be increased.

The 1/100 flood probability of Amsterdam (see Figures 4 and A2) impacts 4.6 km<sup>2</sup> of total land, current and in the future; 2.4 km<sup>2</sup> (3%) of existing urban and 2.1 km<sup>2</sup> (22%) of predicted urban areas. In Houston, SLR will enlarge the 100-year floodplain (see Figure A4). The expanded floodplain will place more urban area under flood hazard zones. As Figures 5 and A3 show, the current 100-year floodplain occupies 217.1 km<sup>2</sup> of total and predicted land; 166.7 km<sup>2</sup> of existing and 50.5 km<sup>2</sup> of future urban. In the SLR scenarios, the projected 2040 SLR in the extreme scenario case (+3ft) permanently occupies 6 km<sup>2</sup> of existing (3.4 km<sup>2</sup>) and future urban area (2.6 km<sup>2</sup>). When the 3ft SLR and the 100-year floodplain are combined, 228.5 km<sup>2</sup> (13%) of Houston is under high flood risk: existing urban 175.9 km<sup>2</sup> (15.8%), and future urban 52.6 km<sup>2</sup> (19%). When examining the projected 6ft SLR, 254.3 km<sup>2</sup> (25.8 km<sup>2</sup> more land than the 2040 SLR case) is under flood risk: existing urban 196.0 km<sup>2</sup> (17.5%), and future urban 58.3 km<sup>2</sup> (21%).

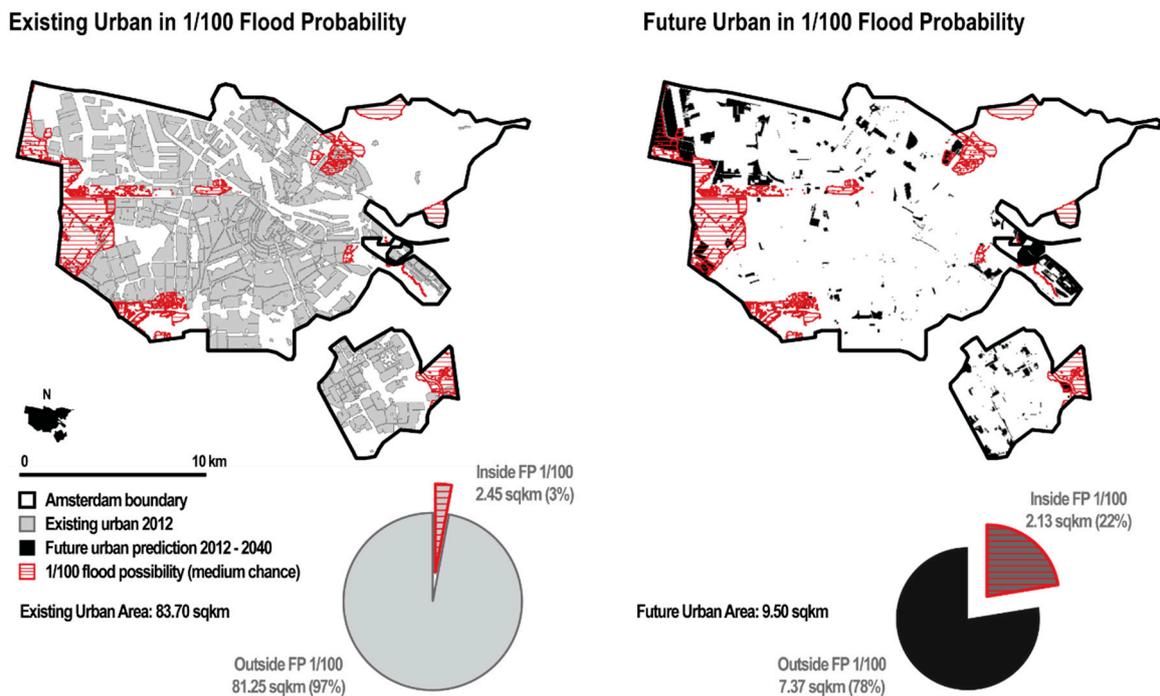


Figure 4. Existing and future urban under flood risk in Amsterdam.

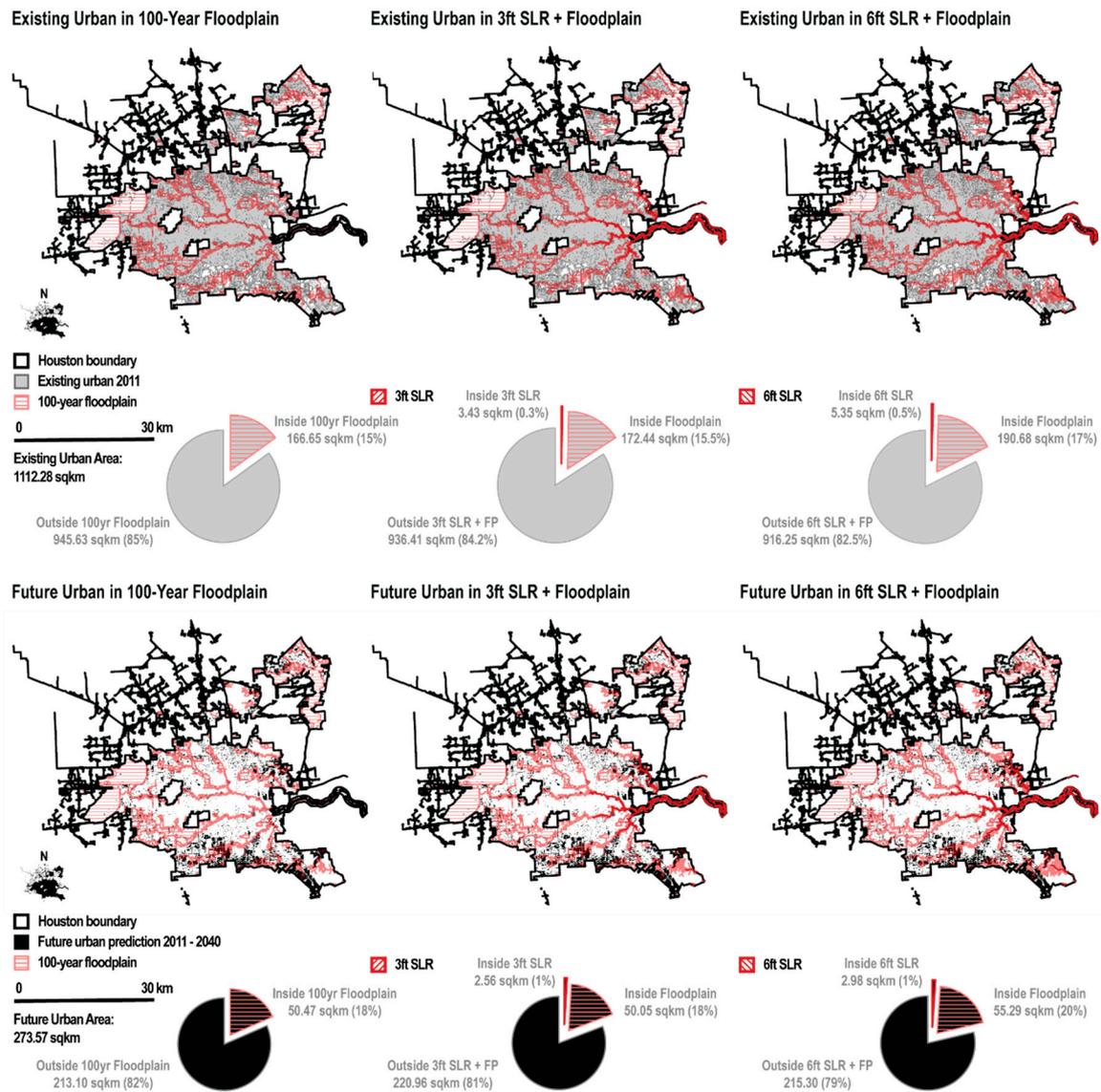


Figure 5. Existing and future urban under flood risk in Houston.

There are three salient findings when comparing the two cities. First, Houston has already placed too much urban development within the current flood-prone zone, compared to Amsterdam. When comparing existing urban areas, only 1.3% (2.5 km<sup>2</sup>) of Amsterdam, is under a 1/100 flood risk, but 9.6% (166.7 km<sup>2</sup>) of Houston is under the 100-year floodplain. Also, when considering future urban growth by 2040 in Houston, flood-prone areas would increase to 217.12 km<sup>2</sup> under the 100-year floodplain. This number raises to 228.48 km<sup>2</sup> under a 3ft SLR scenario, and 254.3 km<sup>2</sup> under a 6ft SLR scenario. Political circumstances in Houston requiring no zoning regulations promote low density sprawl and limited flood protection infrastructure in Houston [74]. If the current development patterns continue, more new development would be within the flood risk area as predicted (Figure 5).

Second, when considering predicted future urban area under flood risk, flood-prone future urban areas in Amsterdam are relatively smaller than Houston. This may be due to the development control in the Amsterdam City Vision Plan 2040. The portions of future development in flood risk are similar in both cities: 22% under 1/100 flood probability in Amsterdam and 19% under future flood risk (+3ft SLR) in Houston. However, when considering the larger size of Houston, the actual flood-prone future urban area in Amsterdam is much smaller than Houston with 52.61 km<sup>2</sup> in Houston and only 2.13 km<sup>2</sup> in Amsterdam.

Third, the increased floodplain by SLR would impact existing and future urban area in Houston, but not in Amsterdam. The water-level of bayous and streams will be raised due to SLR and this will enlarge existing and future urban area in Houston. However, existing dike rings and dike upgrade plans make Amsterdam safer from the effects of sea.

## 6. Discussion

This study forecasts future urban growth prediction, projects future flood risk by climate change, and identifies potential flood risk areas in Amsterdam and Houston. It justifies the efficacy of land use planning and flood protection systems by comparing Amsterdam with Houston to help prepare future comprehensive plans for flood protection. This will guide urbanization direction for both cities, but especially, planners in Houston can use the results to identify where future urban areas would be exposed to future flood risks. Furthermore, this study can be a basis for Houston to employ the Dutch flood protection ideas to make more resilient coastal communities.

The findings show, in Houston, a large amount of existing urban area has been built in the current 100-year floodplain and much future urban development is expected to occur. When wetlands convert to impervious surfaces, the flood damage increases due to lost water storage capabilities [146]. To minimize flood damage, more efficient and effective flood protection tools (e.g., structural, non-structural) should be planned and implemented to manage the floodplain or reduce its size. Zoning regulations and green infrastructure provisions should be considered to control new development and to protect preservation areas [143,144]. The sea level is rising; Houston will be impacted by it through its bayous connected to the Gulf of Mexico. The projected 3ft SLR does impact a large amount of urban area, and, moreover, 6ft or more SLR increase in the future will greatly exacerbate the land under flood risk in Houston. To minimize the climate change impacts, city and regional agencies need to consider grand idea such as inclusion of state or multi-state dikes and levees, similar to the Netherlands. For Amsterdam, the City Vision Plan clearly identifies future development areas, but some existing urban or future development is located within the 1/100 flood probability zone. The plan needs to explore mitigation strategies for development within these identified areas.

While this research takes an important step to analyze both future urban prediction and flood risk, further research is still needed on flood risk estimation and urban areas exposed to flood risk. We used the current 100-year floodplain and 3ft and 6ft SLRs scenarios provided by NOAA to identify future flood risk zones. If future increased impervious surfaces are integrated within the SLR floodplain prediction, a much larger urban land area amount could be within the enlarged floodplain [78]. As Gori et al.'s urbanization and hydrologic study in Houston, TX shows, land change has increased surface run-off, and future urban growth will expand the future 100-year floodplain by 12.5% in 2050 [147]. For a more accurate risk analysis, future studies need to consider an updated floodplain based on the predicted urban growth. In the future impact calculation, the result shows potential future damaged urban area and location exposed to future flood risks. This does not mean that all the identified areas will be flooded in the future. It only shows risk of flooding. Depending on preparation of plan policies and other flood protection measures, the results could differ.

**Author Contributions:** Conceptualization, Y.K. and G.N.; methodology, Y.K. and G.N.; software, Y.K.; validation, Y.K.; formal analysis, Y.K. and G.N.; investigation, Y.K. and G.N.; resources, Y.K.; data curation, Y.K. and G.N.; writing—original draft preparation, Y.K.; writing—review and editing, G.N.; visualization, Y.K.; supervision, G.N.; project administration, G.N.; funding acquisition, G.N.

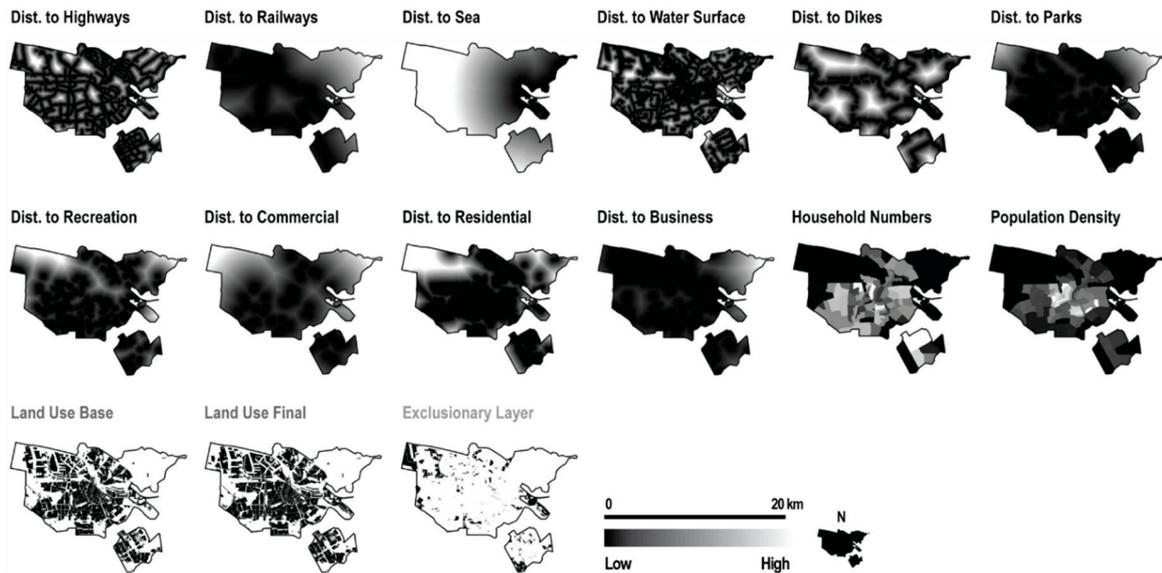
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**Conflicts of Interest:** The authors declare no conflict of interest.

Appendix A

**Amsterdam Raster Datasets**



**Houston Raster Datasets**

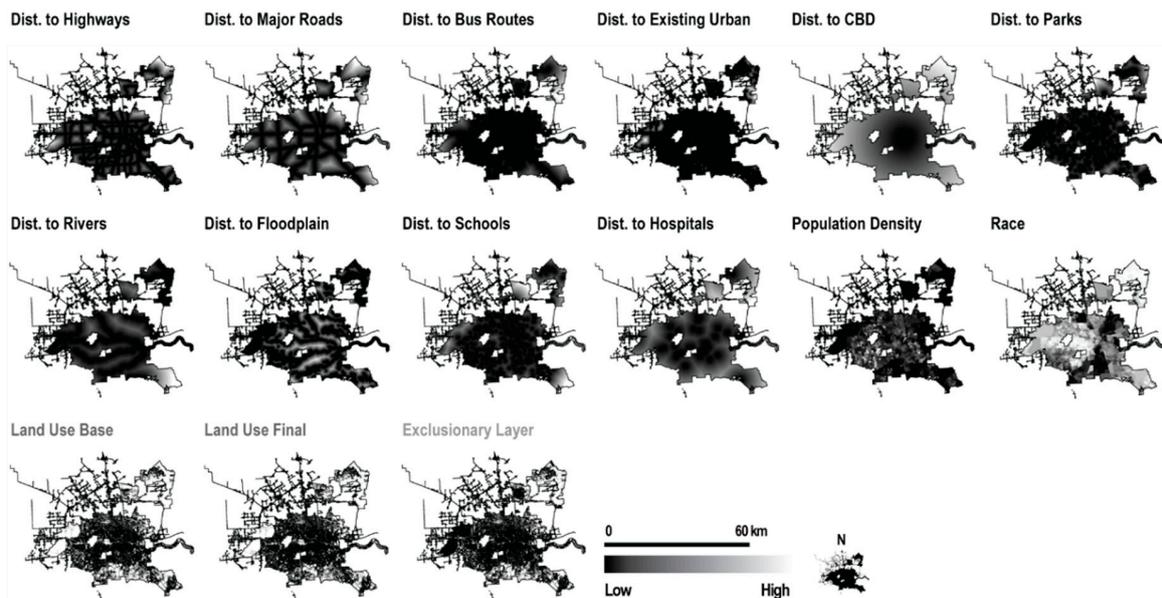
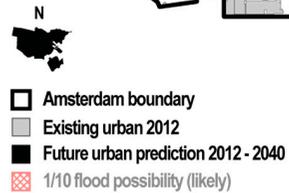
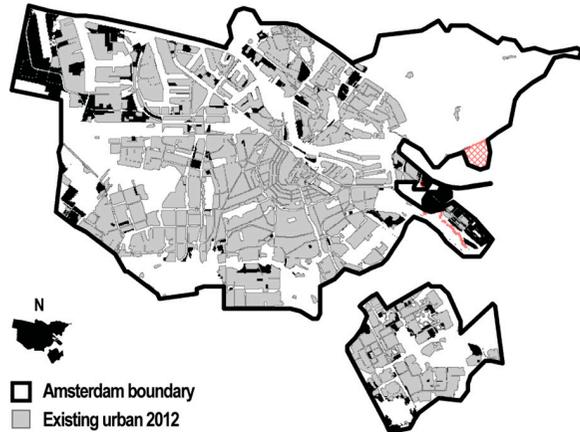


Figure A1. Raster images of driving factors, base maps, and exclusionary layers.

Appendix B

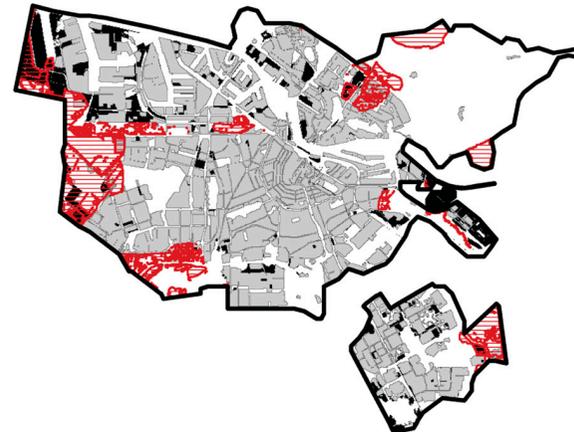
1/10 Flood Probability



0 10 km

Amsterdam Area: 196.90 sqkm

1/100 Flood Probability



1/1000 Flood Probability

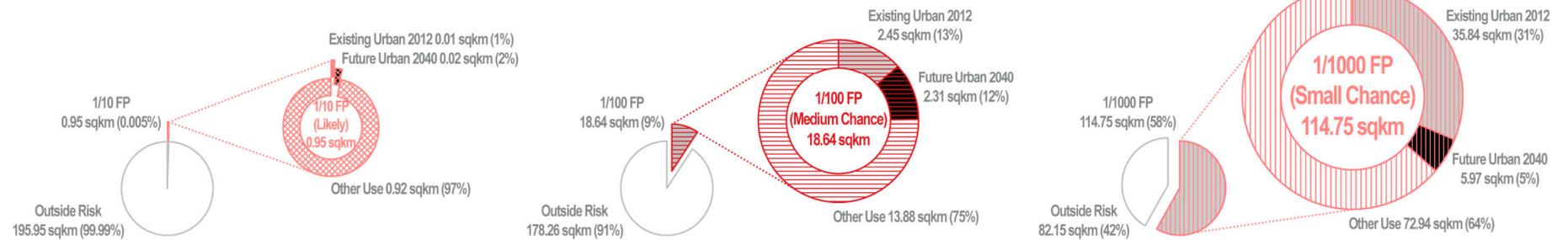
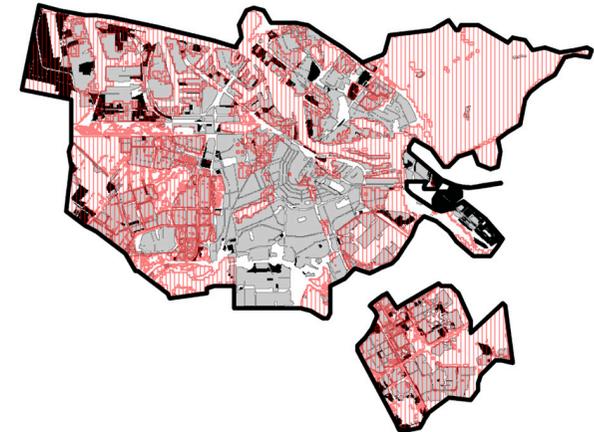
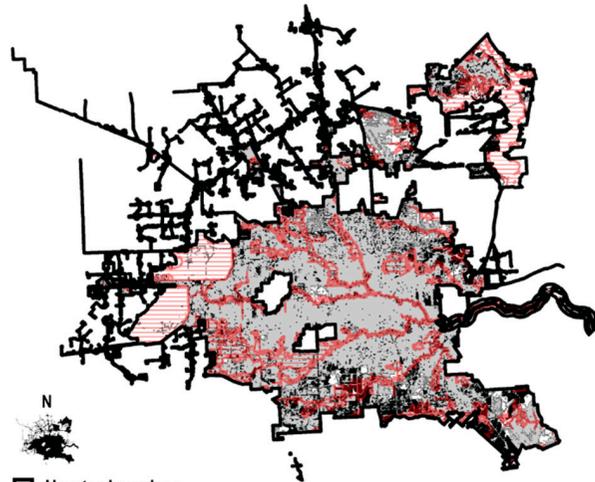


Figure A2. Existing and future urban in flood risks (1/10, 1/100, and 1/1000 flood probabilities), Amsterdam.

Appendix C

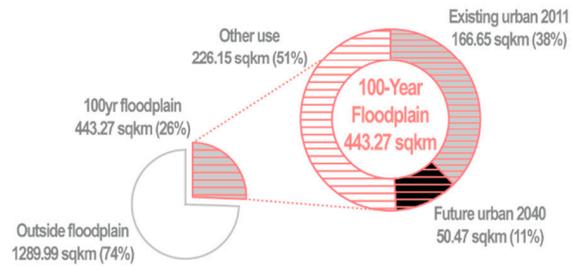
100-Year Floodplain



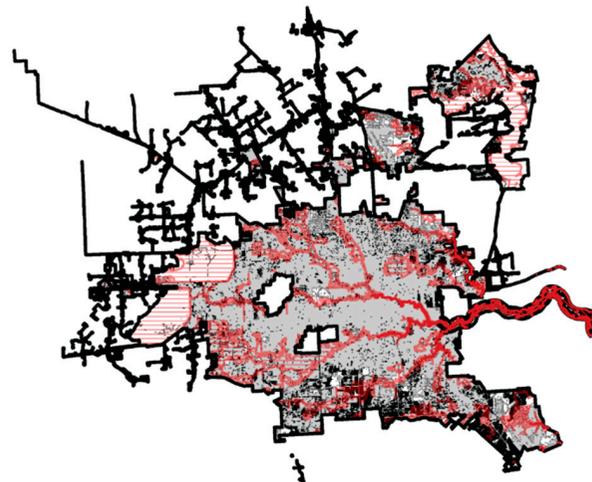
- Houston boundary
- Existing urban 2011
- Future urban prediction 2011 - 2040
- ▨ 100-year floodplain

0 30 km

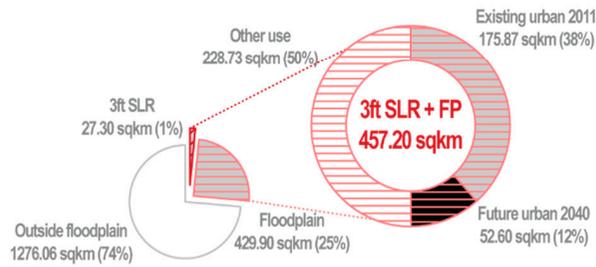
Houston Area: 1733.26 sqkm



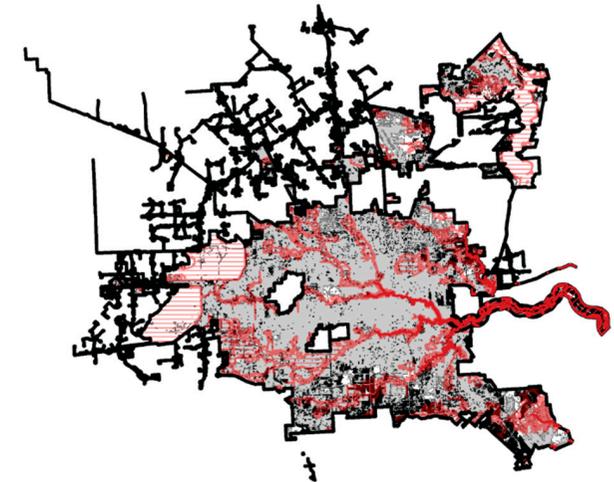
3ft SLR + Floodplain



- ▨ 3ft sea-level rise



6ft SLR + Floodplain



- ▨ 6ft sea-level rise

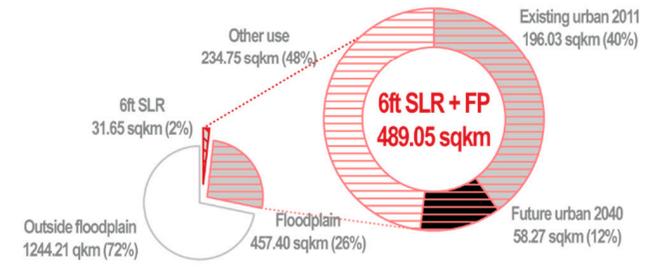


Figure A3. Existing and future urban risk in flood risks (100-year floodplain and SLR scenarios), Houston.

Appendix D



Figure A4. Flood risk in Amsterdam and Houston.

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