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SPECIAL ISSUE PAPER

The impact of Hurricane Katrina on urban growth in Louisiana: an analysis using data mining and simulation approaches

Yi Qiang and Nina S.-N. Lam

Department of Environmental Sciences, Louisiana State University, Baton Rouge, Louisiana, USA

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ABSTRACT

Understanding human dynamics after a major disaster is important to the region's sustainable development. This study utilized land cover data to examine how Hurricane Katrina has affected the urban growth pattern in the Mississippi Delta in Louisiana. The study analyzed land cover changes from non-urban to urban in three metropolitan areas, Baton Rouge, New Orleans-Metairie, and Hammond, for two time periods, pre-Katrina (2001–2006) and post-Katrina (2006–2010). The study first applied a focal filter to extract continuous urban areas from the scattered urban pixels in the original remote sensing images. Statistical analyses were applied to develop initial functions between urban growth probability and several driving factors. A genetic algorithm was then used to calibrate the transition function, and cellular automata simulation based on the transition function was conducted to evaluate future urban growth patterns with and without the impact of Hurricane Katrina. The results show that elevation has become a much more important factor after Hurricane Katrina, and urban growth has shifted to higher elevation regions. The elevation most probable for new urban growth increased from 10.84 to 11.90 meters. Moreover, simulated future urban growth in this region indicates a decentralized trend, with more growth occurring in more distant regions with higher elevation. In the New Orleans metropolitan area, urban growth will continue to spill across Lake Pontchartrain to the satellite towns that are more than 50 minutes away by driving from the city center.

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Mississippi delta; coupled natural-human dynamics; cellular automata; genetic algorithm; Hurricane Katrina; coastal sustainability

1. Introduction

Due to the rich natural resources, convenient transportation, and high recreational value, the coast tends to attract more people than the inland areas. According to the 2010 Census data, 39% of the total population in the United States is living in counties directly on the shoreline and the population density in these coastal counties is more than four times the average population density of the whole United States (U.S. Census Bureau 2011). In recent years, increasing attention has been paid to coastal regions due to their high exposure and vulnerability to natural hazards. A critical challenge facing

CONTACT Yi Qiang yqiang1@lsu.edu Department of Environmental Sciences, Environment, Coast and Energy Building, Louisiana State University, Baton Rouge, Louisiana, 70803, USA

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these vulnerable coastal regions is how to cope with these threats and achieve sustainability especially under the threat of climate change and sea level rise. Understanding the issue of sustainability in the coastal regions requires systematic and thorough analyses of how the human and natural systems interact. As one of the most important indicators of the processes on the earth surface, land cover changes manifest the dynamic interactions between human and natural systems that lead to the alteration of the landscape. Thus, analyzing land cover changes could provide useful insights into the sustainability issue in the coastal regions (Bajocco *et al*. 2012, Mendoza-González *et al*. 2012, Qiang and Lam 2015). In particular, urban growth patterns derived from land cover data can indicate the spatial and temporal variations of human dynamics that may affect a region's long-term sustainability. Modeling urban growth using observable land cover data can help identify the factors that influence sustainability and guide appropriate planning and policy-making (Mahiny and Clarke 2012).

Like most other deltaic regions in the world, the Mississippi Delta has been facing both large-scale, rapid-moving disturbances such as hurricanes and storm surges, and chronic, slow-moving processes such as land subsidence, sea level rise, and the gradual reduction of key ecosystem services. In particular, significant land loss over the years has threatened the low-elevation areas in the region, prompting the question of whether the low-lying deltaic region is sustainable given the impending threat of sea level rise (Lam *et al*. 2009a). On the other hand, during the last decade (2000–2010) there was a steady population growth in the northern part of the region, which is of higher elevation, in contrast with a decline in the southern part where most areas are near or below sea level. This contrasting pattern of population growth and decline between the North and the South may have been accelerated after the strike of Hurricane Katrina in August 2005 (Lam *et al*. 2009b, 2012). The main research questions posted in this study are: how has Hurricane Katrina affected the region in terms of human migration and relocation, what are the factors affecting such human dynamics, and what would the future trend look like under different scenarios?

The goal of this study is to evaluate the impact of Hurricane Katrina on human dynamics in the Mississippi Delta in Louisiana, and to answer the research questions posted above. Unlike the typical studies on human dynamics that focus on individual people movement, this study takes a broad view of human dynamics and examines the cumulated effects of human dynamical activities through a time series of remotely sensed data. We hypothesize that people and businesses became more aware of the factor of elevation and coastal vulnerability after Hurricane Katrina, and they responded by relocating to a nearby region that has higher elevation, which resulted in more urban growth in the northern part of the Mississippi Delta. Such transformation of urban growth pattern reflects human response to natural disasters, which can help us understand the dynamic interactions between human and the changing environment. The findings from this study should increase our understanding of the factors affecting the long-term sustainability in this vulnerable coastal region, as well as other similar deltaic regions in the world. The information will also help decision-makers to better plan for the region especially under the threat of climate change and sea-level rise.

However, the research questions posed are complex and addressing them requires a number of spatial analytical methods. This study demonstrates the use of land cover change data to detect the long-term human dynamics in response to a major disaster in

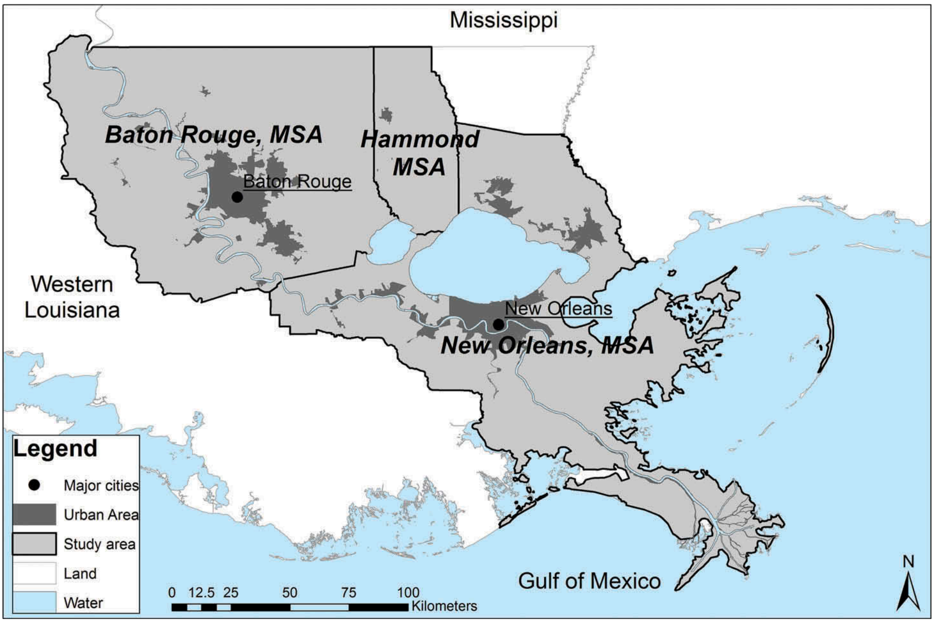

Figure 1. Study area.

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a vulnerable coastal region. Specifically, the study uses land cover change data before and after Katrina to analyze and model urban growth in three metropolitan areas in the Mississippi Delta region (Figure 1). Urban growth in this study refers to a pixel changing from non-urban to urban land cover in a timeframe. First, a smoothing filter is applied to the original land use and land cover data to eliminate noise and detect the general trend. Second, statistical analysis is conducted to examine the relationships between urban growth probability and a number of variables. The difference in statistical relationships before and after Katrina is analyzed. These relationships are then combined into a transition function to model the integrated effect of the variables on urban growth probability. Third, the statistical function is further calibrated by a genetic algorithm (GA). Fourth, the calibrated GA function is applied into a cellular automaton (CA) to simulate urban growth with and without the impact of Katrina. Urban growth patterns and relationships with other variables are then compared between these two periods, aiming to uncover the impact of Hurricane Katrina on urban development in this region.

2. Related work

A considerable amount of work has been conducted in modeling land cover change in general and urban growth in particular. Urban growth is considered a complex and non-linear process driven dynamically by many forces interacting with the surrounding environment. Cellular automata (CA) models, which can be used to dynamically update the status of land cells according to both global forces and local neighborhood conditions, have become the most frequently used spatial modeling framework for urban growth (Clarke *et al.* 1997, 2007, Batty 2007, Schweitzer *et al.* 2011). Moreover, due to its spatial nature, CA can be easily built on raster data and implemented in a geographical information system for further display and analysis (Couclelis 1997, Wagner 1997). In CA modeling, the key challenge is on the derivation of implementable and credible rules to model how the driving forces influence urban growth. In the early years, the transitional rules are developed from expert experience and are manually calibrated by visual comparison between simulated and test sets (Ward *et al*. 2000), which is labor intensive and error-prone. Later, statistical methods such as logistic regression (Wu and Webster 1998, Sui and Zeng 2001) and principal components analysis (Li and Yeh 2002) are used to derive and quantify the relative importance of different variables to urban growth. However, these statistical approaches have inherent weaknesses in handling complex relations and interdependent variables.

To analyze the complex relationships, a variety of data mining techniques have been applied to calibrate the transition rules of land cover change and urban growth. Heuristic algorithms have been used to automatically generate or calibrate functions to describe the non-linear and complex transition functions, which have yielded higher accuracy in urban growth calibration (Lin *et al*. 2011). Based on their explanatory ability, these data mining techniques can be classified into either black-box or white-box approach. The former includes artificial neural networks (Li and Yeh 2001, Qiang and Lam 2015) and support vector machines (Yang *et al*. 2008), which can build functions from ground zero but lack transparency on the mechanism that transfers the input into output. The white-box approach includes methods such as genetic algorithms (Stewart *et al*. 2004), simulated annealing (Feng and Liu 2013), and ant colony optimization (Liu *et al*. 2012), which are used to calibrate the parameters of the transition function that explicitly describes the relationships between urban growth probability and individual variables. Although the white-box approaches are more useful for explaining the urban growth mechanism, they require an initial transition function, which is generally derived from prior knowledge. In urban growth modeling, a transition function usually includes a growth suitability component, which is a linear combination of a number of global forces that drives urban growth, and a neighborhood component, which models the effect of the local neighborhood (Wu 2002, Li *et al*. 2007, Feng and Liu 2013, García *et al*. 2013). Although this form of function has been widely adopted in urban growth modeling (Li *et al*. 2007, Feng and Liu 2013, García *et al*. 2013), in some cases appropriate transformations are needed to describe the complex (e.g. non-monotonous) and heterogeneous relationships between variables and urban growth suitability. In this study, instead of linearly combining the variables, different statistical functions are applied to examine the relationships between urban growth probability and variables. Then, a genetic algorithm, a non-linear data mining technique, is applied to fine-tune the relationships between variables and urban growth probability.

3. Study area and data

3.1. *Study area*

The study area consists of three adjacent metropolitan statistical areas (MSAs) located in the Mississippi Delta in southeastern Louisiana, including Baton Rouge, New Orleans-Metairie, and Hammond (Figure 1). The MSAs are delineated by the United States Office of Management and Budget (OMB). An MSA is one or more adjacent counties in which

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Table 1. Population changes and elevation of the three MSAs in the study area.

Metropolitan statistical area	2001 population	2010 population	Population change (2001–2010)	Avg. elevation (meter)
New Orleans-Metairie, LA	1,311,062	1,173,572	−10.5%	3.11
Baton Rouge, LA	709,897	804,568	13.3%	22.82
Hammond, LA	101,541	121,460	19.6%	34.89

at least one urban core area has a population of at least 50,000. Adjacent counties are included in an MSA if they have a high degree of social and economic integration as measured by commuting to work. The three MSAs in this study occupy 15% of the total Louisiana land area and have 47% of Louisiana's population, which is the most urbanized area in Louisiana. The Baton Rouge and New Orleans-Metairie MSAs are the two largest urban concentrations in Louisiana. Hammond MSA, located between Baton Rouge and New Orleans-Metairie, was newly added to the MSA list due to its high population growth in the past decades. The inclusion of Hammond is necessary as it provides a continuum between Baton Rouge and New Orleans. Also, it may offer an alternative urban growth location because of its higher elevation and its proximity to New Orleans. Table 1 shows the populations, population changes between 2001 and 2010, and the average elevation of the three MSAs. Baton Rouge and New Orleans-Metairie are located in very different natural landscapes and have diverse socioeconomic structures. New Orleans-Metairie MSA is near the Gulf coast and Lake Pontchartrain and has an average elevation of 3 meters (m) above sea level, whereas Baton Rouge MSA is located farther inland at the tip of the Mississippi River Delta and has an average elevation of 22.8 m above sea level. New Orleans is the largest city and is deemed as the commercial center in Louisiana, while Baton Rouge is the state capital that has stronger governance and administrative functions. The southern area near New Orleans is considered highly vulnerable to coastal hazards, including land subsidence, flooding, oil spills, and hurricanes (Lam *et al*. 2009a, 2009b, 2012). As Table 1 shows, population of the New Orleans-Metairie MSA has declined 10.5% between 2001 and 2010, while the population of the other two MSAs has increased 13.3% and 19.6%, respectively.

3.2. *Urban growth*

The LULC data of the study area were obtained from NOAA Coastal Service Center under the Coastal Change Analysis Program (C-CAP). These data were classified from Landsat-5 Thematic Mapper (TM) images through extensive field sampling, validation, and standard quality-control review procedures, which have guaranteed high classification accuracy and consistency (Dobson *et al*. 1995). The spatial resolution of these data is 30 m by 30 m. The C-CAP data use the USGS classification scheme (Anderson *et al*. 1976), which includes seven LULC classes in the study area, including urban, agriculture, rangeland, forest, water, wetland, and barren. For this study, the C-CAP land cover data were reclassified into urban (urban in the original classification) and non-urban (all other types). There are 26,778,265 pixels in the study area.

The resulting urban and non-urban classification shows a very fragmented and scattered pattern in the study area, particularly in the low-density urban area (Figure 2a). Instead of using the urban raster at the original 30 × 30 m pixel resolution,

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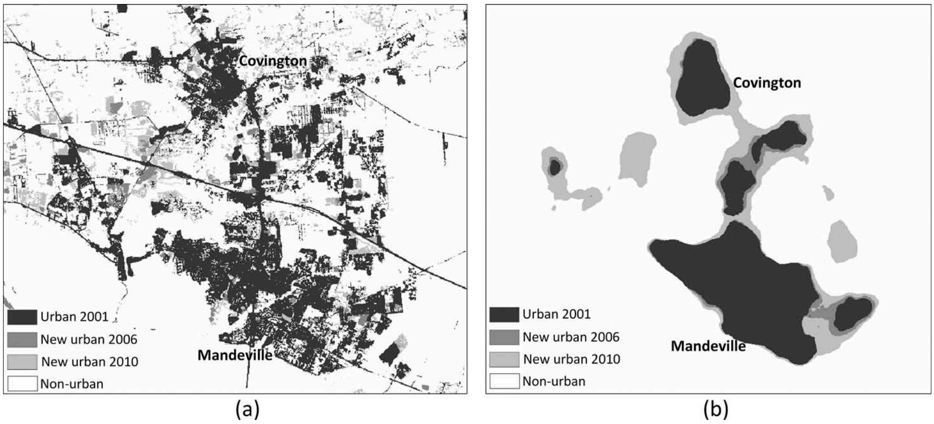

Figure 2. A comparison between the original urban raster (a) and filtered urban raster (b).

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a focal filter was applied to smooth out the scattered urban pixels. The focal filter searches for a circle area with a 33-cell (990 m) radius. The central pixel is defined as a continuous urban pixel if more than half of the pixels within the search area are urban (Figure 2b). The rationale of applying a focal filter and the criterion to define continuous urban pixel are based on the following. First, applying a focal filter helps in eliminating noise and identifying the general trend of urban growth and its relationships with other variables especially for a large study area like this study. This practice of smoothing is similar to the common practice of applying a smoothing filter after spectral image classification to reduce the salt-and-pepper effect (Lillesand *et al.* 2015). Through smoothing, a more continuous urban expansion emerges. Factors of local interactions are expected to be less important, whereas factors of broader-scale urban expansion may be more readily revealed, which would help in the modeling and simulation in this study. Second, the rule that a pixel is considered urban if more than half of the pixels in the filter are urban is similar to the majority rule commonly used in image processing. Third, modeling with the filtered urban area can significantly reduce the computational time needed for urban growth modeling for a large study area like this study. In the remainder of this article, urban pixels refer to the continuous urban pixels after the filter. Currently, NOAA has published C-CAP LULC data covering the study area at four time points, including 1996, 2001, 2006, and 2010. This study focuses on the urban growth during the two most recent time intervals, 2001–2006 and 2006–2010, which can be considered approximately as pre- and post-Katrina periods.

3.3. *Variable selection*

Urban growth is a complex phenomenon and it depends on numerous factors, which may vary across space and time and at different scales (Verburg *et al.* 2004). For example, the factors of urban growth of a developed country can be very different from those of a developing country. Also, some factors that are significant at a local scale may not be significant at a regional scale. In this study, the variables selected for the modeling are based on the literature on urban growth modeling (Wu 2002, Batty

2007, Li *et al*. 2007, Feng *et al*. 2011) and our hypothesis, which is guided by the literature in coastal vulnerability, resilience, and natural and human dynamics (Lam *et al*. 2009b, 2012, 2015, Qiang and Lam 2015). We hypothesize that people and businesses became more aware of the factor of elevation and coastal vulnerability after Hurricane Katrina, and they responded by relocating to a nearby region that has higher elevation. After preliminary testing with a number of variables that have potential effects on urban growth, three variables – distance to city cores, elevation, and proximity to primary roads – were identified as having significant relationship to the urban growth probability in this region.

3.3.1. *Attractiveness of major cities*

Most cities tend to grow in an agglomerative manner to take advantages of the high concentration of resources, labor, and capital in the city center. This tendency results in a sprawling growth pattern which can be observed in major cities around the world (Batty *et al*. 2003). There is a general trend that urban growth is more likely to occur near the urban cores. Following the gravity model in geography, an urban core can be considered as the gravity center that attracts new urban development in the surrounding area, and such attractiveness gradually decays in space. In the study area, the two largest cities, Baton Rouge and New Orleans, can be considered as the gravity centers that have high population and economic concentration. Because of their different geographical locations, the urban growth patterns around these two cities can be used to reflect the impact of coastal hazards on the sustainability of the two metropolitan areas.

The study area is located in a coastal region with diverse landscapes where urban growth is constrained by the landscape, and place connectivity is strongly dependent on the road network. Places that look close to each other in terms of straight-line distance may not be easily accessible to each other due to the lack of direct road connection. In this study, traveling time in the road network is a better metric than the straight-line distance in the Euclidean space. The road network is built from the road polylines obtained from the Census Data using the Network Analyst toolbox in ArcGIS. Different types of roads are assigned with different speeds, which is the average speed limit of the road category. Given the road network, the traveling time between two points is the traveling time through the fastest roads connecting these two points. Using this approach, a raster map layer of traveling time was created for each city (Figure 3), which represents the traveling time from each point to the city center. To simplify the traveling time computation, the city centers are defined as the center points of the urban area polygons defined in 2000 Census boundaries.

3.3.2. *Other variables*

Three additional variables that affect urban growth were included in this study. First, elevation is an important factor that influences urban growth in coastal regions, particularly in the study area, where low-elevation regions are more vulnerable to coastal hazards such as tropical storms, floods, and land loss. The elevation of the study area, obtained from the USGS, was mosaicked from a large amount of LiDAR tiled data sets, which provides a higher accuracy than the traditional DEM data in the National Elevation Dataset of USGS. Then, the 1-meter resolution LiDAR data were resampled into a 30-meter raster to be consistent with the cell size of the other data layers. Second,

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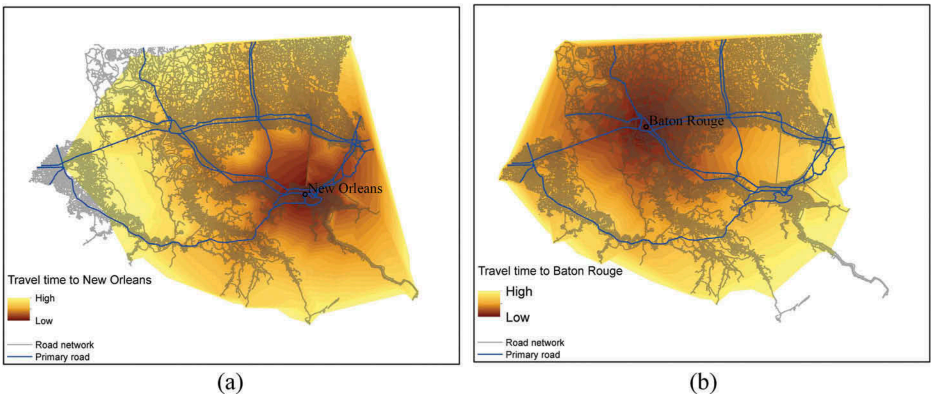

Figure 3. Travel time to the urban cores of New Orleans and Baton Rouge.

proximity to primary roads (category A1 and A2 in Census Feature Class Codes (CFCC)) is considered another important factor of urban growth. A raster layer was created to represent the distance from every pixel to the nearest primary road. Third, a constraint layer was created to confine urban growth in certain land cover types. The criterion used was that if more than half of the neighborhood pixels are water or wetland, the central pixel will not convert to urban. To be consistent with the focal filter applied to smooth the urban raster, the neighborhood used in the constraint layer was also a circle with a 33-cell radius.

4. Statistical analysis

To model urban growth, a transition function needs to be derived to quantify the relationships between urban growth and the selected variables. In this study, urban growth probability refers to the proportion of non-urban pixels that have converted to urban during a time period. Note that the urban and non-urban pixels are from the filtered images as explained in Section 3.2. Statistical analysis is conducted to fit these relationships to appropriate functions. The combination of these functions will form the baseline of the transition function, which will be further calibrated by a GA in the next section. In this section, the relationships derived for the pre- and post-Katrina periods are analyzed and compared. The comparison of these relationships will help uncover the influence of Katrina to the urban growth pattern in the study area.

4.1 *Attractiveness of major cities*

Figure 4 illustrates the relationship between urban growth probability and traveling time to the two major cities for the two periods. Both diagrams show a general tendency that the less travel time between a pixel and the city center, the more likely that the pixel will convert to urban. This tendency reflects the gravity model and the distance decay principle in geography, which states that the interaction between two locations declines as the distance between them increases. Such distance decay effect can be best fitted in a power function (Equation 1),

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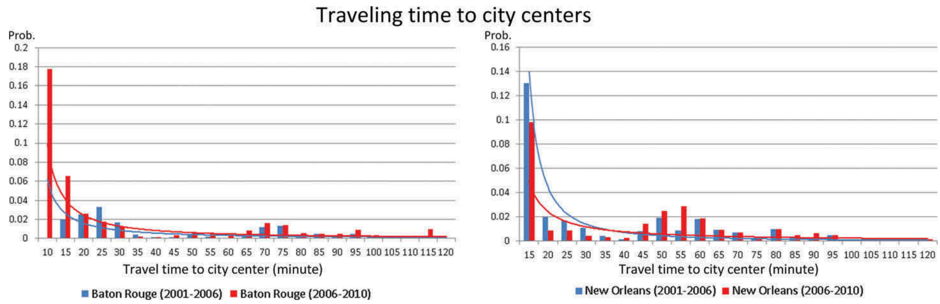

Figure 4. The relationship between urban growth probability and traveling time to city center.

Table 2. Parameters of probability functions derived for the two periods (2001–2006 and 2006–2010).

Equations	Time period	*a*	*b*	*c*	SSE	R^2	Adj. R^2	RMSE	*p*-value
Travel time to NOLA	2001–2006	2.946	−1.948	N/A	0.0011	0.93	0.9265	0.0073	0.001
(Equation 1)	2006–2010	2.024	−1.903	N/A	0.0023	0.7434	0.7306	0.0107	0.001
Travel time to BR	2001–2006	0.1466	−0.8735	N/A	0.000012	0.926	0.9223	0.0025	0.003
(Equation 1)	2006–2010	2.554	−1.657	N/A	0.000067	0.9774	0.9763	0.0058	0.000
Elevation	2001–2006	0.008903	10.84	13.22	1.99E-05	0.9158	0.9065	0.001052	0.000
(Equation 2)	2006–2010	0.01052	11.9	7.681	6.64E-06	0.9647	0.9607	0.000607	0.000
Distance to primary road	2001–2006	13.23	−0.9435	N/A	1.76E-05	0.9551	0.9526	0.000989	0.000
(Equation 3)	2006–2010	33.64	−1.086	N/A	1.27E-05	0.9633	0.9613	0.00084	0.000

Note: BR, Baton Rouge; NOLA, New Orleans.

$$P(x) = a{x_t}^b \tag{1}$$

where $P(x)$ is the probability of pixel x converting to urban, x_t is the traveling time from pixel x to a city center, a is a constant representing the attractiveness of the city center, and b is the distance decay parameter. Table 2 summarizes the parameter values of the four probability functions before and after Katrina. By comparing the a and b parameters of the travel time functions derived for the two periods, it can be observed that the trends of urban growth around the two major cities have reversed. First, the parameter a in the distance decay function of Baton Rouge has increased, which indicates an increase in the central attractiveness of Baton Rouge for urban growth. In contrast, a in the function of New Orleans has decreased, showing a declining central attractiveness of New Orleans for new urban development. Second, the parameter b of Baton Rouge has increased considerably (in a negative manner) after Katrina, which means more concentrated urban development near the city core, whereas parameter b in New Orleans has decreased, implying urban growth around New Orleans becomes more spread out after Katrina. These contrasting trends before and after Katrina as documented from the curves seem to agree with the empirical observations of more population growth in areas outside of New Orleans.

4.2 *Elevation*

Figure 5 (left-hand side) shows the relationship between urban growth probability and elevation before and after Katrina. Both time periods show that the elevation most

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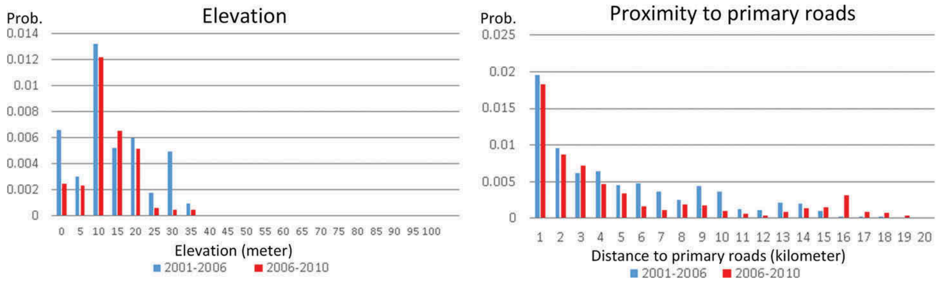

Figure 5. Urban growth probability at different elevations (left) and proximity to primary road (right).

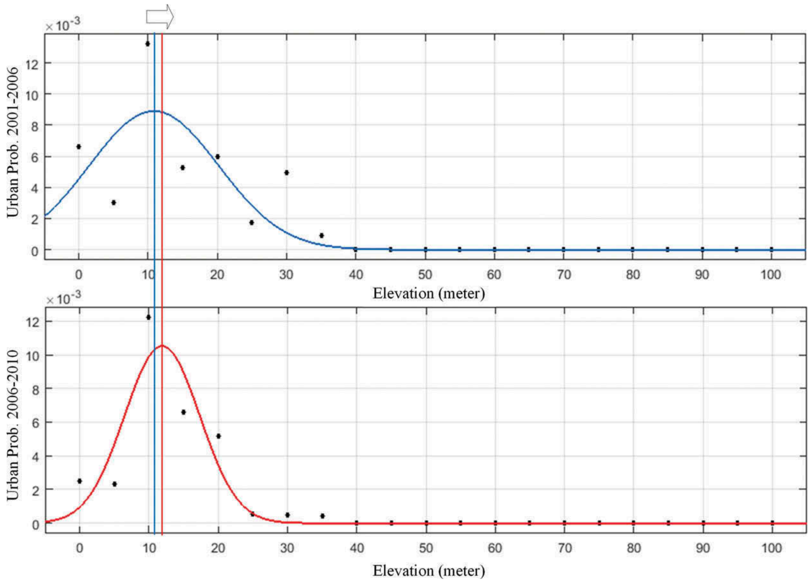

Figure 6. Gaussian curves fitted to the probabilities of urban growth at different elevations. The blue and red lines are for pre- and post-Katrina period, respectively.

probable for urban growth is around 10 m. The trend lines in the two time periods follow a bell shape, which can be fitted into a Gaussian function (Figure 6),

$$P(x_h) = a \times \exp\left(-\frac{(x_h - b)^2}{c}\right) \quad (2)$$

where $P(x)$ is the urban growth probability of pixel x,x_h denotes its elevation. From the two Gaussian functions for the two periods, we can observe that the center lines (indicated by parameter b) have increased from 10.84 to 11.90 m, indicating that the elevation most probable for urban growth increased by about 1 m (see Table 2). In addition, the average elevation of urban growth increased from 6.56 m between 2001

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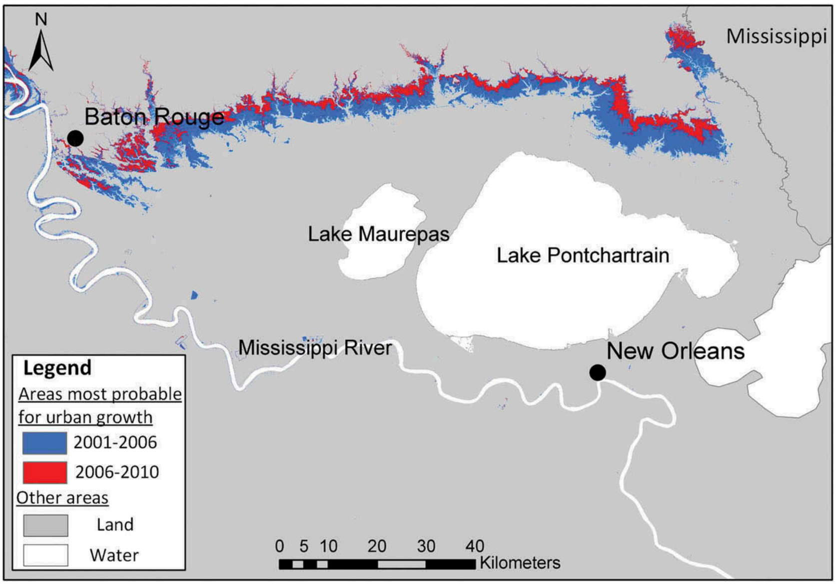

Figure 7. Areas with an elevation in the 95% confidence around the central lines of the two Gaussian functions.

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and 2006 to 6.72 m between 2006 and 2010, which confirms that urban growth has gradually moved to higher elevation regions. Figure 7 highlights the areas that have an elevation within the 95% confidence intervals around the center lines of the two Gaussian functions, showing that the areas most probable for urban growth have moved northward from the coast to inland areas after Katrina. Moreover, the increase in a and the decrease in c in the post-Katrina curve indicate that urban growth has become more concentrated around the central elevation (11.90 m).

4.3 *Proximity to primary roads*

Figure 5 (right-hand side) plots urban growth probability against distance to primary roads, which shows that the closer a pixel is to primary roads, the more likely it becomes urban. This tendency also reflects the distance decay of transportation attractiveness. Again, power functions (Equation 3) are used to fit these relationships:

$$P(x) = a{x_d}^b \tag{3}$$

where $P(x)$ is the urban growth probability of pixel x, x_d is the distance of pixel x to the nearest primary road, a is a constant representing transportation attractiveness, and b is the distance decay parameter.

5. GA calibration

The functions derived in the previous section provide the initial bivariate relationships between urban growth probability and the three variables (elevation, city attractiveness, and proximity to highways). It is noted that these functions could be over-determined by strong spatial autocorrelation. These functions can be combined into a transition function to model the integrated effect of all variables on urban growth (Equation 4). In the transition equation, we include the city attractiveness of both Baton Rouge α_2 and New Orleans α_2' in the model, and assume that the attractiveness is proportional to the population sizes of the two cities as represented by the parameter r. We also assume that the city attractiveness decays in the same rate in space (hence same β_2 for both cities), and that any deviation from this assumption is due to the effects of other factors. Based on these assumptions, Equation (4) can be transferred into Equation (5), which includes four components added together and seven parameters to be calibrated:

$$P(x) = \alpha_1 \times \exp\left(-\frac{(x_h - \beta_1)^2}{\gamma_1}\right) + \alpha_2 {x_{\mathrm{tb}}}^{\beta_2} + \alpha_2' {x_{\mathrm{tn}}}^{\beta_2} + \alpha_3 {x_{\mathrm{d}}}^{\beta_3} \tag{4}$$

$$P(x) = \alpha_1 \times \exp\left(-\frac{(x_h - \beta_1)^2}{\gamma_1}\right) + \alpha_2 {x_{\mathrm{tb}}}^{\beta_2} + r\alpha_2 {x_{\mathrm{tn}}}^{\beta_2} + \alpha_3 {x_{\mathrm{d}}}^{\beta_3} \tag{5}$$

In Equations (4) and (5), $r = \frac{\mathrm{Population_{NO}}}{\mathrm{Population_{BR}}}$, x_{h} is the elevation, x_{tb} is the traveling time to Baton Rouge, x_{tn} is the traveling time to New Orleans. For the seven parameters, α_n (n = 1, 2, or 3) is the constant of each variable, indicating the importance of the variable to urban growth. β_1 indicates the center line of the Gaussian curve which specifies the relation between urban growth and elevation, while γ_1 indicates the kurtosis of the Gaussian curve. β_2 and β_3 describe the distance decay effects of the attractiveness of cities and primary roads, respectively. Since the function includes diverse and non-linear relationships, a genetic algorithm (GA) can be used to calibrate the parameters in the function. GA is a heuristic algorithm that is inspired from the evolutionary ideas of natural selection and genetics (Golberg 1989). GA is widely used to search for the best solution to complex and non-linear problems. In GA optimization, candidate sets of parameters are encoded as number strings, which are called chromosomes. Chromosomes evolve generation by generation toward the best solution, with genetic operators such as selection, reproduction, crossover, and mutation. GA optimization terminates when the performance of the chromosomes does not improve further. Then, the fittest chromosome is selected as the best solution to the problem.

In this study, the possible parameter sets of the transition function are encoded as GA chromosomes. In each generation, the evolved chromosomes are applied in the transition function to predict pixels converted to urban. According to the calculated converting probability, a certain percentage of pixels would change to urban. The fitness of the chromosome is evaluated according to the prediction accuracy. The chromosomes that make less error in predictions are ranked higher in fitness. Based on the fitness ranking, the chromosomes will go through the genetic operators and evolve to the next generation for further evaluation. After a number of generations when the average fitness of the chromosomes does not further increase, the algorithm terminates and the fittest chromosome is the optimal set of parameters for the transition function. Different from the individual functions of urban growth probability derived in the previous section, the output of this transition function is actually a relative ranking of probability that a pixel converts to urban. The general process of the genetic algorithm calibration is illustrated in Figure 8.

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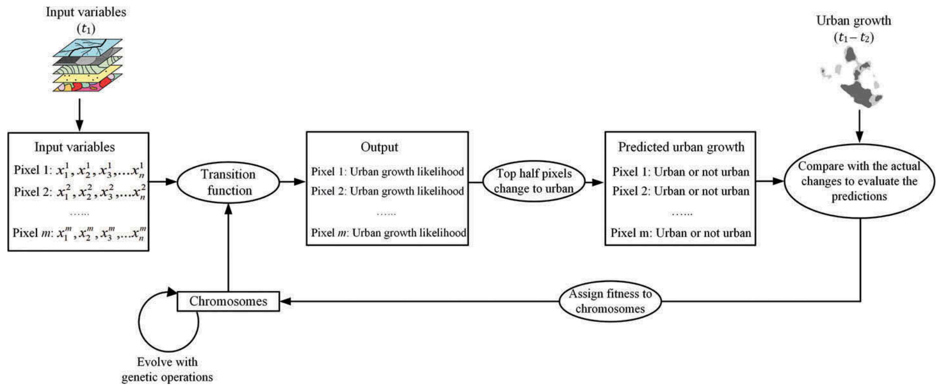

Figure 8. The workflow of GA calibration.

Because less than 1% of pixels have converted to urban in each time period, the sample of pixels used for the GA calibration needs to be rebalanced to ensure enough changed pixels are included in the sample. Since more than 99% of urban growth occurs within 3 kilometer (km) from the existing urban areas, the sample pixels were selected within this range, including all changed pixels and an equal number of unchanged pixels. Using this sampling approach, a total of 221,994 pixels and 182,295 pixels were sampled for the two time periods, respectively. The GA calibration was conducted using the optimization toolbox of Matlab 2015a. Default values were used for most options in the GA toolbox, except population size and crossover function. After some trial runs, we found that using a larger population (i.e., 500) and the heuristic crossover function can improve the goodness of fit of the final solution. The optional settings of the GA calibration are listed in Table 3. For detailed explanation of these options please refer to the documentation of Matlab 2015a.

Five runs were carried out using the optional settings in Table 3, and each run generated the best chromosome. The best chromosome in the five runs was selected as the final parameters for the transition function. The same calibration procedure was conducted for the two time periods, resulting in two sets of parameters that fit the function (Table 4). After calibration, the transition function has reduced the prediction error from 50% by guessing to less than 30%. When comparing the two time periods, Table 4 shows that the importance of elevation (α_1) has significantly increased in the second period and the elevation most probable for urban growth (β_1) has also

Table 3. The optional settings used for the GA calibration.

Option	Value	Option	Value
Population size	500	Selection	Stochastic uniform
Population type	Double vector	Mutation	Uniform
Initial population range	α_1:[0 1] β_1:[0 1] γ_1:[0 1] α_2:[0 1] β_2:[−1 0] α_3: [0 1] β_3:[−1 0]	Crossover function	Heuristic (ratio: 1.2)
Reproduction ratio	0.05*Population size	Mutation	Gaussian
Crossover fraction	0.8	Stall generation	100
Stopping criteria	Fittest chromosome does not improve for 100 generation	Function tolerance	0.0000001
Fitness scaling	Rank of fitness	Maximum generation	100*Population size

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Table 4. Optimal parameters derived from GA calibration for the two periods.

	Elevation			City attractiveness		Dist. to highway		Accuracy		
Parameters	α_1	β_1	γ_1	α_2	β_2	α_3	β_3	Total pixels	Error predictions	Error rate
2001–2006	1.14046	0.42588	0.04289	2.09734	−1.90265	2.31135	−0.57261	221994	64890	0.29231
2006–2010	3.50320	0.42591	0.13124	1.13776	−2.48992	1.71995	−0.44794	182295	47113	0.25844
Parameter changes	↑	↑	↑	↓	↓	↓	↑			

increased. These changes generally match the equations derived in Section 4.2 (statistical analysis). In contrast, the importance of city attractiveness (α_2) has declined, and the attractiveness decays faster in space (β_2), meaning that in the second period, urban growth is more concentrated near urban centers. The importance of primary road proximity (α_3) has also decreased and urban growth becomes more spread out (β_3) from primary roads.

6. CA simulation

After calibration, the transition function is applied to cellular automata (CA) to simulate future scenarios of urban growth. Since all urban growth occurs around existing urban areas, it is natural to infer that urban pixels gradually extend from the fringe of existing urban areas to farther areas. In general, the simulation follows three rules. First, only fringe pixels (i.e., pixels adjacent to an urban pixel) can convert to urban. Second, in the fringe pixels, the top half that have higher transition potential are selected as candidate pixels for urban conversion. The transition potential is calculated by the calibrated transition function derived from the GA (Section 5). Third, each candidate pixel has a certain chance to convert to urban, which is dependent on the number of urban pixels in the neighborhood. In addition, 1000 random non-fringe pixels (i.e., pixels not adjacent to an urban pixel) are allowed to convert to urban in each iteration to represent new urban development that is isolated from existing urban areas. Also, this process can be considered as a stochastic component of the model, which allows the simulation of urban growth that cannot be explained by the transitional function. The simulation terminates when the total number of changed pixels has reached the development quota, which is the product of average changed pixels per year in the previous period and the number of years the simulation runs for. For example, if n pixels have changed per year during the period 2006–2010, the 10-year simulation from 2010 to 2020 will terminate when the total number of changed pixels has reached $n \times 10$.

6.1. *Validation*

The performance of the transition functions needs to be validated before simulating future scenarios. Pontius *et al.* (2004) summarized that a predictive land change model can be validated by four general methods: (1) comparing the agreement between the prediction map and reference map; (2) comparing the predictive model with a Null model that predicts pure persistence (no change); (3) comparing the predictive model with a Random model

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Table 5. Confusion matrix of simulated and actual urban growth of the two time periods.

		Changed	Unchanged	Total
		Simulated Change (2001–2006)		
Actual change (2001–2006)	Changed	45369 (39.72%)	66668 (0.25%)	112037 (0.42%)
	Unchanged	68845 (60.28%)	26597383 (99.75%)	26666228 (99.58%)
	Total	114214 (100%)	26664051 (100%)	26778265 (100%)
		Simulated Change (2006–2010)		
Actual change (2006–2010)	Changed	40896 (43.60%)	51133 (0.19%)	92029 (0.34%)
	Unchanged	52901 (56.40%)	26633335 (99.81%)	26686236 (99.66%)
	Total	93797 (100%)	26684468 (100%)	26778265 (100%)

that predicts change randomly across the landscape; (4) evaluating the goodness-of-fit at multiple scales. In this study, we assessed the accuracy of the simulation model using the first three methods. The validation of the model at multiple scales is beyond the scope of this article and will be carried out in future research.

For the first assessment, Table 5 shows the pixel agreement between predicted and actual urban growth in the two time periods in each category. The statistics for both periods show that the model can accurately predict ~40% of the changed pixels in each period. It is important to note that this prediction accuracy of changed pixels is different from the prediction accuracy reported in conventional urban growth studies (Jenerette and Wu 2001, Feng *et al*. 2011, Okwuashi *et al*. 2012), which compares the initial and simulated pixel statuses using all changed and unchanged pixels. Such practice would give a biased impression of accuracy because only a small portion of land pixels has changed. This study reports the accuracy of the changed pixels only. There were less than 0.5% of pixels changed to urban during each time period, meaning that the prediction accuracy by guess is less than 0.5%. The validation result indicates that the simulation model can increase the prediction accuracy from 0.5% to ~40%. For the second and third assessments, Table 6 shows that due to the small percentage of changed pixels in each time period, there is not much difference in the overall prediction accuracy among the proposed model, Null model, and Random model. However, the proposed model has considerably outperformed the other two models in predicting the locations of changed pixels. Furthermore, by visually comparing the simulated and actual urban growth in Figure 9, we can observe that the simulation has largely captured the different urban growth distributions in the two time periods. The figures show more urban growth in the northern area versus limited urban growth around New Orleans in the south.

6.2. *Simulation*

The validation results show that the simulation model can capture the rules of urban growth in the study area quite accurately. Using different transition functions

Table 6. The prediction accuracies of the proposed model, Null model, and Random model.

	Accuracy of overall prediction			Accuracy of change prediction		
	Proposed model	Null model	Random model	Proposed model	Null model	Random model
Simulation (2001–2006)	99.49%	99.58%	99.17%	39.72%	0.00%	0.44%
Simulation (2006–2010)	99.61%	99.66%	99.32%	43.60%	0.00%	0.36%

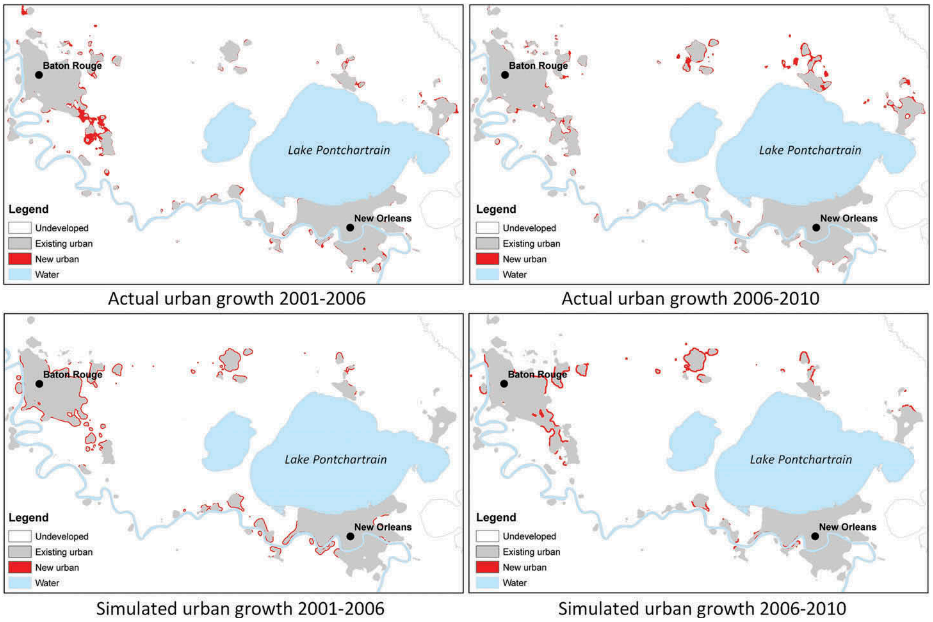

Figure 9. The simulated and actual urban growth of the two periods.

derived for the pre-Katrina and post-Katrina periods, we can simulate future scenarios of urban growth to evaluate future urban growth with and without the occurrence of Hurricane Katrina. Figure 10 shows the simulated urban growth every 10 years from the initial status in 2010 using the two transition functions. The simulation results show that if there was no Hurricane Katrina, more urban growth would occur near Baton Rouge, and areas between Baton Rouge and New Orleans, whereas with the occurrence of Katrina, urban growth would tend to concentrate around the small towns along the north coast of Lake Pontchartrain. In other words, the urban growth pattern without the impact of Katrina would be more evenly distributed among the existing urban areas, whereas urban growth simulated with the impact of Katrina would lead to more new urban development in higher ground.

This trend can also be revealed through the plot of the relationship between the total area of simulated urban growth in 2040 and the travel time to the two largest city cores (Figure 11), which shows that more urban growth occurs at locations having longer travel time to the city cores with the impact of Katrina. In other words, both Baton Rouge and New Orleans MSAs exhibit a decentralizing trend of urban growth in the 30-year simulation when using the post-Katrina function. New urban growth tends to occur further from the city cores in the simulation. This trend is more prominent in the New Orleans MSA where most urban growth will occur in areas with more than 50 minutes (min) travel time to the city core in the next 30 years.

The simulation results reflect adequately the difference in transition rules derived for the pre- and post-Katrina periods. Hurricane Katrina has made elevation a more important factor for urban growth, and has prompted more urban development in higher elevation areas. On the contrary, proximity to urban cores has become a less

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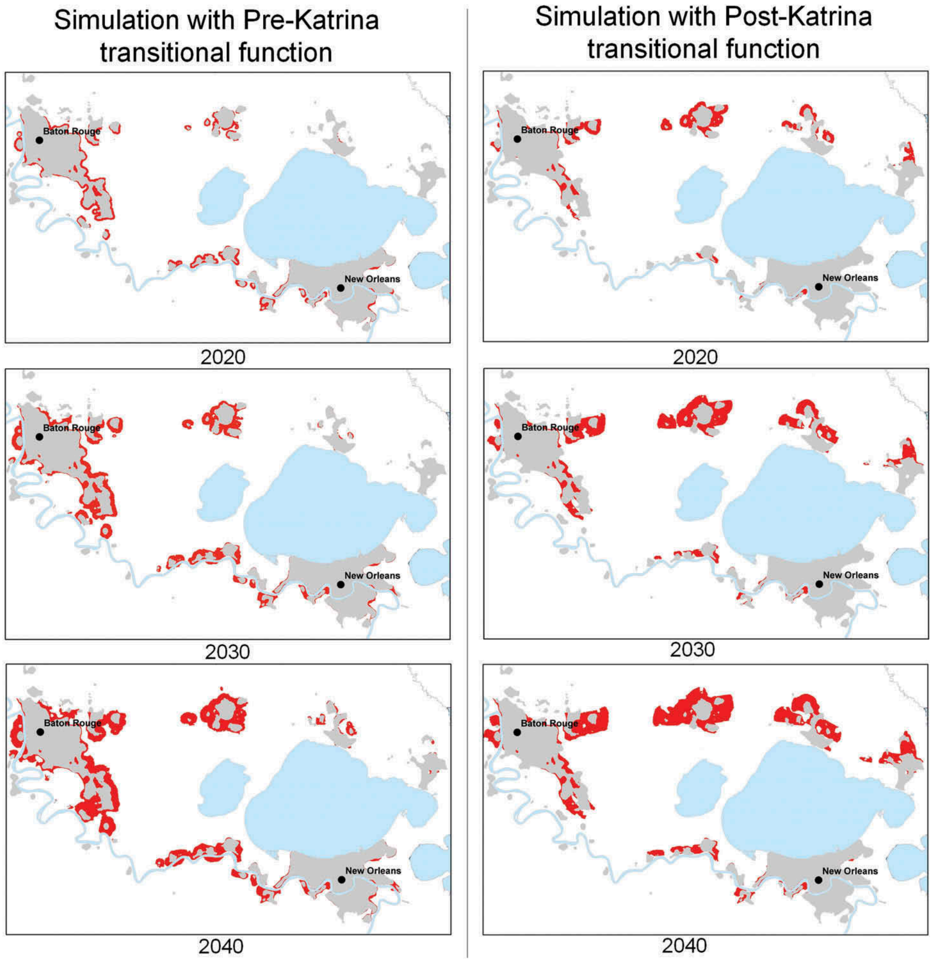

Figure 10. Simulation of future urban growth with pre- and post-Katrina transition functions.

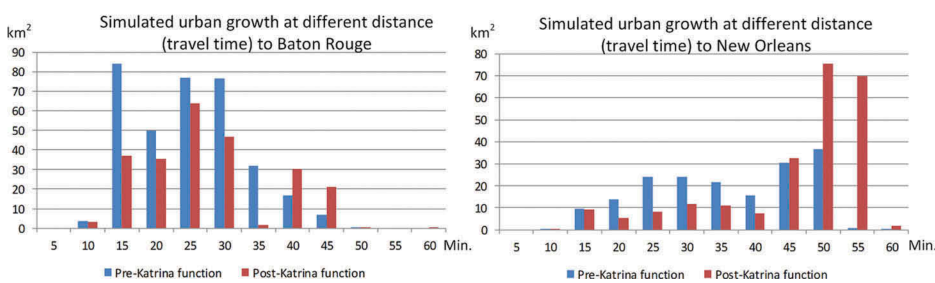

Figure 11. Total area of urban growth in 2040 versus the travel time to the city cores.

important factor. Since the urban core of New Orleans is mostly below 1-meter elevation, the potential of urban growth near New Orleans is limited, and urban growth in the New Orleans MSA will spill over across Lake Pontchartrain to the northern higher-elevation region. Due to its higher elevation, proximity to the I-10 interstate highway, and reasonable proximity to New Orleans, the smaller towns along the north coast of Lake Pontchartrain will be more attractive to future urban growth.

The simulation results presented here assume that the previous trend will persist, which may or may not be true. However, the model can be used to simulate future trends by varying the assumption to develop scenarios such as decreasing elevation to simulate the effects of sea-level rise on urban growth. In this study, the major driving forces that we modeled are the three factors – elevation, distance to city center, and distance to major roads. Given the hazard awareness and sea-level rise threats, these factors are expected to continue to play a major role in urban growth in the region.

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7. Conclusion

This study examined how Hurricane Katrina has affected urban growth in coastal Louisiana. It was hypothesized that people and businesses became more aware of the factor of elevation and coastal vulnerability after Hurricane Katrina, and they responded by relocating to a nearby region that has higher elevation. The study analyzed urban growth in three MSAs, Baton Rouge, New Orleans-Metairie, and Hammond, for two time periods, pre-Katrina (2001–2006) and post-Katrina (2006–2010). This study first applied a focal filter to extract continuous urban areas from the scattered urban pixels in the original remote sensing images. Statistical analyses were applied to determine the initial forms of the transition function. A genetic algorithm was then used to calibrate the transition function, and CA simulation based on the transition function was conducted to evaluate future urban growth patterns with and without the impact of Hurricane Katrina.

Major findings from this study show that elevation has become a much more important factor after Hurricane Katrina, and urban growth has shifted to higher elevation regions. The elevation most probable for urban growth increased from 10.84 to 11.90 m. Moreover, future urban growth in this region was found to be more decentralized from urban cores to more distant regions with higher elevation. Particularly in New Orleans MSA, urban growth will continue to spill across Lake Pontchartrain to the satellite towns that are more than 50 min away by driving from the city center. These findings were based on land cover pixels of 30 m × 30 m but smoothed by a filter with a radius of 33 cells (990 m). As a typical issue in geographical studies, scale and spatial autocorrelation affect the findings, and analysis at a single scale cannot explain the complete process of urban growth at all different scales (Lam *et al.* 2004, Lam 2012). Hence, interpretations of the findings in this study are only valid at the specific scale used. Future research should include a multiscale analysis to further validate the findings obtained in this study.

The significance and implications of this study are three-fold. First, the study contributes to the literature of human dynamics, urban growth modeling, and coastal sustainability by demonstrating a methodology of using land cover change data to detect, quantify, and simulate urban growth via a set of quantitative approaches. Unlike the traditional land cover and urban growth modeling studies, this study analyzed the change of urban growth pattern before and after Hurricane Katrina, which can indicate the impact of Hurricane Katrina on the population distribution in the study area. While individual methods may not be new, the combined use of the methods in analyzing urban growth and coastal vulnerability provides a useful example for studies in other coastal regions and for other hazards. Traditional studies on population migration and relocation are usually based on data of individual people's movement, which are difficult to acquire for a large area. Instead, this methodology takes advantage of remotely sensed data to detect human dynamics in response to coastal hazards, which is especially useful for studies of those regions where population movement data are limited.

Second, although elevation has long been suspected to play a key role in urban development in low-lying coastal regions, its effects have seldom been documented quantitatively. This is especially true in the Mississippi Delta, where the effects of elevation and coastal hazards on urban growth and population distribution have yet to be studied and quantified. This study documents that the elevation that is most probable of new urban growth has increased by approximately 1 m in the Mississippi Delta region. More importantly, this study shows that elevation would not be considered as important had there not been a major disastrous event such as Hurricane Katrina. To the best of our knowledge, there were no central policies or planning guidelines applied in this region to lead to this trend. The urban growth pattern uncovered in this study reflects autonomic individuals' response and adaptation to natural hazards, which can indicate the resiliency and adaptive capacity of the coastal communities. The same methodology can be applied to other low-lying deltaic regions to verify this finding or compare the difference.

Last but not least, the simulated scenarios of future urban growth will serve as a useful planning tool for sustainable development in this region. The decentralizing trend of development identified from this study may lead to decentralized distribution of capital, economy, employment, and resources in the urban system so that the importance of the original city core may gradually decline and new sub-cores may emerge in high-elevation regions. The implications of these urban growth trends could be enormous, and knowledge of these future trends will be needed for planning for a sustainable coast.

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Disclosure statement

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