Version of Record: https://www.sciencedirect.com/science/article/pii/S1618866721003423
Manuscript_bc03f341160f555f2de2929db058dac0

Title Page

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A Longitudinal Analysis of Green Infrastructure Conditions in Coastal Texan Cities

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Acknowledgements

Funding for this research was provided by NOAA Omnibus Texas Sea Grant Support 201, '*Green infrastructure plans for flood and storm water hazards reduction in the Texas coastal region*,' as part of Texas Sea Grant and National Oceanic and Atmospheric Administration (# NA18OAR4170088).

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A Longitudinal Analysis of Green Infrastructure Conditions in Coastal Texan Cities

Abstract

Green Infrastructure (GI) has gained attention as a strategy for minimizing flood damage and enhancing ecological services in developed and developing areas. Previous studies have investigated the positive effects of GI, focusing primarily on how the amount of GI impacts flood mitigation, but not its shape, connectivity, or quantity. Further, these studies have been mostly based on a single time period and not longitudinal. This paper explores GI conditions in high and low flood risk coastal Texan cities over time to identify the longitudinal effects of GI, controlling for a set of socio-economic, climate/biophysical, and development variables. The research examined sixty-eight coastal Texan cities of over 10,000 in population from 2001 to 2016, conducting spatial panel data models developed in 5-year intervals. Multiple landscape indices measuring size, shape, isolation, and connectivity of GI were used to measure its quantity and condition. Results indicate that GI conditions, especially amount and connectivity levels, appear to be improving in low-risk cities while worsening in high-risk cities. For control variables, a reduction in imperviousness was found to be more effective in managing GI quantity and landscape conditions in low-risk cities than in high-risk cities. These results suggest that planners should enhance efforts to improve current GI conditions, specifically in high flood risk cities. Additionally, conservation policies and transfer of development rights should be examined together with imperviousness regulations to increase current GI conditions.

Keywords

Resilience; flood mitigation; low impact development; panel modeling; FRAGSTATS

1. Introduction

Floods are a frequent and growing concern to human societies, leading all other natural disasters in both property damage and mortality worldwide (Doocy et al., 2013; Reja et al., 2017). From 1995 to 2015, flood events influenced 2.3 billion people and caused 157,000 people to die globally (Wahlstrom & Guha-Sapir, 2015; Van Zandt et al., 2020). In the US, from 1984 to 2013, floods (excluding coastal hurricanes) resulted in $238 billion in structural damages. With increases in both population and developed land, the Gulf of Mexico region has experienced the largest share of flooding in the U.S. (Michel-Kerjan, et al., 2012; Kim and Newman, 2020). The Texas coast is the most affected area by annual floods along the Gulf of Mexico and also has the fastest population growth and decreasing wetland and forest areas. For example, the Houston–Woodlands–Sugar Land Metropolitan Statistical Area, the most populated areas along the Texas coast, increased by 1.2 million people (or 35 percent) and lost 8.0 percent of its naturally occurring wetlands from 2000 to 2016 (Jacob, et al., 2014). Simultaneously, since 2000, Texas experienced 43 minor and major storm and hurricane events, including Allison (2001), Rita (2005), Ike (2008), and Harvey (2017).

Both natural and human-related reasons are responsible for increasing flood events globally (Doocy et al., 2013; Newman et al., 2019). In some cases, natural reasons such as changes in climate patterns are induced by human activities. As the release of anthropogenic heat increases, the net amount of evapotranspiration increases along with rising air temperatures (Wuebbles et al., 2017). In coastal cities, increasing ocean temperature and strengthening hurricanes exacerbate flood losses from storm surge (Bender et al., 2010). Simultaneously, population growth and urban expansion continue in high flood risk locations. Rapid increases in impervious surfaces limit the capacity of landscapes to infiltrate and store stormwater runoff. Expanding impervious cover accelerates the conveyance of stormwater to downstream outlets through closed pipe systems, consequently increasing flood volume, nutrient transport, and soil erosion (Schueler et al., 2009; Sohn et al., 2017; Sohn et al., 2019). It should be noted that such development-based impacts are not independent of natural factors, but rather foster increases in climate change effects.

Green infrastructure (GI) has been shown as an effective ecological method to limit the impact of urban development and respond to climate change (Escobedo et al., 2019; Scott et al., 2016). As for the role of GI, there are different views on whether to look at the aspect of urban design or landscape ecological approach. GI can be defined as the interconnected network of open spaces and natural areas such as forest, grassland, wetlands, and waterways (Benedict & McMahon, 2012). It includes green roofs, rain gardens, vegetated swales, infiltration trenches, permeable pavement, wetlands, parks, and other large- and small-scale natural areas for treating stormwater runoff (Copeland, 2013; Thiagarajan et al., 2018; Newman et al., 2020). Recent literature shows that increased GI has positive impacts on decreasing flood risk. Brody et al. (2017) examined coastal counties along the Gulf of Mexico, showing that large patches of open spaces and wetlands have significant effects on reducing flood losses. Kousky and Walls (2014) found that greenways and undeveloped lands assisted in avoiding $7.7 million in flood damages per year in St. Louis County, Missouri. Similarly, site-scale techniques such as rainwater harvesting systems, permeable pavement, and rain gardens were found to be effective in mitigating hydrologic connections of development to sewer systems and, thus, increasing the retention capacity of landscapes in Houston, Texas (Sohn et al., 2017). The 2019 Texas Coastal Resiliency Master Plan promotes GI to address flooding, storm surge, erosion, loss of habitat, negative impacts on wildlife and fisheries, and degradation of water quality and quantity (Bush, 2019). Although many existing studies have been conducted on the importance of GI's role in mitigating flood risk, longitudinal assessments of GIs have been several neglected. This research is needed for guidance of future land use planning and management practices that help rehabilitate degraded GI structure and maintain high-quality GI in the long term. Thus, for effective flood risk and GI management, it is necessary to study how well coastal cities and areas have managed GI over time in association with various environmental and socio-economic factors. This paper determines the current GI conditions in high and low flood risk cities by statistically examining changes in the quantity and configuration of GI in coastal Texan cities from 2001 to 2016. The research uses spatial panel data models developed in 5-year intervals to assess the longitudinal effects of GI while controlling for a set of socio-economic, climate/biophysical, and development variables.

2 Green Infrastructure and Flooding

2.1 Green infrastructure as flood mitigation tool

GI is sometimes used to describe an alternative term to describe gray infrastructure regarding stormwater management in environmental engineering (Hoang and Fenner 2016; Sohn et al. 2020). It can also be used in broader contexts including street canopy, green alleys, and community gardens in urban planning. This type of GI-based research typically explains human health problems and biodiversity in urban area (Tzoulas et al. 2007; Hostetler, Allen, and Meurk 2011; Coutts and Hahn 2015). Grounded in the theory of landscape ecology related to the geographical studies on networking, GI is a fundamental technique to support ecosystem services which foster health and wellbeing (Stone et al., 2019; Newman et al., 2017; Lovell & Taylor, 2013; Tzoulas et al., 2007). GI has multiple services and can serve as cool sinks in urban watersheds that modify heat flux by facilitating evapotranspiration and decreasing the urban heat island effect (Clark et al., 2010; Razzaghmanesh et al., 2016). More recently, GI has gained attention as a strategy for mitigating the impacts of flooding and balancing the effects of urban development and green space preservation (Coleman, et al., 2018; McDonald, et al., 2005; Cheng, et al., 2017). Planners, flood managers, and engineers claim that GI contributes to mitigating flood damage in several ways including: 1) reducing the volume of stormwater runoff (Nordman, et al., 2018), 2) slowing down the peak discharge rate (Kim & Park, 2016; Meyer et al., 2018; Masterson et al., 2019), and 3) increasing water storage capacity and water quality (Coleman et al., 2018).

Lewellyn, et al. (2016) investigated GI and their impacts on flooding in the Philadelphia area from 2012 to 2014. They revealed that GI seized at least 59 percent of the volume of each storm; this capture amount could increase to 93 percent if the GI was properly designed. Coutu and Vega (2007) found that decreased forest land cover increased surface runoff in Chester County, PA, using the Soil and Water Assessment Tool (SWAT). They found that, when examining direct impacts on flood mitigation, significant economic losses could be prevented by implementing GI. Relatedly, Brody et al. (2012) found that an acre of naturally occurred wetland preservation could have avoided $7,457,549 of flood damage cost in the Gulf of Mexico counties from 2001 to 2005. These studies verify that properly located GI in flood-prone areas can help to minimize further loss (Tate et al., 2016; Beatley, 2012).

However, despite efforts of recent studies reporting that GI has positive impacts on reducing flood damage, many researchers have relied primarily on cross-sectional data and concentrated mainly on the amount of GI, not its actually characteristics. Limited studies have identified the longitudinal change in GI landscape patterns. In addition, while evidence shows that GI has benefits regarding both stormwater quantity and quality, there are limited studies dealing with local GI transformation. If local jurisdictions recognize the actual transformation of GI and strategically manage it, flood damage can be further minimized.

2.2. Quantification of green infrastructure landscape pattern

The composition and configuration of GI are extremely important and decisive factors in controlling urban floods (Hendricks et al., 2018). Recent studies have adopted landscape indices to help quantify GI conditions (Brody et al., 2013; Kim & Park, 2016; Zhang et al., 2013). Based heavily on the patch-corridor-matrix model, landscape indices employ simple algorithms to measure the spatial pattern of categorical maps, including area, edge, shape, fragmentation, and connectivity (McGarigal, 2015). They were originally developed to quantify spatial heterogeneity of landscape structure, which define the processes and functions of ecosystems (Kupfer, 2011; Marsh, 2005). Since their emergence, landscape indices have been widely applied across disciplines, and its relationship with flood management research has been recently emphasized in GI policies.

Only a limited number of studies have shown how interactions among GI patches affect surface flow patterns during flood events. Kim et al. (2016) investigated how a network of GI could reduce peak runoff and suggested that a less fragmented and more connected pattern of GI is preferable to amplify water storage. Brody et al. (2017) examined the effects of land configuration on floods focusing on developed lands and natural open space in counties along the Gulf of Mexico. The study examined nine landscape ecology metrics, including mean patch area, cohesion, contiguity, Euclidean nearest neighborhood index, gyration, most extensive patch index, number of patches, patch density, percent of the landscape. It found that large and continuous patches of natural open spaces have the greatest impact on decreasing property loss from floods. There are similar studies that have applied landscape indices to development patterns. Brody, et al., (2011) determined that clustered high-intensity development patterns can help reduce the amount of flood damage, while Brody, et al., (2013) found that close proximity and high connectivity of medium-intensity development can also have a significant impact on reducing flood damages. These prior studies indicate that the pattern of GI, such as the amount, size, shape, isolation, and connectivity, has positive impacts in mitigating flood damage, but most did not observe longitudinal data nor evaluate the effect of landscape configuration and flood risk through time.

2.3. Factors affecting green infrastructure conditions

GI conditions play a beneficial role in mitigating flooding, but, for a variety of reasons, the amount and the condition of GI varies from region to region. According to a study examining the relationship between socio-economic and urban green areas by Nesbitt & Meitner (2016), population density, income, education, and race had a significant correlation with vegetation cover. They found that places with low population density, higher incomes, recipients of higher education, and inhabitants who are white or Asian tend to have higher vegetation cover than the others. In particular, a number of studies show that impoverished people tend to have fewer urban trees and vegetation (Clarke, et al., 2013; Gerrish & Watkins, 2018; Heynen, et al., 2006), and non-Hispanic White persons tend to have more GI in their spatial conditions than other races (Heckert, 2013; Schwarz et al., 2015; Huang & Cadenasso, 2016; Watkins & Gerrish, 2018). Boone et al. (2009) compared park distribution between African Americans and Whites in Baltimore, revealing that Whites tend to live among higher acreages of parks within walking distance even though African Americans tend to live closer to green space. Thus, prior research indicates that cities with different socio-economic factors can have different amounts and conditions of GI.

Climate and biophysical measures are also contributing factors to GI conditions. The flood risk level is directly affected by the environmental setting of a watershed such as floodplain. The size of the watershed area or basin affects discharge; larger areas are linked to increased flooding potential (Brody et al., 2011). Basin shape impacts stream peak flow rates by ascertaining the temporal intensity of water runoff (Brody et al., 2011; Matthai 1990). Increases in precipitation volume and high intensity or long duration reduces soil infiltrability and the retention capacity of the land, thus increasing flood volume and peak flow (Fassman & Blackbourn, 2010; Hood et al., 2007; Sohn et al., 2019). Stormwater on steeper slopes gains more gravitational driving force, increasing flow velocity (Yen et al., 1977). Similarly, low soil permeability, often caused by soil compaction in urban areas, yields more runoff and induces a higher chance of ponding in low-lying areas (Gregory et al., 2006; Gülbaz & Kazezyılmaz-Alhan, 2016). Impervious surface increases can exaggerate these conditions, increasing stormwater volume, velocity, flow rates, and amount.

Impervious surface is a critical measure of the built environment, which has a negative link to the creation of GI-based plans (Liu, Chen, & Peng, 2014). Due to limited spaces in urban watersheds, an increasing number of impervious surfaces that connect one another can serve as a channel to accelerate stormwater conveyance, increasing flood risks (Olivera & DeFee, 2007). Local municipalities thus have adopted a threshold-based land use policy, which limits the level of imperviousness by land use type and/or parcel size to regulate flood volume (Moglen & Kim, 2007). Development in the flood zone is also a contributing factor to worsening GI conditions. The flood zone is the geographical area defined by Federal Emergency Management Agency (FEMA) based on the level of flood risk for given storm return periods. To develop and construct within any Special Flood Hazard Area including the 100-year flood zone, a permit from National Flood Insurance Program is needed. Developments within a confined flood zone make flood damage more significant (Bagstad et al., 2007). Nevertheless, expansion of impervious surfaces and development can fragment urban forests and reshape protected areas, consequently reducing the resilience capacity of watersheds to extreme flood events. In addition, the loss of naturally occurring wetlands reduces a watershed's ability to perform water-cycling and flood mitigation functions, leading to a reduction in the resilience capacity of watersheds.

3. Research Objectives

Previous literature has discussed trends in GI and identified socio-economic related factors such as population density, median income, education level, and race, climatic/biophysical elements such as precipitation depth, slope, and soil permeability, and development attributes such as imperviousness coverage as drivers affecting GI conditions (Brody et al., 2011; Boone et al., 2009; Gregory et al., 2006; Heckert, 2013; Heynen, et al., 2006; Moglen et al., 2007; Nesbitt et al., 2016; Yen et al., 1977). As noted, limited studies have demonstrated the indicators of GI landscape patterns (Brody, et al., 2011; Brody et al., 2013; Hendricks et al., 2018; Kim et al., 2016; Zhang et al., 2013). While such studies have consistently shown that GI has positive effects on flood mitigation, they neglect to show how the spatial arrangement of GI relates to the environmental and socio-economic settings of a city at a varying flood risk level. Also, the observations of previous studies have been examined only cross-sectionally, limiting the evaluation of the changes in GI. To address these inconsistencies, this research asks the question: How well have high and low flood risk coastal Texan cities managed GI amounts and landscape patterns over time under varying environmental and socio-economic conditions? To answer this question, this study examines: 1) the GI condition changes in 69 cities along the Gulf of Mexico from 2001 to 2016 with 5-year intervals, and 2) whether cities with high flood risk have improved their GI conditions compared to cities with low flood risk.

4 Methodology

4.1 Study area

The target area of this research includes sixty-nine cities that have more than 10,000 in population within Texas coastal counties as defined by the National Oceanic and Atmospheric Administration (NOAA) (see Figure 1). Galveston, however, was excluded due to limited and inconsistent data. Each city was selected for analysis if it satisfied one of the two following criteria: (1) more than 15 percent of the county area where the city lies in is located within a coastal watershed, or (2) the county includes at least 15 percent of a coastal watershed defined at the eight-digit hydrologic unit code (HUC) scale by US Geological Survey (USGS). The cities under investigation experienced 5,677 square miles of conversion in land use between 1996 and 2010, especially from forests and wetlands converting to developed or shrublands (Oswalt & Smith, 2014). To identify cities at flood risk in the study area, the percentage of developed land in the 100-year floodplain was used as a proxy indicator; if a city has a percentage of developed land in the floodplain below the median (which is 21.42 percent), the city was defined to be at low risk of flood, and high risk if at or above the median. Based on this, 35 cities among the 68 were defined as low-risk cities and 33 as high-risk cities.

4.2 Data and measurement

4.2.1 Dependent variables: green infrastructure landscape pattern

The dependent variables of this study are a series of land configuration indicators collected from USGS's National Land Cover Database (NLCD) for 2001, 2006, 2011, and 2016 (overall accuracy = 90%; 89%; 88%; and 88%, respectively; Yang et al., 2018). The NLCD provides 30m resolution Landsat-derived land cover maps based on the Anderson Level II classification system (Anderson, 1976). Among 16 classes that the NLCD produced, we extracted the following eight classes – developed open space (21), deciduous forest (41), evergreen forest (42), mixed forest (43), shrub/scrub (52), grassland/herbaceous (71), woody wetlands (90), and emergent herbaceous wetlands (95) – and combined them into a single class, green infrastructure (GI) using ArcGIS 10.5. Human intensive land use including development, and agriculture or land use which does not relate to GI (i.e., water or barren land use), are excluded (Kim et al., 2016; Mell, 2009; Weber & Wolf, 2000). The land cover raster data for each city was then masked and imported into FRAGSTATS 4.2 to compute landscape indices, which were developed by McGarigal and Marks (1995) and used to quantify the spatial structure of GI. Four aspects of GI configuration were examined in this study based on previous literature (Kim et al., 2016; Park & Kim, 2017); they include size, shape, isolation, and connectivity. The corresponding indices selected are the percentage of landscape (PLAND), contiguity index (CONTIG), Euclidean nearest neighbor distance (ENN), and patch cohesion index (COHESION), respectively. These four variables are symbolic of four aspects and well-suited for direct interpretation with low collinearity. While PLAND represents the percentage of GI area in a city, CONTIG measures the mean number and location of contiguous cells of GIs. ENN quantifies the level of isolation by computing the mean shortest straight-line distance between edges of GIs. Lastly, COHESION describes the physical connectedness and 'clumpiness' of GI, measuring the normalized perimeter compared to the size and edge of patches. The higher value of PLAND, CONTIG, ENN, and COHESION indicates that the city has more abundant, contiguous, isolated, and connected patterns of GI. It should be noted that the high value of isolation alone implies a degraded condition of GI. To enhance the interpretation of the parameter estimate, we changed the scale of the CONTIG variable by multiplying by 1000 (Wooldridge, 2016). The definition and measurement methods of each index are shown in Table 1.

4.2.2 Independent variables

Independent variables were composed of socio-economic, climate/biophysical, and development variables. Socio-economic variables were obtained from the US Census Bureau for the 2000 and 2010 data and the American Community Survey (ACS) 2012–2016 five-year estimates at the city level for 2001, 2011, and 2016, respectively. It should be noted that the 2006 socio-economic data are absent, since 1-year estimates ACS data collected after 2005 did not include cities with less than a population of 65,000. Thus, we linearly interpolated 2006 socio-economic values using the data values for 2001 and 2011 (Honaker & King, 2010; Nakai & Ke, 2011). The used approach is a widely accepted method for estimating yearly changes in neighborhood scale (Do, Wang, & Elliott, 2013; Ludwig et al., 2012; Quillian, 1999). Socio-economic variables included population density, median income, education level, and proportion of race based on previous literature (Berke et al., 2015; Elliott & Clement, 2017). We measured population density as population per square mile of the city area and education level as the percentage of persons with no high school diploma who are 25 years or older. Lastly, the proportion of race was measured by the rate of non-Hispanic Whites. We used the square root of population density and education (Kardan et al., 2015; Nicolaus, et al., 2016), and the log transformation for the median income to approximate a Gaussian distribution (Ozturk, 2016).

We also employed climate/biophysical variables, including slope, soil permeability, annual precipitation, and the 100-year floodplain. The mean slope of each city was computed using 30m digital elevation models obtained from the USGS. Soil permeability was defined as the saturated hydraulic conductivity of soils, derived from the Natural Resources Conservation Service (NRCS)'s Soil Survey Geographic Database (SSURGO). Annual precipitation of 2001, 2006, 2011, and 2016 was retrieved from the Parameter Elevation Regressions on the Independent Slopes Model (PRISM) Climate Group. The 100-year floodplain, the area with a 1% chance of flood event in any given year, was used as the area within a watershed. The data was derived from the Q3 Flood Data and National Flood Hazard Layer (NFHL) data published by FEMA (Crowell et al., 2013). The NFHL is derived from the latest flood studies in 2018, but it covers only 32 among the 68 cities. Therefore, to cover the remaining 36 cities, we used Q3 Flood Data released in 2005, the first digital product derived from the Flood Insurance Rate Maps (FIRMs). Finally, the floodplain dummy variable is estimated as 1 if the city has more than a median value of 100-year floodplain area and 0 if does not. It should be noted that biophysical variables are assumed to be time-invariant in this study.

For development variables, we measured the percentage of imperviousness, developed land in the 100-year floodplain, and the level of flood risk. Imperviousness was measured using the mean value of NLCD's impervious dataset. The percentage of developed land in the floodplain was computed by combining three sub-classes of development defined by the NLCD: low-, medium-, and high-intensity development.

4.3 Spatial panel data model

The spatial panel data model refers to data including time-series observations of a number of spatial units, in this case, cities. By estimating the spatial group with time, the panel data model gives a degree of freedom and increases efficiency in the estimation of dynamic factors. When dealing with such factors, there are two methods to develop models: fixed effects and random effects. The fixed effects method is used for analyzing what causes an individual's values to change across time based on the assumption that the individual-specific effects are correlated with the independent variables. In contrast, the random effect method assumes that the entity's error term is not correlated with the predictors, which allow for time-invariant variables to play a role as explanatory variables (Torres-Reyna, 2007; Williams, 2015). In this paper, spatial panel data models with random-effects for the individual city and fixed-effects for the year were used to both analyze time-invariant variable effects and determine whether each year has different relationships with land configuration indicators. The model used in this paper is a two-way error component model, which splits errors into idiosyncratic parts and unobserved heterogeneity in individuals and over time.

To ensure the model has time fixed effects and group random effects, we performed F-test and Breusch and Pagan Lagrangian multiplier test (Torres-Reyna, 2007). Three GI variables – PLAND, CONTIG, and COHESION – had time fixed effect at 5% level of significance while ENN had time fixed effect ad 10% level of significance. In terms of Lagrangian multiplier test, the result confirms there is group random effect.

The four GI variables - PLAND, CONTIG, ENN, and COHESION – were individually regressed on socio-economic, climate/biophysical, and development variables. The spatial panel data models were performed with the combined and low- and high-risk cities, respectively. They are represented as follows:

$$lc_{it} = \beta_1 S_{it} + \beta_2 D_{it} + \beta_3 C_{it} + \gamma B_i + \delta T + \varepsilon_{it},$$

$$\varepsilon_{it} = \alpha_i + \lambda_t + e_{it}$$

where lc_{it} is the land configuration variable for the *i*th city at time *t*; $S_{it}, D_{it},$ and C_{it} stand for the socio-economic, development, and climate variables, respectively, whose values vary by city and across time; B_i stands for the biophysical variables whose values are different for each city only; T stands for time periods as binary variables; β_1, β_2, and β_3 are the estimated parameters for time-variant variables; γ represents the estimated parameters for time-invariant variables; δ denotes the estimated parameters for the binary time regressors; and ε_{it} is the composite error term which is the sum of individual-specific error term (α_i), time-specific error term (λ_t), and within- and between-individual error term (e_{it}).

4.4 Data analysis

To examine the changes of GI amount and configuration over time in high and low flood risk coastal Texan cities, descriptive statistics of GI are evaluated. Then, the results of the panel model with random-effects for the individual city and fixed-effects for the year are analyzed. Standardized beta coefficients are then assessed and compared to each independent variable. The year of the model is included as a dummy variable based on 2001, and when the independent variables are controlled for each year compared to 2001, it is analyzed whether there is a significant change over time.

5 Results

5.1 Descriptive statics by flood risk level

Table 2 reports the descriptive statistics for the selected variables in this study. In general, configuration indices of GI decreased and development variables constantly increased across time (2001– 2016), but their fluctuation varied between groups in low and high-risk cities. For the GI amount, low-risk cities decreased 0.5 percent more than did high-risk cities from 2001 to 2016, but the amount of GI was consistently higher than the high-risk city (average percent of the low-risk city was 36.99, the high-risk city was 28.28). In terms of shape, the value of contiguity (CONTIG) decreased in all groups, implying that the GI shape became less contiguous. Low-risk cities had a higher value of CONTIG, although it tended to decrease more than in high-risk cities over time. In reference to isolation, ENN decreased during the timeframe, suggesting that overall GI became less isolated. Simultaneously, low-risk cities decreased more than did high-risk cities based on ENN value. Low-risk cities consistently had a lower ENN value than did high-risk cities, indicating that they had a less isolated pattern of GI. Lastly, the connectivity of all groups (COHESION) decreased slightly while the COHESION value of low-risk cities was steadily higher than in high-risk cities.

The mean imperviousness and developed land in the floodplain increased in both groups across time. The percent imperviousness increased from 17.71% to 21.76% (in low-risk cities) and 28.20% to 31.97% (high-risk cities) on average from 2001 to 2016. Similarly, the percent of development in floodplain increased from 12.29% to 16.51% and 44.16% to 48.21% for low-risk and high-risk cities, respectively. These statistics affirm not only different patterns of GI but also changes in GI trends in accordance with the expansion of development by the level of flood risk within the study area.

5.2 Spatial panel data model results

Tables 3 and 4 show the results of spatial panel data models using the four land configuration variables; PLAND, CONTIG, ENN, and COHESION. The outcomes of the models explain the changes in GI conditions across years and the statistical impacts of socio-economic, climate/biophysical, and development variables. Models 1, 2, and 3 are the spatial panel data models for the combined, low-risk, and high-risk cities, respectively. The result of Model 2 consistently shows the highest explanatory power among the three models, as shown by the highest within R-square value.

5.2.1 Amount of green infrastructure

When holding the other variables constant, GI is expanding in low-risk cities over time and retracting in high-risk cities over time. This indicates that cities with less development in the 100-year floodplain consistently expanded their GI amounts by 2016, while cities with more existing structures at-risk to flooding actually decreased their amount of GI, presumably increasing their already high risk of flooding.

The socio-economic variables capture significant relationships with the GI amount. As expected, race, the proportion of people who are non-Hispanic whites, has a positive relationship with the GI amount (β_{race}= 0.142, p<0.001 in Model 1, β_{race}= 0.227, p<0.001 in Model 2). Population density in the total and low-risk cities has a positive relationship with the amount of GI ($\beta_{population\ density}$= 0.156, p<0.01 in Model 1, $\beta_{population\ density}$= 0.183, p<0.05 in Model 2), while income is negatively associated in a low-risk city ($\beta_{Median\ income}$= -3.602, p<0.10). Surprisingly, areas with lower educational attainment have greater amounts of GI ($\beta_{undereducation\ level}$= 1.056, p<0.05 in Model 1, $\beta_{undereducation\ level}$= 1.594, p<0.01 in Model 2). Among the socio-economic variables, race has the largest impact, as shown by the standardized beta coefficients. It should be noted that all socio-economic variables lose significance in a high-risk city.

For biophysical variables, a low-risk city with higher soil permeability has more GI implemented ($\beta_{soil\ permeability}$= 0.502, p<0.10), while a high-risk city with steeper slopes but less floodplain area has a larger GI size. (β_{slope}= 10.778, p<0.01, $\beta_{floodplain}$= -0.346, p<0.01, and $\beta_{floodplain\ dummy}$ = 11.557, p<0.05). Meanwhile, all the development variables consistently have significant negative relationships with GI amount. A one percent decrease in imperviousness in a city and development in the floodplain increases GI amounts by 0.387 percent in low risk and 0.233 percent in high-risk cities, respectively. Across all models, development in the floodplain has a greater impact than mean imperviousness. In addition, the control of development in the floodplain is found to be more effective in expanding GI amounts in a low-risk city than it does in a high-risk city.

5.2.2 Shape of green infrastructure

The results from Models 2 and 3 indicate that the GI shape in high-risk cities became less contiguous from 2001 to 2016, while no significant change was detected in low-risk cities (see Table 3). For example, Figure 2 shows the transformation of GI patterns in Katy, one of the high-risk cities in Texas that experienced the contiguity index drop from 0.289 to 0.194 from 2001 to 2016. The red circle highlights the region where GI patterns became more fragmented and less contiguous. When controlling for year effects, Model 1 results show that population density, median income, floodplain area, impervious surfaces, and development in floodplain significantly affect contiguity of GI; a city with the less dense population as well as lower income, floodplain area, and impervious cover has more contiguous shapes of GI. The floodplain and impervious areas in a city are particularly found to be one of the most contributing factors to decreasing GI contiguity in both low- and high-risk cities, as shown by the standardized coefficients (Models 2 and 3).

5.2.3 Isolation of green infrastructure

The results from Models 2 and 3 imply that the GI became less isolated in 2011 and 2016 in high-risk cities, while no significant change was identified in low-risk cities (see Table 4). Considering that GI got smaller and less contiguous, the positive trends of decreasing isolation levels in high-risk cities is an unexpected result. To better understand changes in GI configuration over time, a more thorough examination of each individual city may be required. For example, in Pharr, one of the high-risk cities in Texas, the value of ENN index dropped from 87.36 to 80.26 between 2001 and 2016 (see Figure 3). The decreasing trend of ENN was not attributed to an increasing number or expanding patches of GI. Instead, fragmentation of existing GI mainly reduced the neighborhood distance between GI patches, decreasing the isolation index. A similar effect was found in other cities. Therefore, the interpretation of ENN should be approached with caution. Model 1 results indicate that a city with higher precipitation rates and more impervious cover but with less development in the floodplain has less an isolated GI structure across time. Meanwhile, low-risk cities with higher median incomes, imperviousness, and education levels have a less isolated GI. Most variables have no significant relationship with ENN in a high-risk city.

5.2.4 Connectivity of green infrastructure

The year effects reveal that the connectivity of GI constantly increased from 2001 to 2016 in the low-risk cities, while no improvement was found in high-risk cities (see Table 4). This result is consistent with the increasing contiguity of GI in low-risk cities (see Table 3). Among the socio-economic variables, the median income variable shows a negative relationship with the GI connectivity in Models 1 and 3. As income decreases, GI connectivity increases significantly. In Model 2, population density and percentage of non-Hispanic whites indicate positive relationships with GI connectivity, respectively; if a low-risk city has a higher population density and ratio of non-Hispanic whites, GI connectivity increases.

In terms of biophysical variables, the result of Model 3 indicates that a high-risk city with steeper slopes and low soil permeability has a higher GI connection. While the floodplain area has a negative association, GI connectivity increases if the flood zone in a city exceeds 19.62 percent. It should be noted that these floodplain-related factors are most powerful in predicting the COHESION index in a high-risk city. Meanwhile, none of the climate and biophysical variables significantly affect GI connectivity in a low-risk city. Regarding development variables, impervious surfaces consistently have a negative relationship with GI connectivity in all models, and regulating impervious surfaces is found to be more effective in a low-risk city over high-risk one.

6. Discussion and Conclusion

This study analyzed how well coastal Texan cities at varying flood risk levels have managed GI quantity, shape, isolation, and connectivity over time under various environmental and socio-economic conditions. The findings suggest that, overall, coastal Texas cities are not using GI to its maximum capabilities, especially in high-flood risk cities. Holding other variables constant, while the total amount of GI in coastal Texan cities has increased since 2001, it decreased after 2011, resulting in no significant difference in 2016. The shape of GI patches has, however, decreased, indicating that simpler configurations of GI are being implemented. Because the ENN outputs have remained relatively stable through time, it is also safe to assume that many of the existing GI patches are not being pushed further apart. It was also found that socio-economic variables are important in predicting the GI amount and connectivity in low-risk cities, while biophysical variables are more important in high-risk cities. The higher population densities typically result in higher GI amounts. So, while efforts need to be undertaken to increase the amount of GI, this increase should mostly come through the placement of new GI to connect existing GI patches. Increases in urban density rates couple provide ample space for creating these connections if development is built upward rather than outward. Results also indicate that low-risk cities with a high population density and high social vulnerability (i.e., low educational attainment, non-white, etc.) are prone to have better GI conditions.

When evaluating the quantity and configuration of GI according to the risk level of cities, a few interesting results were found. Overall, GI conditions appear to be improving slightly in low-risk cities but worsening in high-risk cities, comparatively speaking. Low-risk cities have increased significantly in GI amounts, while high-risk cities have decreased significantly. Understanding that GI brings multiple benefits in regards to land value increase, public health benefits, and other quality of life related variables, this finding indicates that the placement of new GI is going into locations that may not need it as much, in regards to flood mitigation. High-risk cities also show stagnant in connectivity, while low-risk cities are increasing in connectivity (improved COHESION INDEX). The closeness and contiguity of existing GI patches also have significantly decreased in high-risk cities. It should be noted that the decreasing distance between patches has caused neither by increasing connectivity nor placement of new GI, but rather by fragmentation of existing GIs. These GI characteristics appear to be relatively stable in low-rick cities. However, a reduction in imperviousness is found to be more effective to control GI quantity, shape, isolation, and connectivity in low-risk cities than in high-risk cities. For example, for every 1% decrease in imperviousness, there is an increase in cohesion index outputs by 0.31 in low-risk cities but by 0.16 in high-risk city. These results imply that more enhanced efforts to improve current GI conditions should be made high-risk cities. Additional policies such as conservation easement and transfer of development rights should be considered together with imperviousness regulation to draw more successful results. Floodplain management will be also as effective to control GI quantity, shape, isolation, and connectivity. GI amount increases by 0.35%, with every 1% decrease in floodplain area of a high-risk city. Similarly, contiguity and connectivity indexes increase by 0.78 and 0.24, respectively, for the same amount of floodplain reduction.

Increases in GI conditions can have potential positive effects on flood mitigation in coastal Texas. Due to the amount of development occurring and the current GI characteristics, retrofit polices, especially for existing private development, would best serve to enhance the current layout of GI in coastal Texas. It is very likely that Texas coastal communities that have land plans, strategies, and codes for land conservation are better positioned to implement green infrastructure practices, and as such, enhance GI's utility as a flood mitigation strategy. While new development presents opportunities for implementing GI, currently vulnerable areas must also be treated with GI enhancements to help prevent future damage. For example, the City of Chicago's Green Alley handbook provides mechanisms for local residents to retrofit their rights of ways near the street for their properties to limit runoff impacts. GI in the public right of way can have a high impact on water quality. Philadelphia has taken an approach to private property retrofitting with GI that limits imperviousness by way of local code at the watershed scale. The code incentivizes reduction in impervious cover based on local site conditions and whatever facilities work best for a particular project. Other, structural-based local facilities such as rainwater harvesting for residential areas can reduce stormwater runoff, conserve water, and provide environmental and economic benefits. While creative incentives and funding mechanisms must be further explored, multi-scale GI facilities linked to local conditions must be further enhanced to develop a healthy structure of an urban ecosystem and limit flood damage in risk, especially in high risk coastal Texan cities.

For future studies, several steps are needed to improve the research of GI on flood risk. First, additional work should include longer-term time series data. For example, measuring GI changes in several decades in different cities will help better control the socio-economic or biophysical variables. With longer time data, especially, the change data for biophysical variables that were previously assumed to be time-invariant would be more effective to control. Second, future study should rigorously examine additional control variables to further isolate the effects of the year, including the planning evaluation of each city, drainage system characteristics, and the number of the housing unit. Lastly, more research is needed on the specific types of land cover and land use. For example, in this study, eight land cover and land use types are combined as one to assess GI. A more sophisticated investigation on land use at the local level, or considering to use normalized difference vegetation index is essential for specific jurisdictions to promote the development of a more resilient community in the future.

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Figures

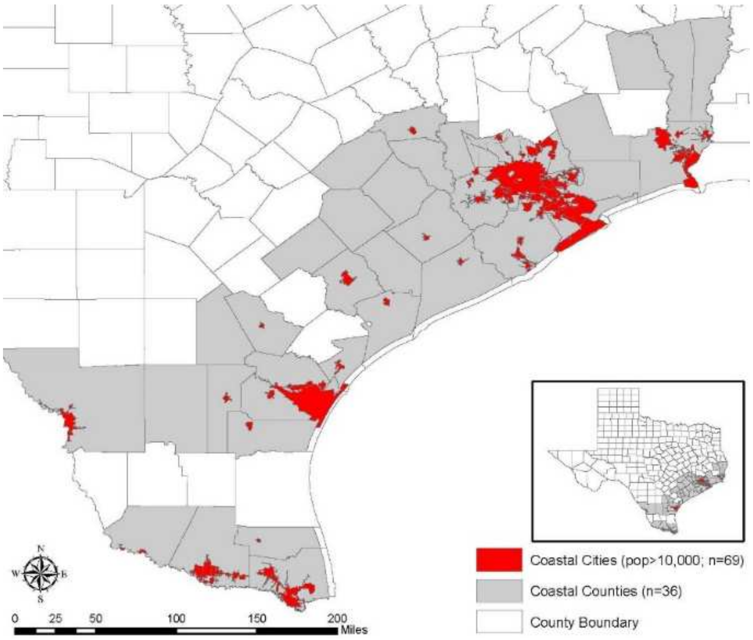

Figure 1. Study Area: Texas Coastal Cities

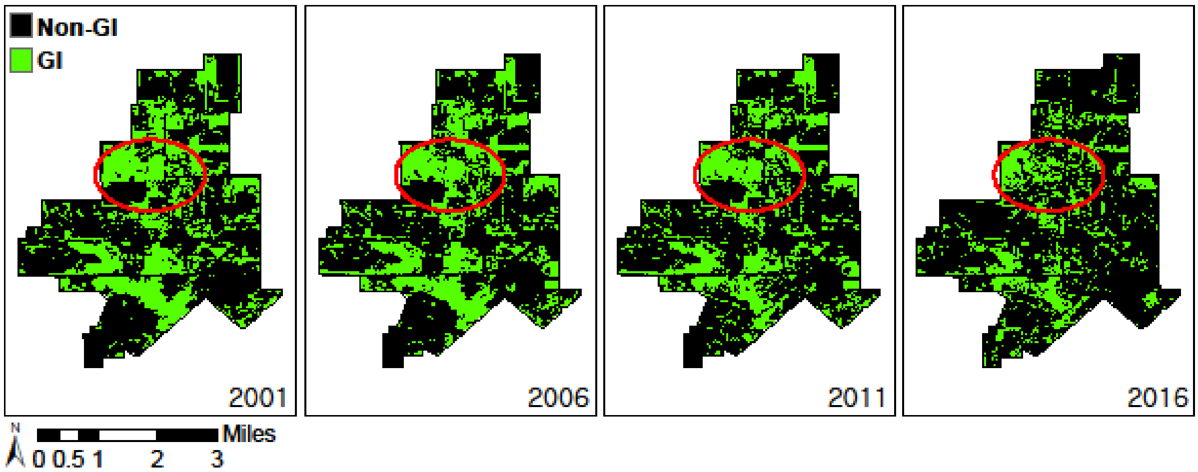

Figure 2. The GI distribution changes in the City of Katy, Texas from 2001 to 2016

Note: Green and black cells indicate GI and non-GI land use. The non-GI area includes developed, agricultural, and barren lands.

Figure 3. The GI distribution changes in the City of Pharr, Texas from 2001 to 2016

Tables

Table 1. Variables and descriptive statistics

Variable		Measurement	Source; Analytic tools	Range	Mean (SD)
Landscape index variables					
Size	Percentage of Landscape (PLAND)	PLAND = $\frac{\sum_{j=1}^{n} a_{ij}}{A} \cdot (100)$; units in percentages	NLCD 2001, 2006, 2011, 2016; FRAGSTATS 4.2.1	3.71 ~ 81.26	32.70 (15.84)
Shape	Contiguity (CONTIG) (x1000)	Average contiguity value for the cells in a corresponding class CONTIG = $\frac{\sum_{j=1}^{n}[(\sum_{r=1}^{z} c_{ijr}/a_{ij})-1]}{(v-1)n_i}$	NLCD 2001, 2006, 2011, 2016; FRAGSTATS 4.2.1	141.10 ~ 347.10	216.70 (28.64)
Isolation	Euclidian Nearest Neighbor Index (ENN)	Average value of the distance (m) to the nearest neighboring patch of the same type, based on shortest edge-to-edge distance ENN = $\frac{\sum_{j=1}^{n} h_{ij}}{n_i}$	NLCD 2001, 2006, 2011, 2016; FRAGSTATS 4.2.1	66.43 ~ 111.27	83.79 (8.64)
Connectivity	Cohesion (COHESION)	COHESION = $\left[1 - \frac{\sum_{j=1}^{n} p_{ij}^{*}}{\sum_{j=1}^{n} p_{ij}^{*}\sqrt{a_{ij}^{*}}}\right] \cdot \left[1 - \frac{1}{\sqrt{z}}\right]^{-1} \cdot (100)$	NLCD 2001, 2006, 2011, 2016; FRAGSTATS 4.2.1	55.05 ~ 99.87	93.28 (7.29)
Socio-economic variables					
Population density (sqrt)		Population per square miles of land area	U.S. Census city/county data, ACS 5-year estimate	9.36 ~ 75.66	41.71 (10.93)
Median income (log)		Median household income; units in dollars	U.S. Census city/county data, ACS 5-year estimate	9.65 ~ 12.14	10.65 (0.40)
Undereducation level (sqrt)		Percentage of persons with no high school diploma who are same or older than 25 years old, with less than a 12th grade education (including individuals with 12 grades but no diploma); units in percentages	U.S. Census city/county data, ACS 5-year estimate	1.37 ~ 8.25	4.85 (1.45)
Race		Proportion of non-Hispanic Whites; units in percentages	U.S. Census city/county data, ACS 5-year estimate	5.20 ~ 99.63	59.47 (26.29)
Climate/Biophysical variables					
Annual precipitation		Annual precipitation of each year; 2001, 2006, 2011, and 2016; units in meter	PRISM	0.23 ~ 2.17	1.08 (0.55)
Slope		Average slope of each city; units in percentage	USGS NHD Plus; ArcGIS	0.08 ~ 4.06	0.60 (0.63)
Soil Permeability		Average saturated hydraulic conductivity of soil; units in μm/s	NRCS SSURGO; ArcGIS	0.34 ~ 58.28	10.93 (10.91)
Floodplain		Percentage of city area within the FEMA-defined 100-year floodplain; units in percentage	FEMA Flood Map Service Center	0.31 ~ 94.55	24.31 (19.34)
Development variables					
Imperviousness		Percentage of impervious surface	NLCD 2001, 2006, 2011, 2016; ArcGIS	1.14 ~ 57.52	24.96 (11.46)
Development in FP		Percentage of developed land in 100-yr floodplain	FEMA Flood Map Service Center and NLCD 2001, 2006, 2011, 2016	0.00 ~ 96.42	30.32 (22.87)

Notes:
p_{ij} = perimeter (m) of patch ij *(in terms of number of cell surfaces)
a_{ij} = area (m^2) of patch ij *(in terms of number of cell surfaces)
n_i = number of patches in the landscape of corresponding patch type i;
c_{ijr} = contiguity value for pixel r in class ij
v = sum of the value in a 3-by-3 cell template
h_{ij}= distance (m) between patch ijs and patch ij, based on patch edge-to-edge distance, computed from cell center to cell center
A = total landscape area (city area in this study)
z = total number of cells in the landscape

Table 2. Mean values of GI conditions and independent variables from 2001 to 2016 by the city's flood risk level

	Overall				Low-risk City				High-risk City			
	2001	2006	2011	2016	2001	2006	2011	2016	2001	2006	2011	2016
Landscape metric variables												
PLAND	34.80 (16.51)	33.70 (16.06)	32.49 (15.55)	29.80 (15.09)	39.14 (16.49)	38.04 (16.08)	36.89 (15.50)	33.87 (15.82)	30.33 (15.54)	29.22 (14.98)	27.96 (14.45)	25.62 (13.26)
CONTIG (x1000)	226.02 (30.14)	222.94 (28.93)	218.51 (27.26)	199.34 (19.81)	232.33 (29.72)	228.87 (27.37)	226.20 (23.24)	201.70 (16.32)	219.53 (29.59)	216.84 (29.61)	210.59 (29.11)	196.91 (22.86)
ENN	84.30 (8.69)	84.63 (9.16)	84.04 (8.86)	82.19 (7.76)	83.09 (8.26)	82.58 (7.74)	81.74 (7.02)	80.40 (6.84)	85.54 (9.07)	86.75 (10.10)	86.40 (9.99)	84.02 (8.30)
COHESION	93.88 (7.02)	93.66 (7.04)	93.29 (7.33)	92.28 (7.80)	96.21 (2.93)	96.00 (3.02)	95.70 (3.06)	94.63 (3.79)	91.49 (9.00)	91.25 (8.99)	90.81 (9.41)	89.87 (9.94)
Socio-economic variables												
Population density (sqrt)	41.21 (10.91)	41.56 (10.87)	41.83 (11.19)	42.25 (10.96)	37.14 (10.35)	37.29 (9.84)	37.35 (9.68)	37.92 (8.97)	45.39 (9.98)	45.96 (10.22)	46.44 (10.86)	46.70 (11.16)
Median Income (log)	10.49 (0.36)	10.61 (0.37)	10.71 (0.38)	10.81 (0.41)	10.53 (0.37)	10.65 (0.37)	10.75 (0.38)	10.85 (0.43)	10.45 (0.36)	10.56 (0.37)	10.66 (0.38)	10.76 (0.39)
Education level (sqrt)	5.23 (1.49)	4.99 (1.43)	4.73 (1.40)	4.47 (1.39)	5.13 (1.45)	4.89 (1.35)	4.63 (1.27)	4.33 (1.36)	5.33 (1.55)	5.09 (1.52)	4.83 (1.52)	4.61 (1.44)
Race	45.35 (27.56)	41.89 (26.45)	38.43 (25.66)	36.44 (25.10)	46.83 (26.00)	43.38 (24.94)	39.92 (24.21)	37.73 (23.56)	43.82 (29.40)	40.36 (28.23)	36.89 (27.36)	35.11 (26.89)
Biophysical variables												

Annual precipitation	1.31 (0.58)	1.18 (0.43)	0.54 (0.20)	1.29 (0.50)	1.31 (0.55)	1.18 (0.39)	0.54 (0.18)	1.33 (0.50)	1.30 (0.63)	1.18 (0.47)	0.54 (0.22)	1.25 (0.50)
Slope	0.60 (0.63)				0.67 (0.73)				0.52 (0.51)			
Soil Permeability	10.93 (10.97)				8.67 (8.91)				13.25 (12.46)			
Floodplain	24.31 (19.45)				21.60 (14.22)				27.11 (23.56)			
Development variables												
Imperviousness	22.88 (11.17)	24.29 (11.38)	25.88 (11.61)	26.79 (11.54)	17.71 (7.60)	19.09 (8.06)	20.67 (8.50)	21.76 (8.50)	28.20 (11.85)	29.64 (11.91)	31.25 (12.03)	31.97 (12.06)
Percentage of Dev in FP	28.00 (23.17)	29.75 (22.87)	31.42 (22.88)	32.13 (22.83)	12.29 (5.45)	14.16 (5.82)	15.75 (6.65)	16.51 (7.23)	44.16 (23.34)	45.79 (22.80)	47.54 (22.4)	48.21 (22.23)
N	69				35				33			

Note: Standard deviations indicated in parentheses.

Table 3. Spatial Panel Model Results; PLAND and CONTIG

	Total (PLAND Model 1)	Low-Risk (PLAND Model 2)	High-Risk (PLAND Model 3)	Total (CONTIG Model 1)	Low-Risk (CONTIG Model 2)	High-Risk (CONTIG Model 3)
Socio-economic variables						
Population density (sqrt)	**0.156****	**0.183***	0.095	**-0.951****	-0.805	**-0.757^{+}**
	(1.702**)	**(1.998*)**	(1.042)	**(-10.380**)**	(-8.782)	**(-8.259^{+})**
Median income (log)	-1.379	**-3.602^{+}**	1.931	**-21.945***	**-41.882****	4.627
	(-0.547)	**(-1.429^{+})**	(0.766)	**(-8.709*)**	**(-16.622**)**	(1.836)
Undereducation level (sqrt)	**1.056***	**1.594****	0.356	-1.128	1.425	**-7.235***
	(1.527*)	**(2.305**)**	(0.514)	(-1.630)	(2.060)	**(-10.461*)**
Race	**0.142*****	**0.227*****	0.073	-0.046	0.135	**-0.382^{+}**
	(3.720***)	**(5.959***)**	(1.915)	(-1.196)	(3.544)	**(-10.029^{+})**
Climate/biophysical variables						
Precipitation	0.021	0.111	0.192	3.495	2.213	6.133
	(0.011)	(0.061)	(0.105)	(1.911)	(1.210)	(3.354)
Slope	2.860	0.005	**10.778****	4.736	-2.954	16.819
	(1.797)	(0.003)	**(6.772**)**	(2.976)	(-1.856)	(10.568)
Soil Permeability	**0.291^{+}**	**0.502^{+}**	0.081	-0.400	**-0.783^{+}**	-0.345
	(3.173^{+})	**(5.464^{+})**	(0.887)	(-4.353)	**(-8.525^{+})**	(-3.756)
Floodplain	-0.149	0.033	**-0.346****	**-0.453^{+}**	**-0.789^{+}**	**-0.781***
	(-2.886)	(0.636)	**(-6.676**)**	**(-8.750^{+})**	**(-15.236^{+})**	**(-15.080*)**
Floodplain dummy	5.497	4.485	**11.557***	-4.258	-8.334	13.128
	(2.748)	(2.242)	**(5.779*)**	(-2.129)	(-4.167)	(6.565)
Development variables						
Imperviousness	**-0.387*****	**-0.327***	**-0.320***	**-0.926***	**-1.446***	**-0.939^{+}**
	(-4.429***)	**(-3.745*)**	**(-3.666*)**	**(-10.595*)**	**(-16.545*)**	**(-10.752^{+})**
Development in FP	**-0.233*****	**-0.402*****	**-0.164***	**0.386***	0.211	0.384
	(-5.325***)	**(-9.168***)**	**(-3.755*)**	**(8.815*)**	(4.810)	(8.768)
Years (dummy)						
Year dummy (2006)	**0.704***	**1.682*****	-0.294	0.456	4.331	**-4.398^{+}**
Year dummy (2011)	**1.382***	**3.316*****	-0.535	1.242	10.262	**-9.073^{+}**
Year dummy (2016)	-0.200	**2.083***	**-2.716***	**-18.175*****	-9.348	**-29.732*****
Constant	57.836***	77.511***	21.184	519.492***	753.086***	234.510^{+}
	(32.610***)	(29.283***)	(34.987***)	(221.026***)	(211.353***)	(228.440***)
$Within\ R^2$	0.766	0.814	0.754	0.636	0.717	0.689
$Between\ R^2$	0.351	0.249	0.559	0.187	0.165	0.298
$Overall\ R^2$	0.360	0.263	0.563	0.279	0.303	0.356
N = Cities x Years (4)	272	140	132	272	140	132

Standardized beta coefficient in parentheses
$^{+}$ p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001
Note: CONTIG models used the dependent variable CONTIG multiplied by 1,000

Table 4. Spatial Panel Model Results; ENN and COHESION

	Total (ENN Model 1)	Low-Risk (ENN Model 2)	High-Risk (ENN Model 3)	Total (COHESION Model 1)	Low-Risk (COHESION Model 2)	High-Risk (COHESION Model 3)
Socio-economic variables						
Population density (sqrt)	0.102	0.069	0.103	0.035	**0.111****	-0.005
	(1.117)	(0.757)	(1.119)	(0.381)	**(1.215**)**	(-0.051)
Median income (log)	-3.506	**-6.232***	4.089	**-1.955****	-0.885	**-3.193***
	(-1.391)	**(-2.473*)**	(1.623)	**(-0.776*)**	(-0.351)	**(-1.267*)**
Undereducation level (sqrt)	0.904	**1.515**$^{+}$	0.813	0.008	0.378	-0.468
	(1.307)	**(2.190^{+})**	(1.176)	(0.012)	(0.546)	(-0.676)
Race	0.004	-0.055	0.066	0.022	**0.069*****	0.014
	(0.100)	(-1.433)	(1.728)	(0.590)	**(1.814***)**	(0.362)
Climate/biophysical variables						
Precipitation	**-2.194****	-1.086	**-4.256*****	-0.337	0.055	-0.477
	(-1.200**)	(-0.594)	**(-2.328***)**	(-0.184)	(0.030)	(-0.261)
Slope	-0.762	-1.771	3.402	**1.690**$^{+}$	0.009	**7.296****
	(-0.479)	(-1.112)	(2.137)	**(1.062^{+})**	(0.005)	**(4.584**)**
Soil Permeability	0.146	-0.104	0.170	**-0.115**$^{+}$	0.032	**-0.221***
	(1.588)	(-1.128)	(1.847)	**(-1.252^{+})**	(0.346)	**(-2.411*)**
Floodplain	-0.005	0.010	-0.086	**-0.123***	0.026	**-0.240****
	(-0.098)	(0.191)	(-1.668)	**(-2.382*)**	(0.495)	**(-4.633**)**
Floodplain dummy	-1.541	-2.666	0.608	**2.757**$^{+}$	0.412	**7.384***
	(-0.771)	(-1.333)	(0.304)	**(1.379^{+})**	(0.206)	**(3.692*)**
Development variables						
Imperviousness	**-0.205**$^{+}$	**-0.384***	0.102	**-0.210*****	**-0.307*****	**-0.162***
	(-2.347^{+})	**(-4.392*)**	(1.164)	**(-2.406***)**	**(-3.519***)**	**(-1.855*)**
Development in FP	**0.145***	-0.032	0.122	-0.036	-0.022	0.021
	(3.305*)	(-0.725)	(2.778)	(-0.812)	(-0.499)	(0.477)
Years (dummy)						
Year dummy (2006)	0.662	0.842	0.191	**0.387***	**0.680****	0.202
Year dummy (2011)	-0.658	0.818	**-3.247***	0.470	**1.361*****	-0.072
Year dummy (2016)	-0.249	1.664	**-2.922**$^{+}$	0.149	**0.882***	-0.339
Constant	114.475***	147.230***	32.605	122.052***	107.739***	133.774***
	(83.867***)	(79.370***)	(84.204***)	(92.817***)	(93.577***)	(92.311***)
$Within\ R^2$	0.350	0.551	0.361	0.536	0.690	0.495
$Between\ R^2$	0.055	0.090	0.383	0.535	0.515	0.518
$Overall\ R^2$	0.066	0.114	0.382	0.534	0.528	0.517
N = Cities x Years (4)	272	140	132	272	140	132

Standardized beta coefficient in parentheses
$^{+}$ p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001