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# Measuring, mapping, and anticipating climate gentrification in Florida: Miami and Tampa case studies

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ABSTRACT

This article introduces an experimental methodology to identify proxy indicators that are conceptually consistent with the processes of Climate Gentrification ("CG"), in which a change in demand preferences among consumers and investors drives the increased consumption for real estate, in part, on lower measures of physical risk from climate change. Evaluated through case studies in the state of Florida, this article builds on the integration of multiple datasets concerning rental properties, evictions, and socioeconomic data, as well as environmental risk indices to build a Climate Gentrification Risk Index (CGRI). In the Miami case study, we find that the CGRI identifies a hotly contested neighborhood that is already known to be in a state of transition consistent with the processes of CG. In the Tampa case, the index highlights a district that exhibits strong metrics for the future accelerated occurrence of CG. Our findings suggest that transitional land uses and flexible zoning in low-exposure areas are key elements for attracting new development consistent with CG and offer insight into the challenges that local governments face understanding the types and rates of change that may be catalyzed in the broader urban processes of public and private sector climate adaptation in the built environment.

## 1. Introduction

Climate change is already shaping the design and planning of cities. As such, urban planning processes play an increasingly important role in both climate mitigation and adaptation. Yet, broader processes associated with the adaptation of markets—that are often outside of the agency of existing public planning models—often amplify existing resource constraints and social vulnerabilities (Keenan et al., 2021). This article introduces an experimental methodology to identify and evaluate proxy indicators that are conceptually consistent with the processes of Climate Gentrification ("CG"). Evaluated through case studies in the state of Florida, this methodology is based on various quantitative geospatial tools for assessing urban processes that speak to long-term land use and development trends that may catalyze residential and commercial disruption and dislocation associated with CG.

CG is a theory that has gained a foothold in practice and in popular discourse by highlighting various pathways from which a change in demand preferences among consumers and investors drives the increased consumption for housing, real estate and land based, in part, on lower measures of physical risk from climate change (Keenan et al., 2018; Anguelovski et al., 2019; De Koning & Filatova, 2020). This shift in valuation and consumption associated with CG has been observed to reinforce cost-burdens on existing populations leading to some anticipated measure of increased displacement over time (Aune et al., 2020). CG is premised, in part, by the emerging evidence that the experiences and perceptions of climate change among buyers, sellers, producers and financiers of real estate are leading to a revaluation of climate risks and asset values (Bernstein et al., 2019; Keenan & Bradt, 2020), as well as the underlying fiscal capacity of local governments who rely on these markets for taxation (Shi & Varuzzo, 2020). The implications of this emergent behavior in high-exposure housing markets is widespread, including everything from risk capitalization of flooding (Hennighausen

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& Suter, 2020) and insurability (Bin et al., 2008; De Koning et al., 2019) to population displacement (Hauer, 2017) and climate migration (Mach et al., 2019). Local governments have an immediate political challenge to manage the disruption of individuals or businesses subject to the cost-burdens of either being forced out, priced out, or crowded out by private investment (Ghaffari et al., 2018), even if such processes are incidental to their broader economic development strategies that are reliant on such dislocations (Stein, 2019). At the heart of this balancing act between CG-driven shifts in capital investment and in situ socioeconomic interests is the management of long-term land uses (Bonjour, 2020) and tax bases (McAlpine & Porter, 2018).

As the risks of coastal hazards attributable to climate change become more tangible within the real estate, mortgage and insurance markets, a theory of CG suggests that higher-elevation areas away from the immediate coast will offer superior long-term investments relative to high-risk areas immediately on the coast (Keenan et al., 2018). While prior research has largely focused on homeowners and for-sale property performance (Baldauf et al., 2020), there has not been any sustained research on how near-term rental market behavior is correlated (or not) with processes of risk capitalization or assignment consistent with long-term capital shifts associated with CG. Rental markets are particularly key because they represent the dominant tenure class for low-to-moderate income (LMI) households who are likely among the most vulnerable to CG-driven disruption. As such, the central research question in this article is whether and to what extent rental market behaviors in coastal geographies of varying degrees of environmental risk and land use classification provide a useful quantitative indicator for an early warning of more robust disruptive processes at work pursuant to CG (Keenan et al., 2018).

Local governments are tasked with actively monitoring emerging vulnerabilities and conflicts in order to inform decision-making in land use planning, economic development and housing policy. This article provides an experimental methodology for observing and possibly providing an early warning system for CG through the use of a composite index. The proposed method builds on the experimental integration of multiple datasets concerning rental properties, evictions and socioeconomic data, as well as risk indices from the newly released National Risk Index (NRI) from Federal Emergency Management Agency (FEMA, 2021). The method is evaluated through two case studies in the state of Florida. Florida represents a unique case study for CG because LMI populations in many areas of what is now urbanized Florida have settled away from the coastlines (Montgomery & Chakraborty, 2015), as a consequence of a combination of racial and ethnic legacy zoning (Whittemore, 2017) and amenity capitalization (Mohl, 1995). In theory, these populations living in comparatively lower inland risk-geographies are uniquely at-risk from being crowded out or disrupted by CG as coastal populations move inland.

In the Miami case study, the index identifies a hotly contested neighborhood that is already in a state of demographic and market transition consistent with the processes of CG. In the Tampa case study, the index highlights a district that exhibits strong metrics for the future accelerated occurrence of CG. In both cases, the findings suggest that transitional land uses and flexible zoning in low-exposure areas are key elements for attracting new development consistent with anticipated capital inflows from CG. The findings provide a measure of support for the methodology and the underlying indicators, offering insight into the challenges that local governments face in understanding the types and rates of change that may be catalyzed in the broader urban processes of public and private sector climate adaptation in the built environment.

## 2. Climate gentrification and early warning systems

CG may arise pursuant to several different pathways, including the shift of capital from high-risk to low-risk geographies; the cost-burdens associated with increased costs from climate change impacts (e.g., insurance, loss in hourly wages); and, the capitalization of risk reduction that may drive rent seeking associated with public resilience investments in infrastructure (Keenan et al., 2018; Shokry et al., 2021). As to the first pathway, CG is distinct from conventional models of gentrification ("CMG") in so far as it represents a broader shift in consumer and investor preferences that may yield changes in demand features (De Koning & Filatova, 2020) across multiple potential scales—from local to regional (Liu et al., 2021). In the United States, CMG are largely centered on bounded place-specific (Lawton, 2020) phenomena that are often driven by a combination of the supply-side investments that seek to capture unrecognized amenities and corresponding local shifts in demand for these underpriced amenities and other attributes, such as proximity to jobs, mass transportation and quality housing (Finio, 2021). In this sense, CMG may be catalyzed by relatively localized shifts in supply and/or demand, whereas CG is catalyzed by broad shifts in awareness and perception of climate risk that translate into shifting consumer and investor locational preferences and corresponding flows in capital (McAlpine & Porter, 2018; Hino & Burke, 2020). While CMG may be bounded to a particular neighborhood or district, CG may extend to a broader geography of resettlement that extends beyond the conventional units of local analysis (Forsyth & Peiser, 2021). For instance, CG might arise in Atlanta or Charlotte from an outflow of coastal populations in Florida and the Carolinas. At a local scale, CG may also manifest within a particular set of adjacent districts that are perceived by consumers and investors to represent distinct alternatives between high and low measures of physical climate risk (Aune et al., 2020; Keenan et al., 2018).

While CG and CMG are distinct in their initialization, in the short-term, they may share similar indicators associated with social and economic disruption and even displacement. In the long-term, shifting land use and zoning patterns may be a macro-indicator of localized CG wherein shifts in consumer and investor preferences may require a spatial readjustment of housing demand, commercial activities, and sector organization in a way that is systemically distinct from the bounded local processes—largely associated with involuntary residential mobility—of CMG. Therefore, to fully capture CG, conventional quantitative CMG indicators should be augmented by a qualitative and quantitative understanding of the regional development and land use trajectories of the subject geographies.

Across a wide variety of indicators, early warning systems (EWS) for displacement and CMG have been widely developed by academics and applied by practitioners (Chapple & Zuk, 2016). Mapping and measuring residential displacement by itself is challenging given that proxy indicators for forced residential mobility are highly volatile, as the data on household motivations are often dependent on narrowly drawn surveys that fail to capture a range of factors shaping mobility (Carlson, 2020). Depending on the choice of indicators or theory of gentrification (Freeman, 2005), residential displacement may or may not even be correlated with CMG processes and outcomes (Carlson, 2020). Beyond displacement, recent research by Preis, et al. highlights that the most popular EWS models for CMG used by cities in the United States have very few overlapping indicators and that the models themselves may produce widely divergent findings when applied to other cities (Preis et al., 2021). This highlights the need for and value of context-specific indicators that are unique to the processes of urbanization in the subject geography—in this case, CG. Indeed, the methodological challenges associated with the quantification of CMG (Easton et al., 2020) opens the door for context-specific EWS models that may include a wide variety novel indicators, including, as this article does, those associated with environmental/climate risk and vulnerability that are unique to Florida and to the conceptual pathways of CG. In this sense, this measurement of CG fits within a broader sub-field of environmental gentrification that has sought to understand how social change, real estate economics, land use zoning and environmental risk are connected (Melstrom et al., 2021; Melstrom & Mohammadi, 2021).

## 3. Methodology

### 3.1. Study areas

The study areas consist of the metropolitan regions of Miami and Tampa, Florida. Specifically, this article focuses on the districts of Little River (red shaded area in Fig. 1d) and Miami Shores (green shaded area in Fig. 1d) in Miami-Dade County (collectively, "Miami Districts") in the region of southeast Florida and in Oak Park and Dixie Farms (collectively, "Dixie Farms", red and orange shaded areas in Fig. 1e) and Palmetto Beach ("Palmetto Beach", green shaded region Fig. 1e) in Hillsborough County (collectively, "Tampa Districts") and in the region of central-west Florida. The two regions have been selected because they represent optimal test-case scenarios on both the east and west coasts of Florida relative to the trajectory of long-term exposure to floods and sea level rise (Hines et al., 2020; Holmes & Butler, 2021).

### 3.2. Data

The methodology proposed in this study is based on defining quantitative criteria for the detection of at-risk communities by combining rental data from Zillow®, socioeconomic data from the Social Vulnerability Index (SVI) from the Centers for Disease Control and Prevention (CDC), risk indices from the newly released National Risk Index (NRI) from Federal Emergency Management Agency (FEMA), localized eviction data, and in some cases, future land use maps promulgated by local authorities. Here, the following is a brief summary of the datasets that comprise the *Socio-Economic Physical Housing Eviction Risk* (SEPHER) dataset. A summary of the datasets used in SEPHER is available in Table S1 and refer the reader to Tedesco et al. (2021) for a more detailed description.

Socioeconomic data derived from the census are distributed by the Centers for Disease Control and Prevention (CDC, 2021) as a Social Vulnerability Index (SVI) containing data on the four following categories: 1) socioeconomic status, 2) household composition and disability, 3) minority status and language, and 4) housing and transportation. The dataset ranks a total of 15 social factors, including poverty, lack of vehicle access, and crowded housing, and groups them into the previously mentioned themes (Flanagan et al., 2011). The index is available for the years 2000, 2010, 2014, 2016, and 2018. Spielman et al. (2014) stresses the uncertainty in the American Community Survey (ACS) (U.S. Census Bureau, 2019) due to sampling and small area estimate constraints. The CDC SVI data draw variables from the ACS for the years 2014, 2016, and 2018. In this article, select ACS variables are utilized in urban areas where these aforementioned small area low population concerns are less of an issue.

Data about mortgages are reported every year by thousands of financial institutions are disclosed by the Consumer Financial Protection Bureau of the United States Government to the public under the Home Mortgage Disclosure Act (HMDA). Data is currently available for the period 2007–2017 and contains information concerning, for example, whether the application was approved or denied, pre-approvals and loans sold from one institution to another, the property characteristics, the applicant demographics, ethnicity, race, and gender. The data are stripped of sensitive information and are aggregated to protect applicant and borrower privacy (Consumer Financial Protection Bureau, 2021).

Eviction data is provided by *The Eviction Lab* at Princeton University. The lab has collected, cleaned, geocoded, aggregated, and publicized all recorded court-ordered evictions that occurred between 2000 and 2016 in the United States, consisting of >80 million records (Desmond et al.,

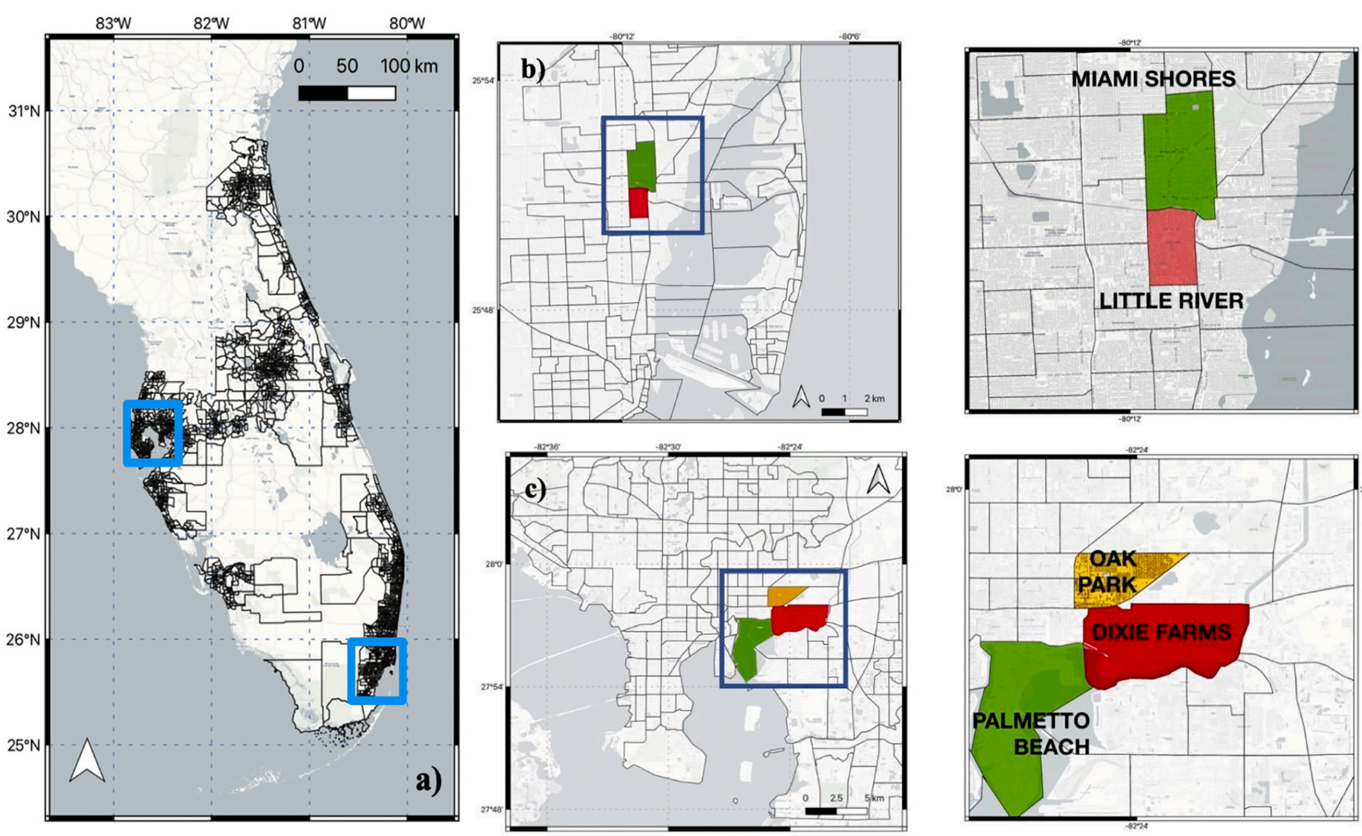



**Fig. 1.** a) Map of tracts where data is available after merging all of the datasets for Florida. Blue boxes indicate the two selected areas of interest in Miami and Tampa. b through e) Selected tracts over the Miami (b,d) and Tampa (c,e) areas. In Miami, red area refers to Little River where the green area to Miami Shores. In Tampa, the red region refers to Dixie Farms, the orange region to Oak Park and green region to Palmetto Beach. Panels b) and c) show the regional extent of the Miami and Tampa areas considered in this study. Panels d) and e) show details of the areas containing the selected tracts.

2018).

The National Risk Index (NRI) is developed by FEMA's Natural Hazards Risk Assessment Program (NHRAP) to combine the frequency of natural hazards with social factors and resilience capabilities. The goal is to take a holistic, multi-hazard approach and create a nationwide baseline of natural hazard risk. Through various partnerships and working groups, FEMA developed a methodology and procedure to create the National Risk Index (NRI) dataset. The dataset and the accompanying application seek to identify communities most at-risk to hazards.

Rental trends are computed from the Zillow Observed Rent Index (ZORI, 2021). ZORI is a smoothed measure of the observed market rate rent across a given region and is weighted to the rental housing stock to ensure representativeness across the entire market, not just those homes currently listed for-rent. The index is dollar-denominated by computing the mean of listed rents that fall into the 40th to 60th percentile range for all homes and apartments in a given region, which is once again weighted to reflect the rental housing stock. More details are available in the documented methodology of ZORI (2021).

The final master dataset is generated at the census tract level for the entire United States by joining the variables through the open source QGIS software. The only exception is the Zillow Observed Rent Index (ZORI) that is available at zip code level. In this case, the values at zip code level are assigned evenly to the corresponding census tract within each zip code. Areas where no data are available are excluded by necessity from the analysis.

### 3.3. Construction of indices

The number of variables in the original selection ($n = 26$, Fig. 2) is reduced to 17, as highlighted by the bolded variables in Fig. 2, before being used in a Principal Component Analysis (PCA). Thereafter, a PCA is performed to linearly transform correlated variables to capture the most variance with reduced features over the two geographic regions of interest containing the Miami Districts and the Tampa Districts (Cartone & Postiglione, 2020; Demšar et al., 2013). This method is effective to reduce the number of variables and identify meaningful dimensions.

Tables 1 and 2 show the PCA loads for the first 8 principal components in the case of Miami (Table 1) and Tampa (Table 2). Bold fonts indicate the highest values within each component (e.g., the variables having the most influence on each principal component). Despite differences between the results obtained over the two regions and districts, the variables describing the percentage of population with no vehicle, with no high school diploma and the unemployment, as well as annual average rent increase, are driving the first two components of the two datasets, explaining ~50 % of their variances. This is consistent with previous work aimed at mapping gentrification and displacement through socio-economic and other datasets (Tate, 2013; Spielman et al., 2020; Urban Displacement Project, 2021). For example, the Los Angeles Index of Neighborhood Changes uses six measures indicative of

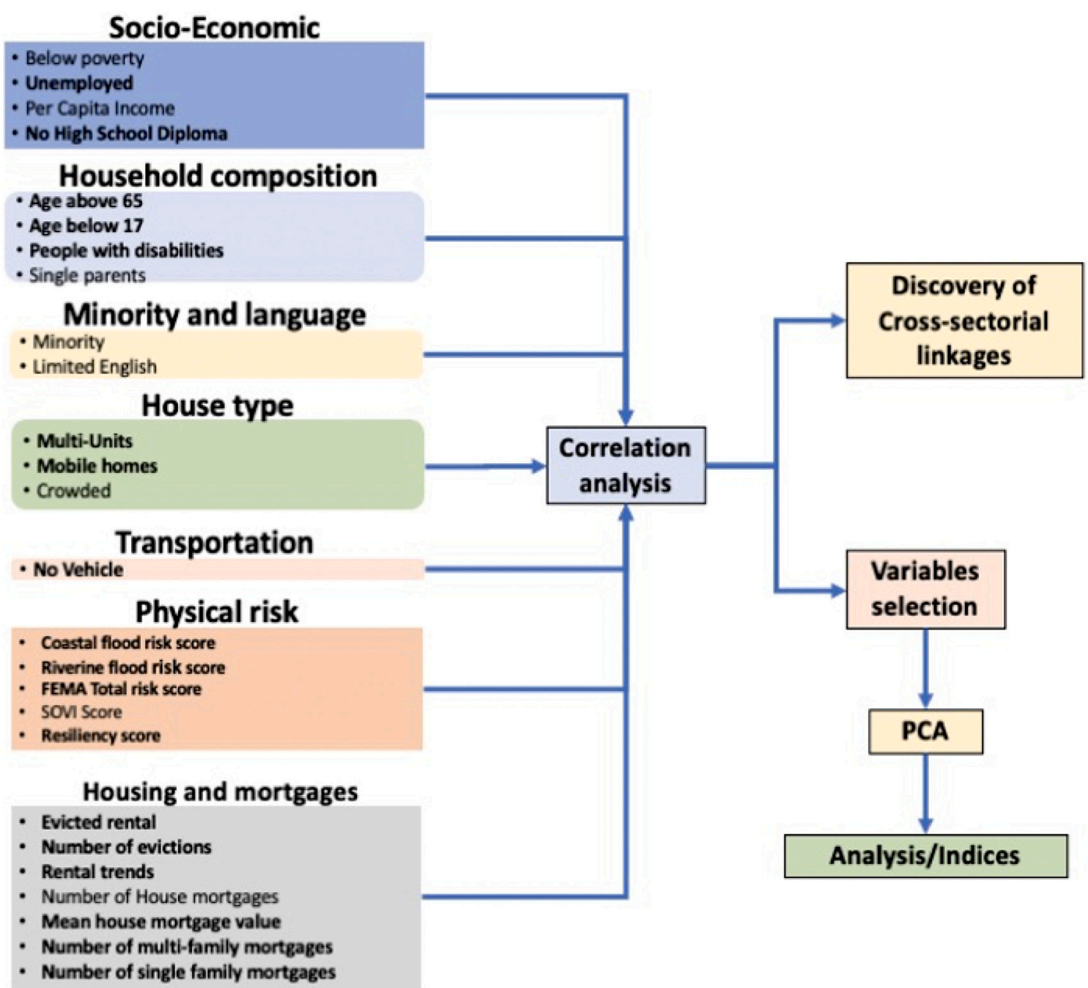



**Fig. 2.** Schematic showing the methods and variables used in this study. The variables on the left are used for the quantitative analysis together with the scheme adopted for studying the correlation and further selection of features for the Principal Component Analysis (PCA) analysis. Bolded variables are the ones selected for the PCA analysis.

**Table 1**
Principal Component Analysis (PCA) loads for the first 8 principal components in the case of Miami. One (two) asterisk indicates values at a 95 % (90%) statistical significance level.

| | PC1 | PC2 | PC3 | PC4 | PC5 | PC6 | PC7 | PC8 |
|---|---|---|---|---|---|---|---|---|
| Unemployed | 0.188 | −0.395* | 0.154 | −0.009 | 0.018 | −0.044 | 0.274* | −0.039 |
| No High School | 0.363* | −0.293** | −0.038 | 0.037 | 0.056 | 0.047 | −0.159 | 0.003 |
| Age > 65 | 0.15 | 0.088 | −0.503* | 0.234 | 0.076 | −0.228 | −0.067 | −0.113 |
| Age < 17 | −0.172 | −0.29** | 0.283 | −0.136 | 0.162 | −0.263 | 0.089 | 0.355* |
| Disabilities | 0.336* | −0.083 | −0.313 | 0.208 | 0.065 | −0.206 | 0.119 | −0.162 |
| Multi-Unit | 0.142 | 0.394* | 0.062 | −0.067 | −0.056 | 0.305* | 0.439* | −0.022 |
| Mobile Homes | −0.027 | −0.111 | −0.012 | 0.309 | 0.328* | 0.557* | −0.467* | 0.273 |
| No Vehicle | 0.404* | 0.019 | 0.104 | −0.114 | 0.23 | 0.081 | 0.214 | −0.153 |
| Resiliency score | −0.141 | −0.047 | 0.18 | 0.559* | 0.181 | 0.048 | 0.128 | −0.474* |
| Coastal Flood index | 0.168 | 0.351* | 0.132 | 0.25 | 0.217 | −0.147 | 0.035 | 0.212 |
| Riverine Flood index | 0.157 | 0.219 | 0.146 | 0.397* | 0.026 | −0.102 | 0.243 | 0.558* |
| Average annual rent increase | 0.156 | −0.434* | 0.009 | 0.147 | 0.035 | −0.166 | 0.06 | 0.134 |
| Percentage of evicted rented | 0.263 | 0.199 | 0.327 | −0.011 | −0.335* | 0.007 | −0.264 | −0.093 |
| Number of evictions | 0.227 | −0.121 | 0.471* | 0.006 | −0.071 | −0.012 | −0.019 | −0.139 |
| Mean mortgage value | −0.087 | 0.209 | 0.009 | −0.253 | 0.511* | −0.433* | −0.112 | 0.003 |
| Mortgage multi-family | 0.243 | 0.167 | 0.251 | −0.115 | 0.294 | −0.113 | −0.391* | −0.216 |
| Mortgage single family | −0.242 | 0.056 | 0.19 | 0.364* | −0.352 | −0.386* | −0.198 | −0.087 |

**Table 2**
Principal Component Analysis (PCA) loads for the first 8 principal components in the case of Tampa. One (two) asterisk indicates values at a 95 % (90%) statistical significance level.

| | PC1 | PC2 | PC3 | PC4 | PC5 | PC6 | PC7 | PC8 |
|---|---|---|---|---|---|---|---|---|
| Unemployed | −0.086 | −0.247** | −0.27** | 0.157 | −0.158 | 0.08 | −0.581* | 0.520* |
| No High School | −0.024 | −0.290** | 0.408 | 0.178* | 0.156 | −0.045 | 0.129 | 0.081 |
| Age > 65 | −0.423* | 0.195* | −0.008 | −0.075 | 2 | 0.178 | 0.150 | 0.1 |
| Age < 17 | 0.415 | −0.103 | −0.153 | 0.232 | −0.033 | 0.162 | −0.065 | −0.032 |
| Disabilities | −0.392 | −0.02 | −0.261 | −0.020 | −0.144 | −0.093 | −0.128 | −0.232 |
| Multi−Unit | −0.211** | −0.210* | 0.371* | −0.197 | −0 | −0.196* | 0.093 | −0.128 |
| Mobile Homes | −0.112 | −0.0 | −0.381 | −0.011 | 0.508 | −0.186** | 0.270* | −0.139 |
| No Vehicle | −0.222** | −0.378** | −0.124 | 0.005 | −0.295 | −0.002 | −0.118 | −0.291 |
| Resiliency score | 0.33 | −0.156 | −0.077 | −0.197 | −0.069 | −0.387* | 0.095 | 0.230** |
| Coastal Flood index | −0.282** | 0.045 | 0.194** | 0.448* | 0.186 | −0.012 | 0.233* | 0.261** |
| Riverine Flood index | −0.001 | 0.093 | 0.102 | 0.701* | −0.144 | −0.506 | −0.021 | −0.051 |
| Average annual rent increase | −0.330* | −0.018 | 0.124 | 0.113 | 0.111 | 0 | 0.166 | 0.301 |
| Percentage of evicted rented | 0.045 | −0.409* | 0.277* | 0.0687 | −0.174 | 0.035 | 0.325 | −0 |
| Number of evictions | 0.062 | −0.504 | 0.009 | 0.101 | −0.061 | 0.124 | 0.159 | −0.116 |
| Mean mortgage value | 0.062 | −0.158 | 0.384* | – | 0.409 | −0.262* | −0.261 | 0.162 |
| Mortgage multi−family | −0.033 | −0.282** | 0.261** | 0.009 | 0.431 | 0.103 | −0.398* | −0.216 |
| Mortgage single family | 0.267 | 0.229** | 0.096 | 0.256** | −0 | 0.273* | −0.14 | −0.287 |

gentrification to study demographic changes in the Los Angeles area, including change in percent of residents 25 years or older with Bachelor's Degrees or Higher, percent change in median household income and change in median gross rent (Urban Displacement Project, 2017).

Building on the results of the PCA analysis, we define three indices. The first index is referenced as the *Rental Stress Index (RSI)* is defined as:

$$\mathrm{RSI} = (\Delta_{\mathrm{Rent}})^{*}(\mathrm{RP}_{\%})/\mathrm{PCI} \quad (1)$$

where $\Delta_{Rent}$ is the average (2014–2018) change in rent expressed as a relative percentage of the initial value of 2014, $RP_{\%}$ is the percentage of rental properties within the considered tract (expressed as a fraction ranging between 0 and 1) and the per capita income (PCI) in 2018 US dollars. The RSI accounts for those factors related to rental pressure (e.g., the higher the rent increase the greater constraints there are on property selection and access), for the rental burden (through the ratio between the rent increase and the PCI), for the economic status of the population (through the inverse of the PCI) and for the higher exposure to risk of stress associated with the higher number of rental properties within each tract. The index values are normalized to range between 0 and 1, with 0 being the lowest risk and 1 being the highest risk. We point out that our approach deviates from other literature work using household income rather than PCI. This is also due to our focus in social vulnerability.

The second index addresses the physical risks and it is named the *Flood Risk Index (FRI),* obtained from the linear combination of the coastal and river scores within the NRI dataset:

$$\mathrm{FRI} = \text{Coastal Flood Score} + \text{Riverine Flood Score} \quad (2)$$

where the Coastal and Riverine scores are obtained from the FEMA NRI dataset. The index is normalized to range between 0 (no risk) and 1 (maximum risk).

The third index uses social change as a proxy for either the displacement and/or succession of resident populations that may be occurring with CG (Carlson, 2020). Given the relatively short period of time (2014–2018), this index is referenced as the *Social Change Index (SCI),* which is defined as:

$$\mathrm{SCI} = \mathrm{Unemp}_{\%}{}^{*}\left(\Delta_{\mathrm{NoVeh}}{}^{*}\,\Delta_{\mathrm{NoHiSchDpl}}\right)^{*}(\mathrm{LMI}_{2014}/\mathrm{LMI}_{2018}) \quad (3)$$

where $\Delta_{NoVeh}$ and $\Delta_{NoHiSchDpl}$ are, respectively, the changes in the percentage of people with no vehicle ($\Delta_{NoVeh}$) and with no high school diploma ($\Delta_{NoHiSchDpl}$) and $Unemp_{\%}$ is the percentage of unemployed people. LMI means the different in low-to-moderate income (LMI) households between an aggregate period from 2010 to 2014 ($\mathrm{LMI}_{2014}$) and between a period from 2015 to 2018 ($\mathrm{LMI}_{2018}$). $\mathrm{LMI}_{2018}$ is the most up-to-date measure of local LMI population for official policy activity pursuant to the U.S. Department of Housing and Urban Development. The SCI aims at capturing those changes associated with a gentrification or displacement occurring between the two periods. The choice of the variables in this case is based on the results of the PCA analysis and is consistent with previous work, as cited. The normalized (to the absolute maximum) index can range between −1 and 1, with positive values indicating displacement and negative values associated with an influx of people to the tract. For consistency purposes with other indices, the SCI is also constrained between −0.5 and 0.5 by simply shifting and scaling the values between −1 and 1 through a linear transformation. Values below 0 indicate influx and those above 0 displacement.

Lastly, we build a *Climate Gentrification Rental Index (CGRI)* by adding the three indices introduced above as follows:

$$CGRI = (RSI + (1 - FRI) + SCI)/3 \tag{4}$$

Here, (*1-FRI*) is used as a metric for the index because we are interested in those regions where the flood index is low (e.g., low risk) and where a link between gentrification, climate and land speculation (higher value for *1-FRI*) might exist.

## 4. Results

### 4.1. Miami-Dade County and the Miami Districts

The Miami case study looks at two neighboring districts, including the historically vulnerable and marginalized district of Little River and the wealthier district of Miami Shores. Little River has a comparatively

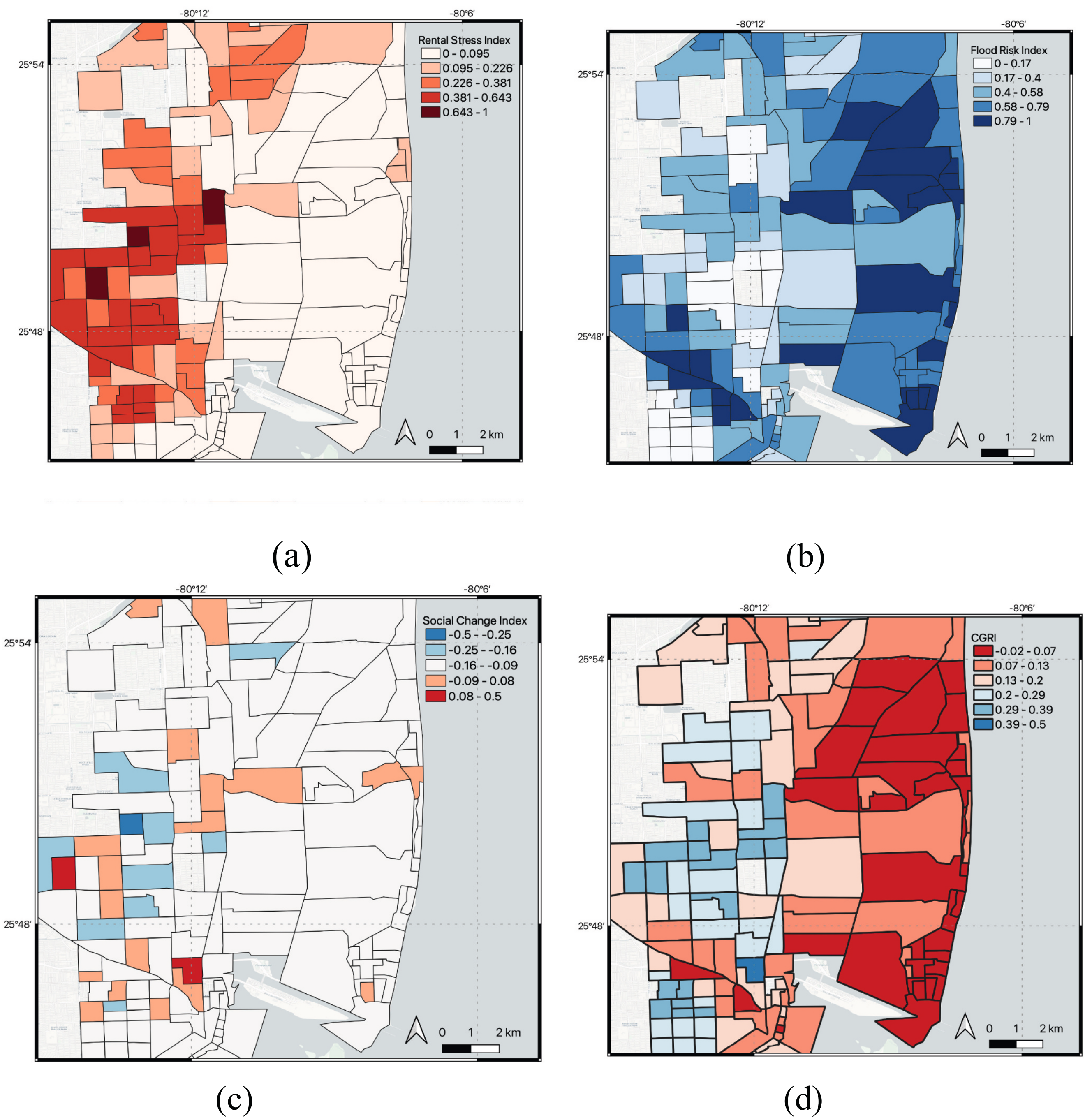



**Fig. 3.** Maps of a) Rental Stress Index, b) Flood Risk Index, c) Social Change Index and d)Climate Gentrification Risk Index for the Miami-Dade region of interest. d) Annualized flood frequency from the FEMA NRI dataset together with areas subject to flooding obtained from NOAA (https://coast.noaa.gov/slrdata/) in the case of 3 ft. (light blue) and 6 ft. (dark blue) SLR scenarios.

lower risk for flooding and sea level rise inundation and the results highlight that it is also comparatively much more vulnerable to climate gentrification. As will be further highlighted, this is confirmed by the results of the CGRI and by interviews with market participants, consumers and local policy officials at the City of Miami. Overall, an analysis of the population living below the poverty level, unemployment, and PCI indicates that both the percentage of people living below the poverty level and the PCI in Miami (Supplemental Fig. 1) changes drastically when moving from the coast to inland portions of Miami-Dade County (Supplemental Fig. 1(e)). This pattern is consistent with the distribution of the percentage of unemployed people. In 2014, the Little River district was characterized by low PCI ($8220) and relatively high poverty (61.1 %) and unemployment levels (28.1 %). We point out that all PCI values are expressed in 2018 dollars. On the other hand, the tract containing the Miami Shores area, which is contiguous to the one with Little Miami and located on its northern border, is characterized by relatively higher PCI ($38,891) and lower poverty (7.7 %) and unemployment (9.1 %) levels. When considering the spatial distribution of differences between 2014 and 2018, a reduction in the percentage of people living below the poverty level over the Little River area is observed, accompanied by a slight increase in PCI and a reduction of unemployed people. The Miami Shores area does not show similar changes with the poverty level, remaining almost unchanged, with a moderate increase of PCI and a negligible change in unemployment. There are no observed patterns specific to people with disabilities (e.g., one of the variables identified by the PCA analysis to be driving a large part of the dataset variance together with people with no vehicle and no high school diploma, *see* Supplemental Fig. 1(a)). However, a marked distinction between the areas with high and low percentage of people with no high school diploma (Supplemental Fig. 1(c)) and with no vehicle (Supplemental Fig. 1(e)) is observed, consistent with the distribution of the PCI and unemployment percentages.

The RSI for the Miami area (Fig. 3a) shows a pattern that also is geographically consistent with the PCI and unemployment, reaching a value of 0.726 for Little River (Table 3), with a mean and standard deviation of 0.113 and 0.117, respectively, over the whole Miami-Dade area (Table 4). On the other hand, the Miami Shores tract shows a negligible RSI value of 0.036, pointing to the socioeconomic stress induced by the strong gradient between the two close districts.

**Table 4**
Statistics of SCI, RSI, FRI and CGRI for the Miami-Dade and Tampa regions and corresponding values for the Little River and Miami Shores tracts (Miami) and the Dixie Farms and Palmetto Beach (Tampa) tracts.

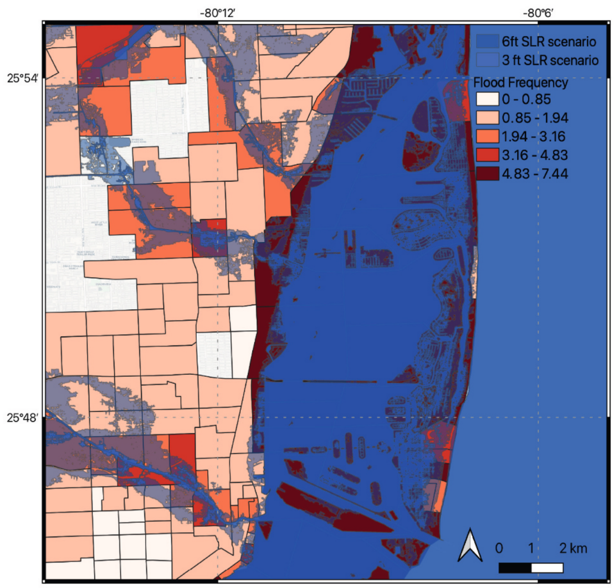
| | RSI | FRI | SCI | CGRI |
|---|---|---|---|---|
| All Miami tracts | | | | |
| Mean | 0.113 | 0.358 | 0.124 | 0.293 |
| Median | 0.076 | 0.338 | 0.112 | 0.293 |
| St dev | 0.117 | 0.218 | 0.076 | 0.09 |
| Q1 | 0.038 | 0.225 | 0.108 | 0.247 |
| Q3 | 0.143 | 0.455 | 0.127 | 0.335 |
| All Tampa tracts | | | | |
| Mean | 0.191 | 0.516 | −0.112 | 0.188 |
| Median | 0.131 | 0.535 | −0.124 | 0.175 |
| St dev | 0.192 | 0.271 | 0.083 | 0.124 |
| Q1 | 0.036 | 0.321 | 0.131 | 0.086 |
| Q3 | 0.131 | 0.535 | −0.124 | 0.175 |

The FRI (Fig. 3b) in the case of Little River is 0.416 where it is 0.276 for Miami Shores. For the FRI the mean and standard deviation are, respectively, 0.358 and 0.218. The SCI (Fig. 3c) also shows a strong contrast between the Little River and Miami Shore tracts. For the Little River, the SCI value is −0.071, while it is −0.124 in the case of Miami Shores.

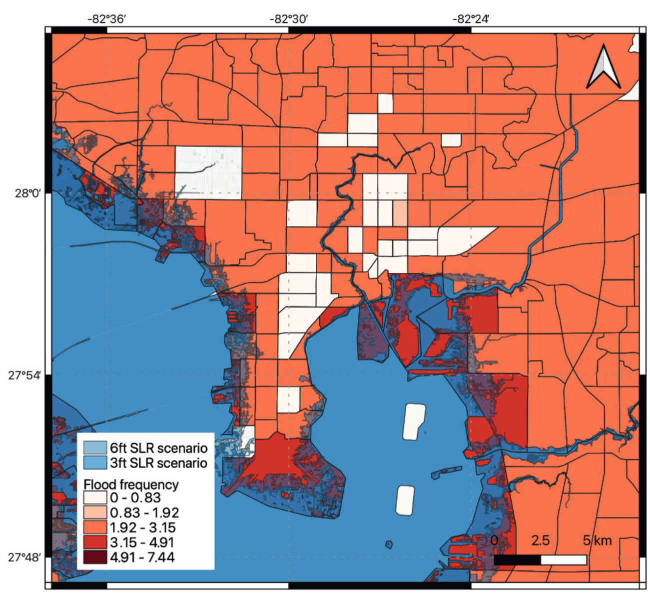
Most importantly, the CGRI index (Fig. 3d) synthesizes the overall difference between the two districts under study. The Little River CGRI shows a value of 0.413 in contrast to the comparatively lower value of 0.212 for the Miami Shores tract (Table 3). The Little River CGRI is more than two standard deviations above the mean of the distribution for the whole area. Miami Shores values are, instead, closer to the mean. For reader's convenience, Fig. 4(a) highlights the extent to which environmental exposure to flood risk in contextual districts is much higher relative. In particular, Miami Shores has a significantly higher risk of flooding and inundation than most of the geography of Little River, which is at a higher elevation.

**Table 3**
Selected districts and tracts used for the in-depth analysis in this study for the two regions of Miami and Tampa. The first column contains the name and the GEOID for each tract. The remaining columns report the RSI, FRI, SCI and CGRI for each of the tracts. Colors refer to Fig. 1 for identifying the geographic location of the tracts.

| **Tract name (tractid)** | **RSI** | **FRI** | **SCI** | **CGRI** |
|---|---|---|---|---|
| Selected Miami Tracts | | | | |
| Little River (#12086001402) | 0.726 | 0.416 | -0.071 | 0.413 |
| Miami Shores (#12086001104) | 0.036 | 0.276 | -0.124 | 0.212 |
| Selected Tampa tracts | | | | |
| Dixie Farms (#12057003600) | 0.543 | 0.495 | 0.276 | 0.441 |
| Palmetto Beach (#12057005302) | 0.181 | 0.845 | 0.156 | 0.164 |
| Oak Park (#12057003600) | 0.295 | 0.061 | 0.35 | 0.528 |




(a)




(b)

**Fig. 4.** Annualized flood frequency from the FEMA NRI dataset together with areas subject to flooding obtained from NOAA (https://coast.noaa.gov/slrdata/) in the case of 3 ft. (light blue) and 6 ft. (dark blue) SLR scenarios.

### *4.2. Hillsborough County and Tampa Districts*

The four indices presented for the Miami region were also computed for the Tampa region and are reported in Fig. 5. The census tract that falls within the district of Dixie Farms located within the western portion of the Tampa city appears to be at high-risk of CG, according to the results obtained with the indices. This area is colloquially known as the "Dixie Farms." This census tract has an FRI value of 0.495 and it is contiguous to tracts to the west ("Palmetto Beach," *see* Fig. 1) where flooding risk is high and to the north. The RSI is among the highest (0.543, with a mean for the whole Tampa area of 0.191 and a standard deviation of 0.192), because of the combination of the relatively high average rental increase and the high unemployment and poverty levels characterizing this tract. The SCI and the CGRI for the Dixie Farms tract are also relatively high being, respectively, 0.276 and 0.441. This tract is characterized by a high presence of minority population (~ 90 %). Moreover, the percentage of unemployed people for this tract decreased from 17.9 % to 9.8 % between 2014 and 2018, and the percentage of people living below the poverty level decreased from 62.7 % to 30.4 %. The PCI increased from \$8554 in 2014 to \$16,724 in 2018. The percentage of minority population (~ 55 %) and people with limited English remained similar (~ 5 %), but the percentage of mobile homes decreased considerably from 41.8 % to 26.0 %. For this tract, the population decreased from 3137 people in 2000 to 910 in 2016 to reach a value of 831 in 2018. Despite the poverty level remaining practically unchanged (39.8 % in 2014 and 39.1 % in 2018), unemployment dropped from 20.8 % to 12.9 %.

## 5. Discussion

Little River is gentrifying rapidly. Part of this behavior may be attributed to environmental and climate-related risk aversion behavior associated with CG. It may also be possible that the district is subject to a supply-side CMG because of the district's proximity and adjacency to amenity-rich and comparatively wealthier districts, such as Miami Shores to the north and the Miami Design District to the south. In fact, it may be a combination of both phenomena in the sense that increased demand from consumers associated with CG is being supported by existing momentum for increased supply of housing and real estate associated with CMG in adjacent districts.

As an indicator of displacement and social stress (Chum, 2015) the number of evictions in Little River increased from 123 in 2014 to 163 in 2016, reaching a peak value of 254 in 2015 (Fig. 6). On the other hand, evictions decreased from 15 in 2014 to 6 in 2016 for the Miami Shores district. This time horizon is defined by the availability of rental Zillow data. A look at a longer time series (Fig. 7a) indicates that the total number of evictions in Little River tripled starting in 2007 in conjunction with the Global Financial Crisis, remaining relatively stable until 2014, whereas it increased to about 5 times the pre-2008 values in 2015 and 2016. On the other hand, the number of evictions remained relatively constant for the Miami Shores district. Moreover, the ratio between the rent and the income (e.g., rent burden, not shown), remained relatively stable for Miami Shores and increased considerably for Little River, highlighting the potential financial pressure on the socially vulnerable households living in Little River and confirming the potential of the index to suggest areas at risk of CG and CMG. As highlighted in Fig. 3(d), the distinction here is that environmental and flood risk in Little River is comparatively lower than much of the region. In this sense, lower environmental risk is perceived by the market as a form of positive amenity, which is likely shaping demand-side processes.

In the case of Tampa, Dixie Farms is undergoing a rapid amount of change. Interviews with local real estate stakeholders suggest that this might be having a spillover effect into Oak Park. The number of evictions for Dixie Farms area reached a high point ($n = 96$), with a mean of 43 evictions and a standard deviation of 23 for the years 2000–2016 (Fig. 7b). This strongly contrasts with the trend of the evictions identified for the district of Palmetto Beach, showing a rate of −0.55 evictions/year ($R^2 = 0.39$). A considerable increase in the number of evictions (2.86/year; $R^2 = 0.72$) occurs for the tract located north of Dixie Farm (Fig. 7b). This area contains the northern portion of the Dixie Farm neighborhood.

Both CG and CMG phenomena are dependent on the prospects for future development associated with rezoning and other forms of public support. In Miami Shores, the prospects for significant rezoning are slim because of powerful political constituencies and because of relatively homogenous residential patterns that do not lend itself to an accessible increase in density. By contrast, Little River is composed of a variety of concentrated land uses—residential, industrial and commercial—that lend themselves to greater densification. Future land use land cover for the city of Miami shows that most of the future planned development

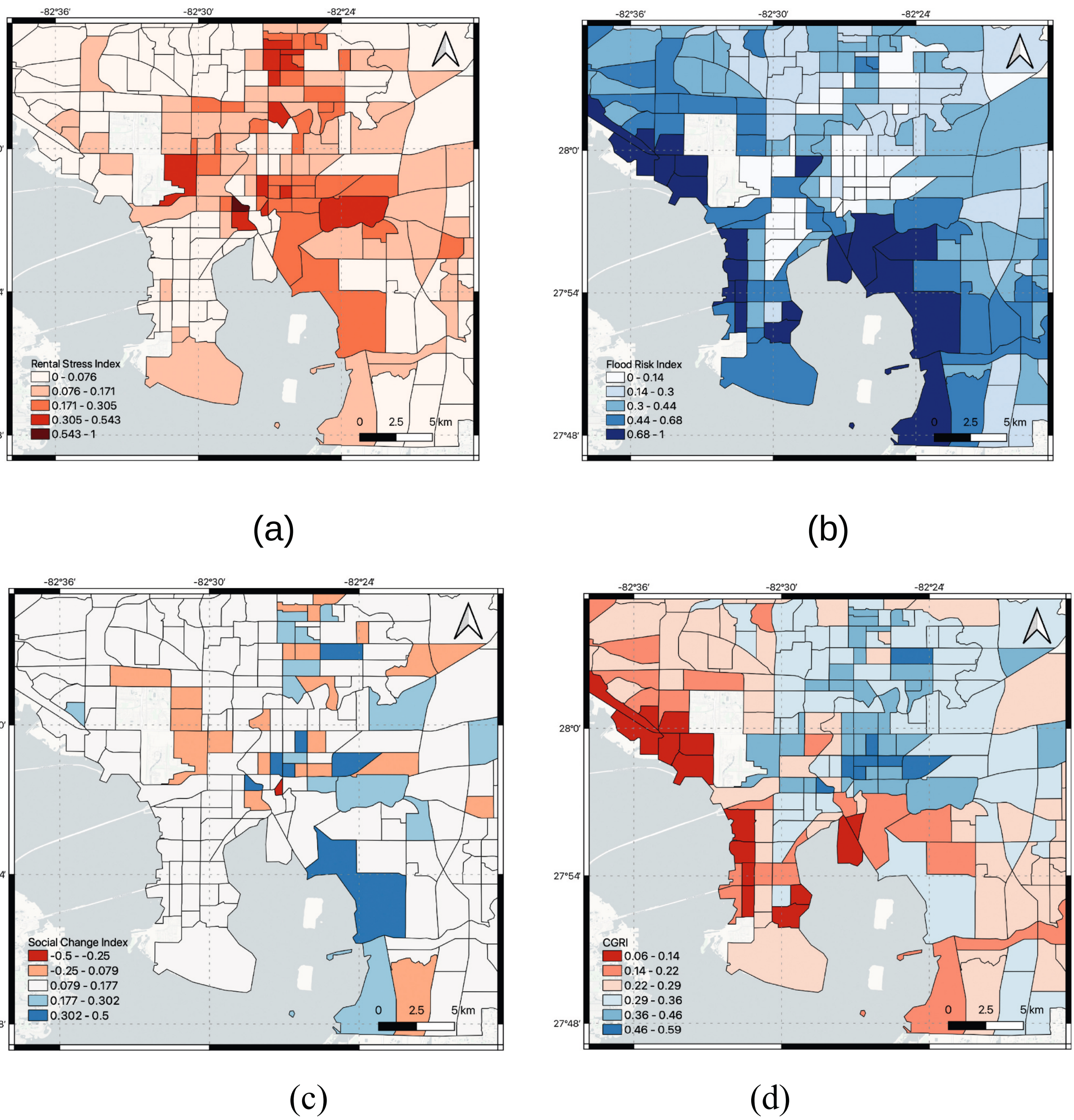



**Fig. 5.** Maps of a) Rental Stress Index, b) Flood Risk Index, c) Social Change Index and d) Climate Gentrification Risk Index for the Tampa region of interest. d) Annualized flood frequency from the FEMA NRI dataset together with areas subject to flooding obtained from NOAA (*https://coast.noaa.gov/slrdata/*) in the case of 3 ft. (light blue) and 6 ft. (dark blue) SLR scenarios.

focuses on single-family homes in the northern part of the tract (closer to the Miami Shores tract) and on commercial/industrial buildings. Interviewees in the real estate development industry conducted suggest that rezoning commercial tracts (e.g., from commercial or industrial to mixed-use) adjacent to residential zones has a spill-over effect for the prospect of greater value in the adjacent residential properties, which are often built to much lower intensities and frequently viewed as ripe for redevelopment.

Beyond diverse land uses, Little River is also home to a variety of housing types, including mobile homes (see Supplemental Fig. 3(a)). The owners of mobile home parks in Florida have long used the ground lease rental income to offset carrying costs while they wait for demand for land to catch-up with the location of their properties (Sullivan, 2018). In recent decades, high-risk mobile home parks impacted by flooding were quick to sell, which left a smaller number of remaining parks in comparatively lower-risk areas nearer urban cores, as is the case in Little River (Kusenbach et al., 2010). When mobile home park owners sell their land for redevelopment, housing displacement is a substantive concern among low-income occupants. The underlying land economics of the sale also sends a signal to other owners of low-intensity properties that it might be an optimal time to sell-out.

This is almost certainly the case in Little River, as well as in Tampa with Dixie Farms, where multiple mobile home parks were sold and depopulated within the time horizon of this research (*see* Supplemental Fig. 3(b). Like Little River, Dixie Farms has a diverse range of land uses. In particular, the district is home to a CSX Intermodal Terminal. Unlike

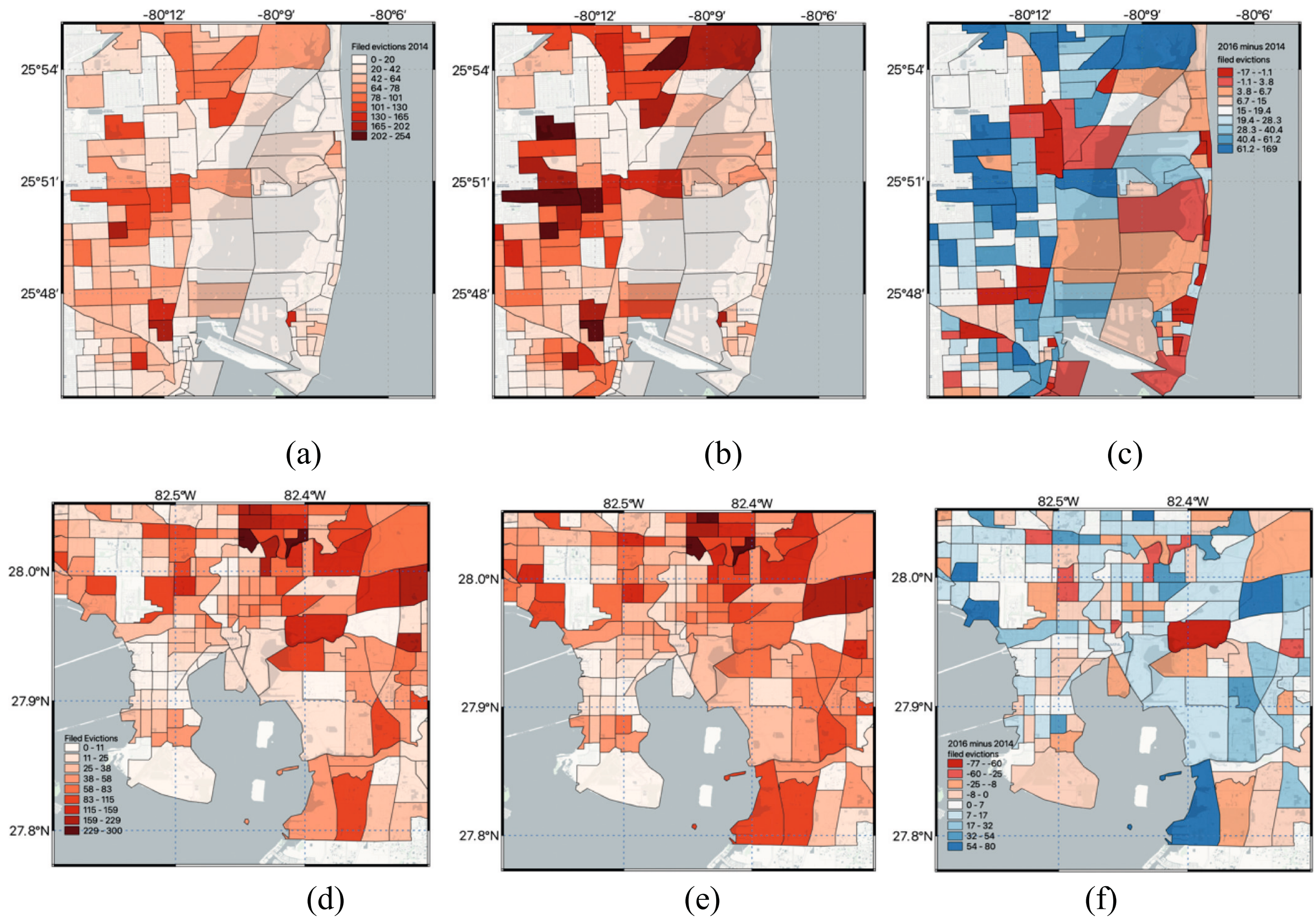



**Fig. 6.** Number of filed evictions in the (a,b,c) Miami and (d,e,f) Tampa areas in (a,d) 2014, in (b,e) 2016, and the difference between these years (c,f).

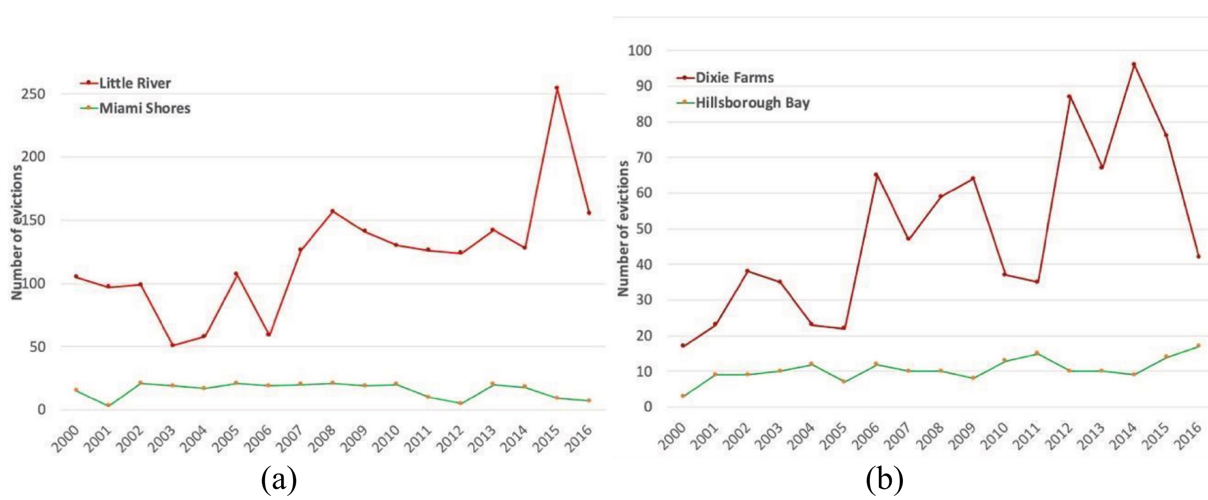



**Fig. 7.** Time series of number of filed evictions for the a) Miami and b) Tampa regions between 2000 and 2016. In both districts, the areas where gentrification has been identified by our index are shown in red (e.g., Little River and Dixie Farms) where the contiguous areas where gentrification has not been suggested are plotted as green lines (Miami Shores and Oak Park).

in Miami, CG is not widely understood as a broader public policy problem in Tampa. Interviewees with the City of Tampa and Hillsborough County by the authors suggest that one of the reasons for this is that this district within Tampa is perceived to have a great deal more developable land in the suburbs than does Miami-Dade County, which is bound on three sides by water. What is unique about Dixie Farms is that it is slated to continue to intensify industrial and commercial uses to the exclusion of residential uses. Here, we are likely seeing CG driven not by residential capital, but by industrial and commercial capital. The exposure to sea level rise throughout Tampa Bay is very high, including areas in and around the Port of Tampa, McKay Bay and Hillsborough Bay, which contain many heavy industrial uses (City of Tampa, 2021). As land becomes scarce for both residential and commercial development, it is anticipated that there will be increased conflicts between competing land uses (Helbron et al., 2011). This conflict looks very similar to the growth management conflicts in prior generations in Florida, except that environmental exposure is reducing the inventory of infrastructure serviced land and ecologically supporting habitats (Chapin, 2017). Dixie Farms is likely a bellwether for this conflict. Recent reports of toxic exposure to the local population, including a local elementary school, from a lead smelting plant highlight these immediate conflicts (Johnson et al., 2021). As industrial and commercial interests consolidate in Dixie Farms, the price of land will increase and that will undermine the affordability for and maybe even the health of local residents. Indeed, with increased development there may be negative spillover effects from pollution-driven externalities to neighboring residential districts, unlike the positive spillover effects in Miami associated with mixed-use rezoning associated with amenity-driven housing and retail development. The industrial consolidation in Dixie Farms likely was instigated independent of climate change considerations because of the existing infrastructural capacity and relative proximity. However, interviews suggest that climate change risks from flood and inundation may have very well accelerated the concentration of industrial uses out of necessity (e.g., lack of suitable non-floodable land). Current regional activities in Tampa have put industrial planners on notice that sea level rise and infrastructural adaptations are a major challenge (Holmes & Butler, 2021). Dixie Farms is likely an harbinger of what is to come as space for water-dependent industrial uses becomes more and more scarce.

## 6. Conclusions

In 2018, the city commission of Miami enacted a resolution directing city staff to research and monitor activities associated with CG (City of Miami, 2018). Interviews with city staff tasked with executing this resolution have suggested that the task is easier said than done. Interviewees with the City of Miami's Chief Resilience Officer and staff suggested that existing data sources are poor and non-environmental related factors that undermine affordability and drive displacement make it difficult to discern any clear pattern of behavior or trend. Yet, there is overwhelming qualitative evidence from a variety of stakeholders in districts north of downtown, such as Little River, that investors and consumers see long-term value in the high-elevation land and re-development. Concurrently, city officials and market participants acknowledge that the broader trends for real estate investment in lower risk areas are undeniable over the long-term. The policy challenge has been to find the right metrics to help policymakers and community members understand where capital is moving to first in the long-term reassignment of value relative to environmental exposure. Having this intelligence in places like Miami and Tampa would allow the appropriate up and down zoning, the allocation of affordable housing and anti-eviction resources, as well as the strategic investment of public resources in property rehabilitation that eases the cost-burden pressures on vulnerable communities. This article aims at addressing some of the underlying issues discussed above and introduces a method for providing an early warning of the convergence of social and environmental vulnerability that operate in silence parallel to more formal land use rezoning and property redevelopment processes.

When looking at the cities of Miami and Tampa, one can argue that an important element shaping potential CG is the heterogeneity in housing and land use types that are complementary for the capacity of the land to be rezoned in the future. In Miami, it is the influx of residential capital and in Tampa it is the influx of industrial capital that are driving this demand for rezoning and available land. This reinforces the proposition that CG drives not just housing displacement but also the displacement of small businesses. Therefore, future research in the monitoring of CG should pay close attention to the displacement of small business and the local labor force (Ferm, 2016). But, it might also work in the opposite direction insofar as increased labor-supporting commercial and industrial activity crowds out residential uses, as is likely to be the case in the Tampa districts. Here, contiguous tracts and conflicting land uses allow for more accessible rezoning of industrial expansions and consolidations to the exclusion of local affordable housing, particularly with mobile home parks and older multi-family housing on large tracts of property. The implications are that cities need to plan for long-term land use changes and an underlying morphology that balances residential and commercial interests (King et al., 2016). This is critical for not only managing capital improvement plans for infrastructure necessary to service these uses, but also for anticipating where residential and commercial dislocation and stress is going to take place. At that juncture, local authorities can make more proactive efforts to transition conflicting land uses and to make provisions or priorities for the production or preservation of affordable housing in conflict adjacent areas. In Florida, these transitional areas can be designated as Adaptation Action Areas, which allows for greater flexibility in accommodating various uses and demands (South Florida Regional Planning Council, 2014).

Upon further testing and validation, the method proposed herein may be applied to a broad scope of geographies and risks from flooding on the East Coast to forest fires on the West Coast. With a proliferation of resilience and adaptation indicators, the challenge is to develop indicators that provide continuity for longitudinal analysis, but are also flexible enough to incorporate future advances in risk measurement through revised risk indices (Keenan & Maxwell, 2021). Developing the right set of indicators will be useful for greater transparency and accountability by and between public and private stakeholders. However, greater transparency can work two ways. It can provide information for local communities to push back on policies that may lead to displacement. It might also accelerate greater awareness among consumers and investors and operate to accelerate revaluation of land, capital shifts and CG.

In many ways, climate change is ushering in a new era of growth management in Florida after years of decline associated with legislative deregulation (Boda, 2018). Tracking social stress and environmental risk is not as easy as simply looking at where evictions take place and where flood exposure has been measured. By looking comprehensively at where environmental risk, socioeconomic changes and land use patterns are converging, local governments can plan for long-term land uses that advance both mitigation and adaptation goals. A failure to do so will result in further undermining the climate crisis and increasing social inequalities. For that matter, local community stakeholders can utilize this model and method to hold local governments accountable in scenarios where economic development policies are not sufficiently accounting for the distributional nature of social costs. The findings of this article provide a direct challenge for future research that develops tools to not only respond to the impacts of climate change, but also to anticipate where future social, economic and environmental impacts converge. In this regard, it is hoped that the method presented in this article will stimulate a more sustained commitment to measuring CG and CMG in the advance of more resolute stewardship of forward-looking growth management, land use and infrastructure policies by local governments.

## Credit authorship contribution statement

The lead author co-conceived the study, prepared the index datasets and co-developed the research. The second author co-conceived the study, conducted field research, data analysis and co-developed the research. The third author prepared the data and contributed to the quantitative analysis. All authors contributed to the writing of the manuscript and analysis of the results.

## Declaration of competing interest

The authors declare no conflict of interest.

## Data availability

Data will be made available on request.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cities.2022.103991.

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