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Social segregation of ecosystem services delivery in the San Antonio region, Texas, through 2050

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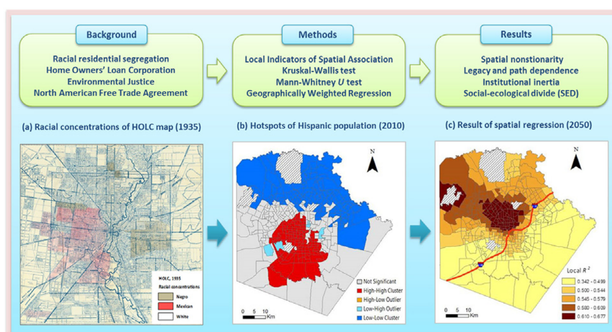
HIGHLIGHTS

- A novel empirical study of ecosystem service-based racial segregation is presented.
- Historical legacy and path dependence of environmental injustice are demonstrated.
- NAFTA corridor-related health risks are the most significant for the Hispanics.
- Persistent residential segregation is likely to degrade sustainability through 2050.
- Institutional transformations are essential to mitigate the social-ecological divide.

GRAPHICAL ABSTRACT



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ABSTRACT

Inequality in access to ecosystem services is inextricably linked with environmental justice in socially heterogeneous urban settings. Historically, San Antonio has been the gateway to Mexico and is strategically located along the North American Free Trade Agreement (NAFTA) corridor. It is also characterized by some of the most distinct residential segregation among U.S. cities. However, little is understood about the ways in which historically institutionalized residential segregation initiated by the Home Owners' Loan Corporation (HOLC) and NAFTA have affected socio-ecological outcomes. Here, this paper presents a novel empirical study of racial residential segregation. The study utilizes quantitative and spatially explicit estimates of regulating ecosystem services and biodiversity, and links the supply of ecosystem services to the distribution of human well-being within a heterogeneous social-ecological system. Specifically, the paper employed 1930s HOLC redlining maps and applied the ceteris paribus approach for racial concentrations to reflect a historical legacy and path dependence by institutional inertia. The results point to the social-ecological divide in that Hispanic and African American minorities derive fewer ecosystem benefits and face greater health risks and socio-economic disadvantages ($p < 0.01$). Notably, NAFTA corridor-related health risks are the most significant for the Hispanic population ($p < 0.01$). These patterns are likely to persist and may be amplified by 2050 (adjusted $R^2 = 0.646$). The findings highlight that institutional transformations are essential for the greater social-ecological equity in the San Antonio region under NAFTA and, potentially, new United States-Mexico-Canada Agreement. Additionally, by assessing the EJ

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implications of spatially heterogeneous distribution of ecosystem services supply, the paper provides methodology that enhances science-based planning and better environmental decision-making to avoid or mitigate social-ecological divides in rapidly urbanizing regions both in the U.S. and around the world.

1. Introduction

Urban ecosystem services, recognized as ecological infrastructure for human well-being, provide not only a variety of benefits but are also characterized by social disparities due to variations in the delivery of these benefits and external costs to different neighborhoods and communities (Barnaud et al., 2018; Schwarz et al., 2015; Wolch et al., 2014). In general, the extensive ecological footprints of cities interact with the delivery of ecosystem services in dynamic and complex ways (Alberti et al., 2003) because of economic externalities (Fisher et al., 2009), uneven social distribution of benefits (Ernstson, 2013), and collective action for institutional design (Farley, 2012; Muradian and Cardenas, 2015; Ostrom, 2008). Thus, access to ecosystem services in urban neighborhoods and communities are inherently linked with environmental justice (EJ) in socially heterogeneous urban settings (Jephcote and Chen, 2012; Schwarz et al., 2015; Watkins and Gerrish, 2018).

Recent ecosystem services valuation studies have recognized the linkage between the supply of these services and EJ to improve the multi-layered dimensions of sustainability, including urban resilience, quality of life, public health, and hazard reduction in social-ecological systems (SES) (Aragão et al., 2016; Costanza et al., 2017; UN, 2015; WHO, 2017). Also, the valuation should consider the consequences of changes in social and ecological factors, and their feedbacks on social-ecological processes (Daw et al., 2011; Jacobs et al., 2016; Syrbe and Walz, 2012; Wolff et al., 2015). In this context, the concept of EJ is significantly tied with overall social-ecological resilience and sustainability in increasingly interconnected urbanizing landscapes (Agyeman et al., 2016; Fischer et al., 2015).

Despite the growing emphasis on integrating ecosystem services and EJ, most studies have focused on theoretical and fragmented analyses rather than on empirical, institutional, and integrative assessments (Bennett et al., 2015; Liu et al., 2013; Ostrom, 2009). Little research has been conducted to understand the effect of social-ecological processes on EJ (Haase et al., 2014; Jennings et al., 2016; Marshall and Gonzalez-Meler, 2016), which represents a critical knowledge gap (Güneralp and Seto, 2013; IPBES, 2018; Norman et al., 2012; SCBD, 2010).

This paper addresses that knowledge gap by reporting an integrative empirical EJ assessment of the supply of ecosystem services as well as air pollution-related public health risks along a social-ecological divide (SED) in Bexar County, Texas. SED refers to the disparities in quality of life driven by asymmetries in the supply of ecosystem services, which enhance human well-being, and economic disservices, that diminish human well-being in terms of socio-economic factors. Specifically, the paper focuses on the linkage between institutionalized patterns of residential segregation and EJ.

This aligns with sustainability concerns in the San Antonio region of Texas. First, with an intensive carbon-based economy and expanding gray infrastructure (Moran et al., 2018; Seto et al., 2016), Texas ranks first among the U.S. states in carbon dioxide (CO_2) emissions and eighth in per capita energy use by the transportation sector (USEIA, 2016). Second, detrimental effects of particulate matter (PM) on vegetation and human health have reportedly been increasing along the NAFTA corridor (CEC, 2010). Third, racial residential segregation has historically been significant in San Antonio (HOLC, 1935; Walter et al., 2017); furthermore, disparities of socio-economic and health outcomes in the region have been aggravated by the recent rapid economic development and urbanization (Chetty et al., 2016; Fry and Taylor, 2012). Therefore, the paper addresses the following three questions: (1) What are the institutionalized patterns of racial residential segregation and the implications for EJ and sustainability across the San Antonio region? (2) How do socio-environmental factors that determine the spatial distribution of urban ecosystem services explain the social-ecological disparities within the region? (3) What are the likely future ramifications through 2050 of persisting racial residential segregation patterns and NAFTA?

2. Methods

2.1. Study area

The study area is Bexar County, which includes the City of San Antonio, the seventh most populous and the third fastest growing city in the U.S. (Fig. 1; USCB, 2015, 2017). Historically, San Antonio has been the gateway to Mexico as an important commercial center (HOLC, 1935; Huh, 2018). The city is located in south Texas between the Edwards Plateau and the Gulf Coastal Plain and intersects in the north with the environmentally sensitive Edwards aquifer recharge zone (EARZ) (SAWS, 2014). This region is also referred to as 'Flash Flood Alley' due to its location along the Balcones Escarpment, which is characterized by steep slopes and periodic flash flooding (Ashley and Ashley, 2008; TWRI, 2016). It is also strategically located along the NAFTA corridor that connects Canada to Mexico via Interstate Highway (IH)-35 and it functions as a major transportation hub for commercial traffic within this corridor (CEC, 2010; TTI, 2007; TxDOT, 2007, 2013). Furthermore, San Antonio is one of the most residentially segregated cities in the U.S. with spatially discrete racial concentrations (Fry and Taylor, 2012) and diverging health disparities with shorter life expectancy for low income groups (Chetty et al., 2016).

TIGER/Line® shapefiles for 2010 census tracts (USCB, 2010a) were used as the spatial unit of analysis. The unit also represents the minimal scale at which ambient diesel PM and health risks are provided by the 2011 National Air Toxics Assessment (NATA) (USEPA, 2015). Bexar County consists of 366 census tracts with approximately 60% being composed of Hispanics on a county scale in 2010 (USCB, 2010b). Five census tracts were excluded due to a lack of data and the remaining 361 census tracts were used for the analysis (Appendix A.1.2). These census tracts and the racial proportionality in each tract were applied to divide Bexar County into 256 Hispanic, 4 African American, and 101 White dominated sub-areas (Fig. 1).

2.2. Institutional processes for historical legacy and path dependence of racial segregation

Two types of maps were used to determine historical legacy and path dependence of racial residential segregation: (a) racial concentration map and (b) residential security map by the Home Owners' Loan Corporation (HOLC) (HOLC, 1935). The HOLC served as a financial institution and resulted in discriminatory racial housing policies and practices for the mortgage redlining and urban racial segregation in 1930s (Crossney and Bartelt, 2005; Grove et al., 2018). In this paper institutions refer to the informal (e.g., traditional social norms, cultural customs), and formal (e.g., deeds, laws) rules that structure socio-economic, political, and ecological interactions (Muradian and Cardenas, 2015; North, 1991; Ostrom, 2008). The HOLC redlining maps of San Antonio indicate that Mexican populations were confined to the west and south, African American populations to the east, and areas north of San Antonio were

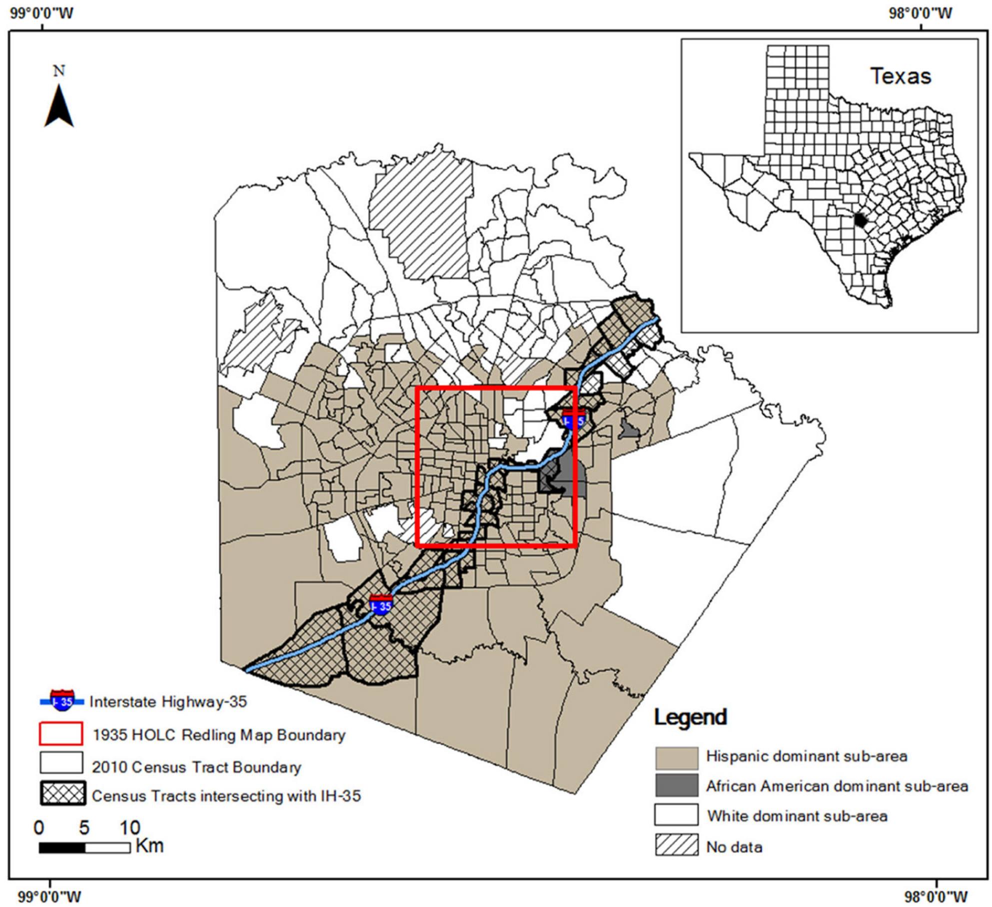

Fig. 1. Three racially dominant sub-areas, 1935 HOLC redlining map boundary, and the census tracts intersecting with IH-35 corridor in Bexar County.

reserved for the White population (Fig. 2(a)), and also that racial concentrations are largely congruent with the grades of urbanization and security (Fig. 2(b)).

HOLC redlining maps created in 1935 and residential hotspots in 2010 were compared to assess the persistence of the residential segregation patterns; based on geographic inertia and the limited social mobility of some lower income racial groups we assumed that historical patterns will likely persist to 2050. Local Indicators of Spatial Association (LISA) (Anselin, 1995) was employed to identify hotspots of racial concentrations and patterns of residential segregation in 2010. According to Texas State Data Center (2014), Texas population is projected to double by 2050 (Potter and Hoque, 2014). To estimate the future population in Bexar County, one half migration scenario and population data were acquired from the Texas Demographic Center (2018). Specifically,

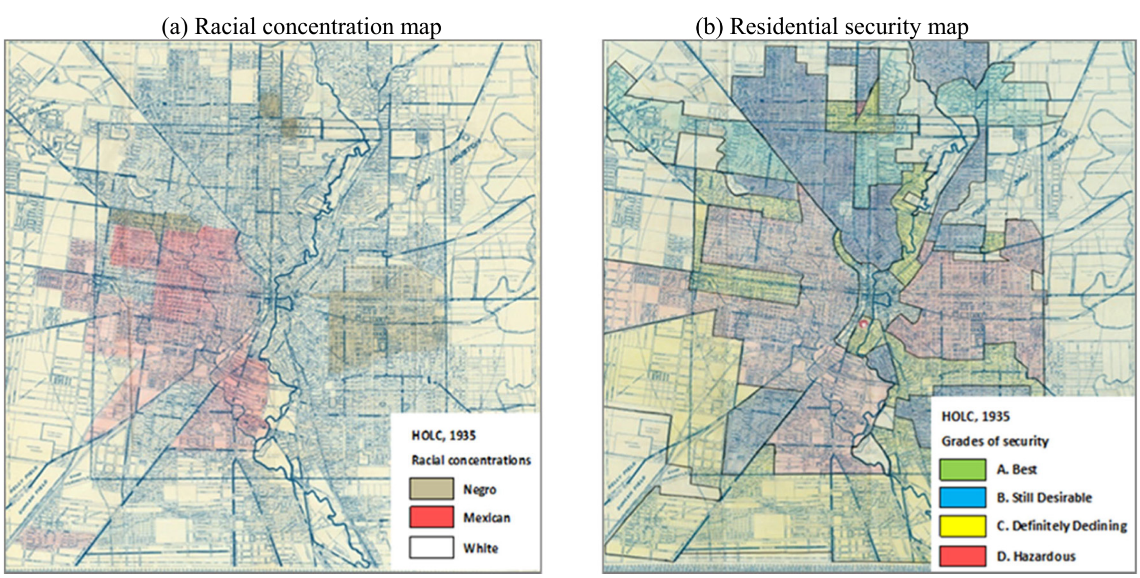

Fig. 2. Home Owners' Loan Corporation (HOLC) (1935) redlining maps of San Antonio.

it is estimated that in 2050 Bexar County will have a total population of 2,656,573 with an overall 10% increase in the proportion of the Hispanic population compared to 2010.

To estimate the distribution of population, the ceteris paribus principle (i.e., all other things being equal) was applied, which is widely used in the valuation of ecosystem services to simplify the estimation of ecosystem-service values within a partial equilibrium framework (Norgaard, 2010) as well as for regression analysis (Wooldrige, 2013). The principle indicates that institutional inertia characterized by persistent racial concentration policies and practices, will have legacy effects on future outcomes (Crossney and Bartelt, 2005; Grove et al., 2018; Liu et al., 2007). Specifically, with explanatory variables being constant except the change in the proportion of Hispanic population, by 2050 this will lead to an overall 10% increase of Hispanic population within the same Hispanic dominant census tracts ($n = 256$).

2.3. Quantification of urban ecosystem services and extraction of socio-environmental variables

Mean Normalized Difference Vegetation Index (NDVI) was used to estimate the provision of ecosystem services (carbon storage and biodiversity) in a rapidly urbanizing area. The rationale for this is that NDVI is positively correlated with green biomass that in turn is positively correlated with photosynthetic carbon sequestration and species diversity (Casey et al., 2016; St-Louis et al., 2006); it can be used as an empirical indicator of socio-ecological conditions (Markevych et al., 2014; Wolfe and Mennis, 2012); and it is easily derived from remotely sensed data (Rouse et al., 1974; Yi, 2017; Yi et al., 2017). Cloud-free Standard Terrain Correction Thematic Mapper (TM) Landsat 5 images from December 2010 were utilized to correspond with 2010 Census data (Yi, 2017; Yi et al., 2017, 2018; https://earthexplorer.usgs.gov/). NDVI is computed from the ratio of wavelengths of reflected invisible near-infrared (NIR) band (0.76–0.90 μm) and absorbed visible red bands (0.63–0.69 μm) at a 30-m spatial resolution (Eq. (1)) (Jensen, 2005; USGS, 2018).

$$NDVI = \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + \rho_{red}} \quad (1)$$

Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) was employed to quantify biodiversity and carbon storage (Sharp et al., 2016; Yi, 2017; Yi et al., 2018). The ecological production function method (EPFM) used in InVEST empirically quantifies habitat quality for biodiversity and terrestrial ecosystem services (Tallis and Polasky, 2009; Polasky et al., 2011). The model parameters were previously calibrated or validated using empirical data (COLE, 2016; IPCC, 2006; Polasky et al., 2011). In addition, 2010 Census and 2011 NATA data were used to extract specific socio-environmental information of each census tract for statistical analyses (USCB, 2010b; USCB, 2014; USEPA, 2015).

2.4. Analyses of the spatial associations between NDVI and socio-environmental variables

All the variables were grouped into four categories (Table 1). Quantile-Quantile (Q-Q) plots and Shapiro-Wilk normality test were conducted to determine whether the data for the variables presented in Table 1 meet the normality assumption. The results of these tests indicated that the data were not normally distributed and exhibited non-linear patterns for non-parametric statistical tests ($p < 0.05$). A correlation matrix and Spearman's ρ were reviewed to derive a regression model across the 361 census tracts. Kruskal-Wallis test was conducted to identify statistically-significant differences of socio-environmental variables among the three racially dominant sub-areas (Kruskal and Wallis, 1952), and the Mann-Whitney *U* test for *post-hoc* comparisons of differences between pairs of geographic areas.

It was further examined whether communities and neighborhoods within census tracts that intersect with the NAFTA corridor exhibit different socio-ecological outcomes than those that are outside of the corridor. For this purpose, we used the container approach (McEntee and Ogneva-Himmelberger, 2008; Talen and Anselin, 1998) to divide Bexar County into two sub-areas, the first consisting of 36 census tracts that intersect with the NAFTA corridor and the second consisting of 325 census tracts located to the east and west of the corridor. We then applied the Mann-Whitney *U* test to examine the socio-ecological disparities of census tracts located within or outside of the NAFTA corridor (Mann and Whitney, 1947).

Table 1
Socio-environmental variables in four categories and data description.[a]

Variable (abbreviation) in each category	Data description	Source
(1) Ecosystem services		
Normalized Difference Vegetation Index (NDVI)[b]	Proxy indicator of urban ecosystem services (UES)	EarthExplorer (USGS, 2010), Yi (2017), Yi et al. (2017)
Biodiversity (BIO)	Index of habitat quality	InVEST (Sharp et al., 2016), Yi (2017), Yi et al. (2018)
Carbon storage (CS)	Sum of four terrestrial carbon pools	InVEST (Sharp et al., 2016), Yi (2017), Yi et al. (2018)
(2) Race and demographics		
Hispanic proportion (HP)[c]	Proportion of Hispanic population	American Community Survey (USCB, 2010a, 2010b)
African American proportion (AA)[c]	Proportion of African American population	American Community Survey (USCB, 2010a, 2010b)
White proportion (WP)	Proportion of White population	American Community Survey (USCB, 2010a, 2010b)
Proportion of children under 15 years (CP)	Proportion of children under 15 years	American Community Survey (USCB, 2010a, 2010b)
Proportion of seniors 65 years and older (SP)	Proportion of seniors of 65 years and over	American Community Survey (USCB, 2010a, 2010b)
(3) Socio-economics		
Median household income (MI)[c]	Median income for a household	American Community Survey (USCB, 2010a, 2010b)
Uninsured rate for health insurance coverage (UI)	Proportion of uninsured health coverage	American Community Survey (USCB, 2014)
Poverty rate (PR)	Proportion under the federal poverty level	American Community Survey (USCB, 2010a, 2010b)
Unemployment rate (UR)	Proportion of unemployment	American Community Survey (USCB, 2010a, 2010b)
Supplemental Nutrition Assistance Program rate (FR)	Proportion of federal food stamps recipients	American Community Survey (USCB, 2010a, 2010b)
Proportion of bachelor's degree or higher (EA)	Level of educational attainment	American Community Survey (USCB, 2010a, 2010b)
(4) Air pollutant and health risks		
Ambient diesel particulate matter (PM) (DPM)[c]	Concentration of ambient diesel PM	National Air Toxics Assessment (USEPA, 2015)
Diesel PM hazard index (DHI)	Incidence of non-cancer diesel PM hazard	National Air Toxics Assessment (USEPA, 2015)
Respiratory hazard index (RHI)	Incidence of respiratory hazard from air toxics	National Air Toxics Assessment (USEPA, 2015)
Cancer risk index (CRI)	Incidence of cancer risk from air toxics	National Air Toxics Assessment (USEPA, 2015)

[a] Each variable is used for Shapiro-Wilk normality test, non-parametric Spearman's correlation analysis, Kruskal-Wallis test, and Mann-Whitney *U* test.
[b] Dependent variable for Ordinary Least Squares (OLS) and Geographically Weighted Regression (GWR).
[c] Independent variable for OLS and GWR.

Exploratory spatial data analysis (ESDA) was used to examine spatial autocorrelation (Tobler, 1970) and to identify the hotspots or cold spots using the global and local Moran's I (Anselin et al., 1995). Also, stepwise regression analysis was employed to develop the ordinary least squares (OLS) model (Eq. (2)). Through the use of the variance inflation factor (VIF) multicollinearity was identified among the explanatory variables and the least number of statistically significant explanatory factors was determined; VIF >7.5 indicated redundancy of the explanatory variable in the regression analysis (ESRI, 2017).

$$y_i = \beta_0 + \sum_{k=1}^{m} \beta_k x_{ik} + \varepsilon_i \tag{2}$$

where y_i is the dependent variable at location i, β_0 is the intercept parameter, β_k is the global regression coefficient for the kth explanatory variable, x_{ik} is the value of the kth explanatory variable, and ε_i is the random error. Four explanatory variables for the OLS were selected to examine the associations with the NDVI as follows: 1) proportion of Hispanic population (%); 2) proportion of African-American population (%); 3) median household income (US$); and 4) ambient diesel particulate matter (PM) (μg/m^3) at a census tract scale.

Due to the OLS assumption that the relationship between dependent and independent variables is constant, OLS regression models tend to be spatially auto-correlated and inhibit characterization of spatial non-stationarity or heterogeneity (Mennis, 2006). On the other hand, Geographically Weighted Regression (GWR) is a spatial regression method that accounts for varying local relationships among non-stationary variables, such as ecosystem services, socio-demographic factors, and environmental characteristics (Fotheringham et al., 1998, 2002) (Eq. (3)).

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{m} \beta_k(u_i, v_i) x_{ik} + \varepsilon_i \tag{3}$$

where (u_i,v_i) is the coordinates and $\beta_k(u_i,v_i)$ is the continuous function at location i ($i = 1,2, \ldots ,n$). Thus, GWR indicates that spatial variations can be measured in a spatially explicit way (Mennis, 2006; Ogneva-Himmelberger et al., 2009). Both OLS and GWR were applied using the same variables for 2010 and 2050, respectively and the local variations of socio-environmental variables were examined. Akaike's Information Criterion (AIC) was used to measure the goodness of fit with Gaussian kernel function to define the optimal bandwidth of local relationships. Geospatial and statistical analyses were conducted using ArcGIS® 10.4 (ESRI, 2016) and IBM SPSS® Statistics 24.0 (IBM, 2016).

3. Results

3.1. Spatial distribution of socio-environmental variables

Descriptive statistics of 18 socio-environmental variables are presented in Table 2 and the quantile classification maps illustrate the spatial distribution of each variable in Fig. 3 (ESRI, 2018). In the category of ecosystem services, NDVI values range from 0.18 to 0.57 with higher values to the north side of Bexar County (Fig. 3(a)), while biodiversity values range from 2.94 to 9.38 score ha^{-1} with higher values in suburban areas (Fig. 3(b)), and carbon storage values range from 22.51 to 112.28 Mg C ha^{-1} with similar distribution patterns as NDVI with higher values in the north (Fig. 3(c)).

In the category of race and demographics, the proportion of Hispanics ranges from 7.8% to 98.0% and predominates in the south and west of the city (Fig. 3(d)) while that of African-Americans ranges from 0.2% to 62.9% and is predominantly located in the east (Fig. 3(e)). By contrast, the proportion of Whites ranges from 1.4% to 81.9% primarily in north (Fig. 3(f)). The proportion of children under 15 years ranges from 2.9% to 39.2% with higher values mainly in the Hispanic dominant areas, while the proportion of seniors 65 years and older ranges from 0.0% to 37.8% without any specific areas of concentration (Fig. 3(g), (h)).

In the category of socio-economics, median household income ranges from $11,019 to $180,760 per annum with higher values in the White dominant north side of the city (Fig. 3(i)). On the other hand, uninsured rate for health insurance coverage ranges from 2.6% to 44.7% with higher values to the Hispanic dominant south and west and in the urban center (Fig. 3(j)). Poverty rate ranges from 0% to 68.9% and Supplemental Nutrition Assistance Program (SNAP) rate (i.e., proportion of food stamps recipients) ranges from 0% to 55.9%; both are clustered in the urban center and Hispanic and African American dominant areas (Fig. 3(k), (m)). Similarly, unemployment ranges from 0.0% to 30.7% with higher values occurring in minority communities (Fig. 3(l)). By contrast, educational attainment reflected by proportion of college education ranges from 0.0% to 79.2% with higher values in the northern areas (Fig. 3(n)). In the category of air pollutant and health risks, ambient diesel particulate matter (PM) and health risks from air toxics are all centered in the inner city of San Antonio. Ambient diesel PM values range from 0.25 to 2.63 μg·m^{-3}, while diesel PM hazard index ranges from 0.02 to 0.26, respiratory hazard index from 1.01 to 6.17, and cancer risks index from air toxics from 32.99 to 77.34 incidence per million, (Fig. 3(o)–(r)).

3.2. Non-parametric Spearman's correlation analysis

The correlation matrix for the degree of correlation among all the socio-environmental variables in 2010 is provided in Table 3. Similar correlation patterns exist among the variables within each category. For example, carbon storage (CS) and biodiversity (BIO) are the positively correlated with NDVI ($p < 0.01$). Hispanic proportion (HP) is

Table 2
Descriptive statistics of socio-environmental variables (2010, $N = 361$).

Variable (unit) in each category (color)	Minimum	Maximum	Mean	Std. deviation
(1) Ecosystem services (green)				
Normalized Difference Vegetation Index (unitless)	0.183	0.573	0.359	0.074
Biodiversity (score·ha^{-1})	2.948	9.386	5.827	1.570
Carbon storage (Mg C·ha^{-1})	22.518	112.286	51.942	20.882
(2) Race and demographics (yellow)				
Hispanic proportion (%)	7.800	98.000	59.620	23.816
Hispanic proportion in 2050 (%)[a]	7.800	100.000	70.970	27.700
African American proportion (%)	0.200	62.900	7.354	8.587
White proportion (%)	1.400	81.900	29.660	20.968
Proportion of children under 15 years (%)	2.900	39.200	22.534	5.386
Proportion of seniors 65 years and older (%)	0.000	37.800	10.691	5.136
(3) Socio-economics (red)				
Median household income (US$)	11,019	180,760	51,370	27,578
Uninsured rate for health insurance coverage (%)	2.600	44.700	19.530	8.970
Poverty rate (%)	0.000	68.900	14.526	12.036
Unemployment rate (%)	0.000	30.700	7.405	4.467
Supplemental Nutrition Assistance Program rate (%)	0.000	55.900	12.390	10.824
Proportion of bachelor's degree or higher (%)	0.000	79.200	24.641	19.580
(4) Air pollutant and health risks (gray)				
Ambient diesel particulate matter (PM) (μg·m^{-3})	0.255	2.638	0.811	0.357
Diesel PM hazard index (incidence·million^{-1})	0.027	0.267	0.086	0.036
Respiratory hazard index (incidence·million^{-1})	1.010	6.177	1.751	0.468
Cancer risk index (incidence·million^{-1})	32.990	77.347	41.837	4.602

[a] Hispanic proportion in 2050 is based on the one half migration scenario from Texas State Data Center (2014).

negatively correlated with NDVI, also with biodiversity and carbon storage ($p < 0.01$), while African American proportion (AA) is similarly negatively correlated with NDVI ($p < 0.01$) but not with biodiversity and carbon storage. By contrast, White proportion (WP) is positively correlated with NDVI, biodiversity, carbon storage, median household income, and advanced education ($p < 0.01$).

In terms of socio-economic variables, Hispanic proportion is negatively correlated with median household income (MI) and bachelor's degree of higher advanced education (EA) but positively correlated with poverty level (PR), unemployment rate (UR) and SNAP rate (FR) ($p < 0.01$). For the White proportion, the correlations are opposite for all five socio-economic variables ($p < 0.01$). Diametrically opposed positive and negative correlations also exist for Hispanic and White proportions, respectively, with respect to ambient diesel particulate matter (DPM), diesel respiratory hazard index (DHI), respiratory hazard index (RHI), and cancer risk index (CRI) ($p < 0.01$). For the African American proportion, there are no consistent patterns with respect to any of these variables. In terms of environmental factors, ambient diesel particulate matter is negatively correlated with NDVI ($p < 0.01$), while diesel respiratory hazard index, respiratory hazard index, and cancer risk index are all positively correlated with the ambient diesel particulate matter ($p < 0.01$). These results indicate a high degree of correlation and, therefore, redundancy among variables and support stepwise regression analysis to derive a parsimonious model.

3.3. Non-parametric Kruskal-Wallis test for three racially dominant sub-areas

The results from Kruskal-Wallis test revealed statistically significant differences ($p < 0.01$) among the three racially dominant sub-areas in terms of 14 socio-environmental variables (Table 4). These results confirm differences between the racially dominant sub-areas presented in the previous two sub-sections. Specifically, the Hispanic and African American dominant sub-areas exhibit lower values than White dominant sub-areas for the supply of beneficial ecosystem service variables

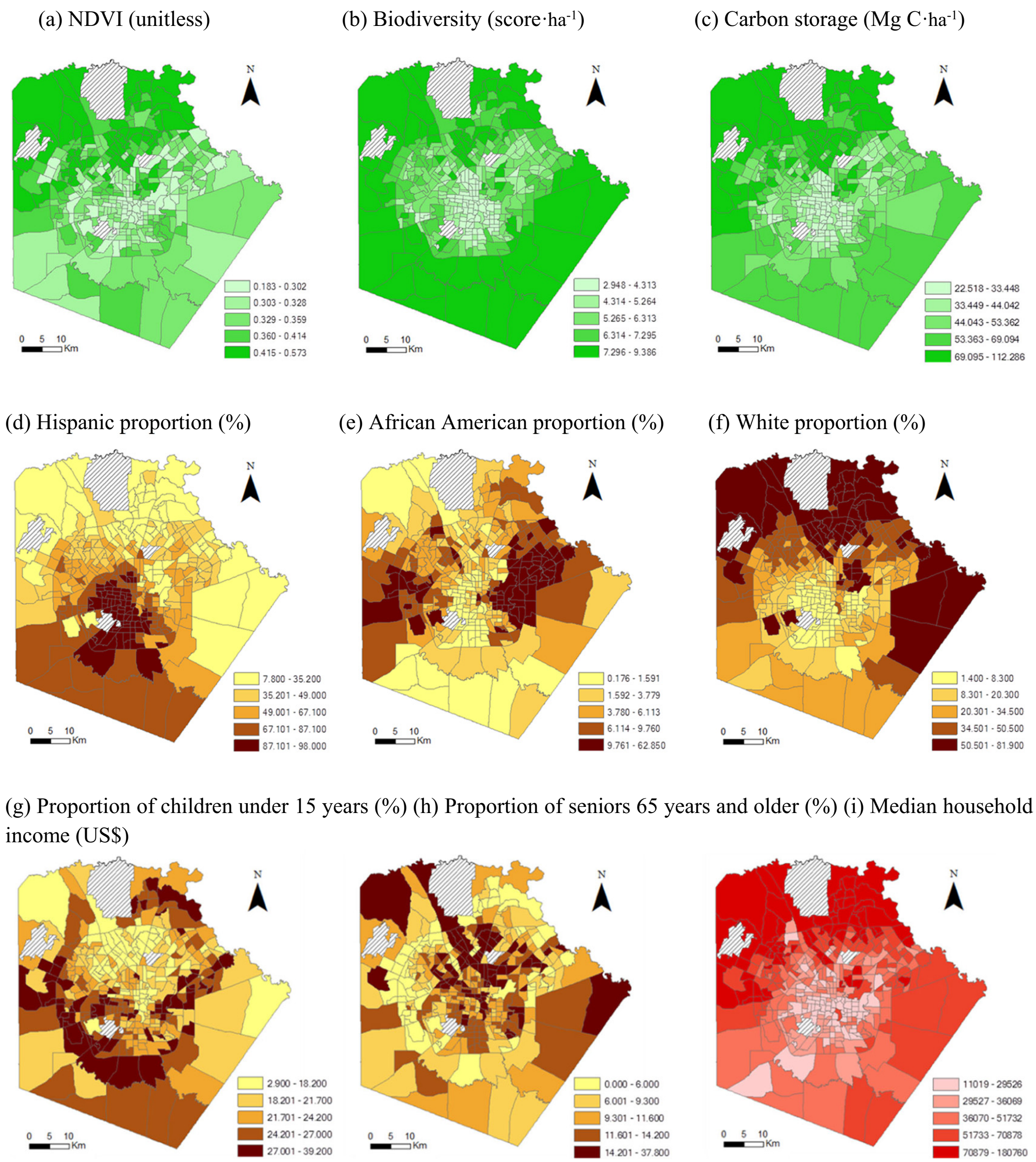

Fig. 3. Spatial distribution of socio-environmental variables in Bexar County (2010).

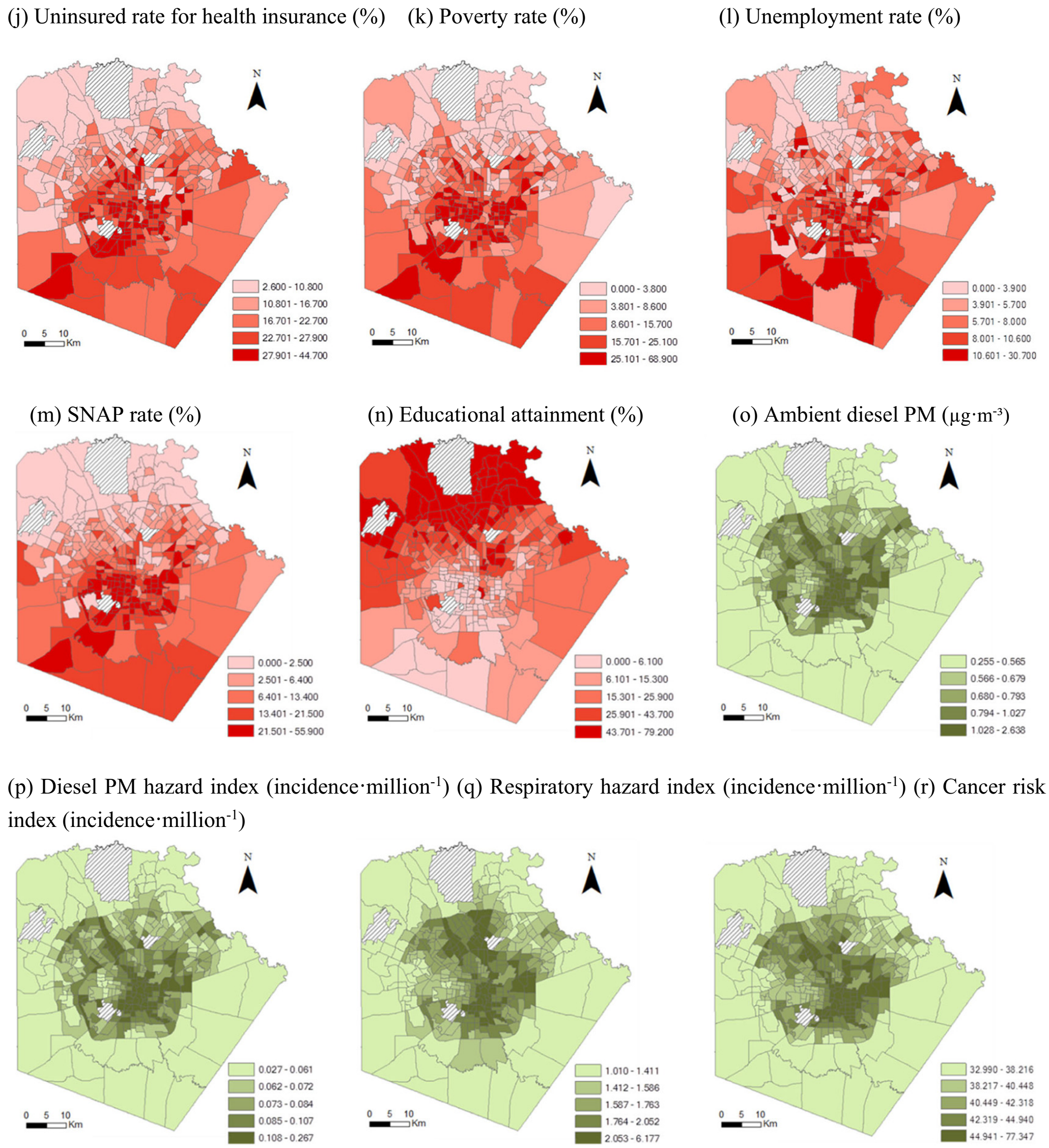

Fig. 3 (*continued*).

(i.e., regulating ecosystem services, biodiversity and habitat quality), median household income, and advanced education. By contrast, they exhibit higher values for uninsured rate for health insurance, poverty rate, unemployment rate, SNAP rate, ambient diesel particulate matter, diesel hazard index, respiratory hazards index, and cancer risk index.

3.4. Non-parametric Mann-Whitney U test inside and outside the NAFTA corridor

Mann-Whitney *U* test determined statistically significant differences among socio-environmental variables of census tracts located within the NAFTA corridor and those located outside of the corridor (Fig. 1; Table 5). The results indicate that NDVI, biodiversity, and carbon storage were statistically significantly lower in the NAFTA corridor sub-area ($p < 0.01$). Importantly, the Hispanic proportion was significantly higher and the White proportion significantly lowers in the NAFTA corridor than the non-corridor sub area ($p < 0.01$). There was also a greater proportion of people 65 years and older within the NAFTA corridor subarea ($p < 0.1$).

Median household income and advanced education were significantly lower within the NAFTA corridor (i.e., IH-35) sub-area, whereas uninsured rate for health insurance coverage, poverty rate, unemployment rate, and SNAP rate were significantly higher ($p < 0.01$). All four variables for air pollution created by diesel particulate matter and associated health risks were also significantly higher within the NAFTA corridor sub-area ($p < 0.01$). Thus, the benefits and burdens of socio-environmental outcomes relating to the NAFTA corridor are unequally distributed among the two racial groups to the disadvantage of the Hispanic population.

3.5. Exploratory spatial data analysis for local hotspots

Local indicators of spatial association identify clusters of high values, low values, and spatial outliers (Anselin, 1995). The 2010 racial hotspots from LISA for Hispanic and African American mirror the historical legacy

Table 3
Correlation matrix of social-environmental variables.

Variables	NDVI	BIO	CS	HP	AA	WP	CP	SP	MI	UI	PR	UR	FR	EA	DPM	DHI	RHI
BIO	0.656**																
CS	0.812**	0.924**															
HP	−0.534**	−0.638**	−0.721**														
AA	−0.116*	0.105*	0.083	−0.359**													
WP	0.601**	0.639**	0.750**	−0.928**	0.138**												
CP	−0.237**	−0.034	−0.213**	0.374**	0.144*	−0.478**											
SP	0.037	−0.187**	−0.108*	0.062	−0.389**	0.004	−0.544**										
MI	0.655**	0.648**	0.718**	−0.746**	0.056	0.805**	−0.150**	−0.149**									
UI	−0.583**	−0.610**	−0.687**	0.769**	−0.172**	−0.783**	0.188**	0.158**	−0.794**								
PR	−0.587**	−0.547**	−0.643**	0.719**	−0.053	−0.773**	0.288**	0.052	−0.856**	0.754**							
UR	−0.441**	−0.351**	−0.469**	0.544**	0.016	−0.602**	0.340**	−0.023	−0.596**	0.539**	0.579**						
FR	−0.617**	−0.567**	−0.697**	0.788**	−0.081	−0.845**	0.383**	0.093	−0.827**	0.772**	0.846**	0.662**					
EA	0.604**	0.574**	0.736**	−0.850**	0.138**	0.888**	−0.425**	−0.068	0.769**	−0.781*	−0.748**	−0.623**	−0.859**				
DPM	−0.435**	−0.641**	−0.516**	0.364**	−0.012	−0.386**	−0.213**	0.216**	−0.533**	0.447**	0.433**	0.242**	0.370**	−0.284**			
DHI	−0.447**	−0.622**	−0.516**	0.376**	−0.019	−0.406**	−0.186**	0.212**	−0.548**	0.461**	0.443**	0.253**	0.393**	−0.304**	0.978**		
RHI	−0.271**	−0.466**	−0.329**	0.204**	−0.106*	−0.221**	−0.371**	0.343**	−0.431**	0.351**	0.327**	0.118*	0.242**	−0.133*	0.836**	0.836**	
CRI	−0.311**	−0.557**	−0.411**	0.264**	−0.043	−0.300**	−0.309**	0.303**	−0.487**	0.382**	0.378**	0.160**	0.298**	−0.196**	0.893**	0.889**	0.946**

Notes: Normalized Difference Vegetation Index (NDVI), Biodiversity (BIO), Carbon storage (CS), Hispanic proportion (HP), White proportion (WP), African American proportion (AA), Proportion of children under 15 years (CP), Proportion of seniors 65 years and older (SP), Median household income (MI), Uninsured rate for health insurance coverage (UI), Poverty level (PR), Unemployment rate (UR), Supplemental Nutrition Assistance Program rate (FR), Proportion of bachelor's degree or higher (EA), Ambient diesel particulate matter (DPM), Non-cancer diesel PM hazard index (DHI), Respiratory hazard index (RHI), Cancer risk index (CRI).

* $p < 0.05$ (2-tailed).

** $p < 0.01$ (2-tailed).

of racial residential concentrations of the 1935 HOLC redlining maps. For example, Hispanic population clusters in the south and west side of the city, whereas African American population is concentrated in the east side, respectively (Fig. 4). In the study high-high (HH) cluster of NDVI (i.e., hotspots in red) is located to the north of Bexar County and intersects with the hotspots of high median household income (Fig. 4(a), (b)).

On the other hand, low-low (LL) cluster of NDVI (i.e., cold spots in blue) is located in the urban center and mostly intersects with the hotspots of ambient diesel PM, African American, and Hispanic communities (Fig. 4(a)–(e)). Furthermore, based on the ceteris paribus approach for institutional inertia, the projected concentration of the Hispanic population in 2050 will reflect the legacy of the 2010 population distribution. In other words, the spatial concentration of the Hispanic population in the south and west of the city and the related effects of the heterogeneous distribution of ecosystem services supply, socio-economic, and air pollution parameters posed by NAFTA will likely persist through 2050 (Fig. 4(e), (f)).

3.6. OLS and GWR regressions for the spatial associations

Multivariate regression model was formulated after the correlation matrix and VIF for all social-environmental variables were examined to detect multicollinearity or strong relationships between variables (Tables A1, A2). The resulting OLS model indicates that explanatory variables are not redundant in the regression equation (i.e., VIF < 2.8) (Table 6) and multicollinearity does not exist in the best fit prediction model (Eq. (4)).

$$NDVI_i = \beta_0 + \beta_1 HP_i + \beta_2 AA_i + \beta_3 MI_i + \beta_4 DPM_i + \varepsilon_i \quad (4)$$

Specifically, the F-ratio indicates that the overall regression model is a good fit to predict the NDVI and the four independent variables are statistically significant ($F\,(4, 356) = 117.481$, $p < 0.05$, *Adjusted* $R^2 = 0.564$) (Table 6, Table A1). In the regression the NDVI is negatively associated with increase of Hispanic (HP) and African American proportion (AA), and ambient diesel particulate matter (DPM). By contrast, the NDVI is positively associated with increase in median household income (MI).

On the other hand, the OLS model exhibited spatial autocorrelation in the residuals ($I = 0.073$, $p < 0.01$), indicating that it did not meet the spatial homogeneity assumption of OLS regression models that incorporate spatial variables. The z-score ($z = 6.154$) indicates that there is <1% likelihood that the clustered pattern could be the result of random distribution. In addition, the Koenker (Breusch–Pagan) statistic indicates that the results are significant either due to non-stationarity or heteroskedasticity ($p < 0.05$). However, Jarque-Bera Statistic indicates that the residual is normally distributed and the OLS model is not biased due to missing key variables (Table A1).

The GWR model detects locally varying associations and indicates that the spatial autocorrelation in the residuals does not exist ($I = 0.013$, $z = 1.323$) and results in an improved adjusted R^2 of 0.643 and Akaike's Information Criterion (AICc) compared to the non-spatial OLS (Table 6). Condition number also indicates the reliable range of the model prediction (i.e., <30). Furthermore, the GWR models for 2010 and 2050 provide an effective way to investigate where there are strong and weak associations in terms of local R^2 maps over time (Fig. 5). The predicted GWR models in 2050 indicate that similar spatial patterns will most likely occur across the region for the association between NDVI and four socio-environmental variables (Tables 6, A3). Moreover, given the historical trends of deforestation in San Antonio between 1984 and 2010 (Yi, 2017; Yi et al., 2017, 2018) and the combined effect of amplified residential segregation and decreasing NDVI, it is expected that minority populations could be further negatively affected through 2050.

Table 4
Kruskal-Wallis test of socio-environmental variables in Hispanic, African American, and White dominated census tracts in Bexar County.

Variable in each category	Mean rank [1] Hispanic ($n = 256$)	Mean rank [2] African American ($n = 4$)	Mean rank [3] White ($n = 101$)	$\chi 2$	p	Mann-Whitney *U* test
(1) Ecosystem services						
Normalized Difference Vegetation Index (unitless)	146.49	77.00	272.58	109.756	<0.001	1, 2 < 3
Biodiversity (score·ha^{-1})	145.60	197.00	270.10	103.183	<0.001	1, 2 < 3
Carbon storage (Mg C·ha^{-1})	141.42	168.50	281.82	131.162	<0.001	1, 2 < 3
(2) Demographics						
Proportion of children under 15 years old (%)	201.83	267.38	124.78	42.254	<0.001	1, 2 > 3
Proportion of seniors 65 years and older (%)	176.46	203.38	191.61	1.713	0.435	
(3) Socio-economics						
Median household income (US$)	141.34	95.25	284.91	139.809	<0.001	1, 2 < 3
Uninsured rate for health insurance coverage (%)	220.65	204.75	79.56	132.605	<0.001	1, 2 > 3
Poverty rate (%)	219.23	239.75	81.78	126.942	<0.001	1, 2 > 3
Unemployment rate (%)	201.70	236.75	103.52	77.559	<0.001	1, 2 > 3
Supplemental Nutrition Assistance Program rate (%)	222.45	260.00	72.80	151.289	<0.001	1, 2 > 3
Proportion of bachelor's degree or higher (%)	137.27	129.13	293.89	164.125	<0.001	1, 2 < 3
(4) Air pollutant and health risks						
Ambient diesel particulate matter (PM) (μg·m^3)	202.28	238.00	124.81	41.116	<0.001	1, 2 > 3
Diesel PM hazard index (incidence·million^{-1})	202.73	232.75	123.87	42.353	<0.001	1, 2 > 3
Respiratory hazard index (incidence·million^{-1})	192.23	234.00	150.24	12.815	0.002	1, 2 > 3
Cancer risk index (incidence·million^{-1})	198.00	258.75	134.82	28.794	<0.001	1, 2 > 3

1 denotes Hispanic dominant sub-area; 2 denotes African American dominant sub-area; 3 denotes White dominant sub-area.

The GWR models indicate that the NDVI is inversely associated with Hispanic and African American proportion (Adjusted $R^2 = 0.643$ and 0.646, respectively in Tables 6, A3). The quantile maps of local R^2 illustrate that the association will likely increase in the north-western side with a spatially fixed Hispanic population through 2050 despite the overall 10% population increase in Bexar County (Fig. 5(a), (b)). The results have advantages over OLS to identify the spatial patterns, compared to the value of global R^2 from OLS, which is 0.56 because GWR takes into account local variations, whereas OLS indicate the homogeneous relationships. Notably, the GWR results illustrate the division of local R^2 along the NAFTA corridor, such that south-eastern communities have lower local R^2 (<50%), whereas north-western communities have higher local R^2 (≥50%). Thus, the GWR provides more specific regional information than the OLS and demonstrates the spatially amplified likelihood of environmental injustice through 2050.

4. Discussion

Globalization and rapid urbanization are intensifying the need for a multi-faceted approach to developing a fundamental understanding of complex social-ecological systems. Such an approach could contribute to informing strategies and policy alternatives that support future sustainability through the enhanced understanding of the interconnections between socio-economic and ecological systems that affect future sustainability and equity in diverse human societies (Bowen et al., 2017; Muradian and Cardenas, 2015; Ostrom, 2009; Paavola and Adger, 2005; Schaefer et al., 2015; Seto et al., 2017; Stafford-Smith et al., 2017). In the Bexar County study area, the results indicate that residential segregation is a persistent phenomenon that has led to significant racial disparities in access to ecosystem services and health and socio-economic outcomes (Fry and Taylor, 2012; Williams and Collins,

Table 5
Mann-Whitney *U* test of differences in socio-environmental variables between census tracts intersecting with the NAFTA corridor and outside of the NAFTA corridor.

Variable in each category	Mean rank [1] NAFTA corridor ($n = 36$)	Mean rank [2] Non-corridor ($n = 325$)	Mann-Whitney *U*	p	Score
(1) Ecosystem services					
Normalized Difference Vegetation Index (unitless)	82.92	191.86	2319.00	<0.001	1 < 2
Biodiversity (score·ha^{-1})	129.50	186.70	3996.00	0.002	1 < 2
Carbon storage (Mg C·ha^{-1})	115.31	188.28	3485.00	<0.001	1 < 2
(2) Race and demographics					
Hispanic proportion (%)	228.39	175.75	4144.00	0.004	1 > 2
African American proportion (%)	176.92	181.45	5703.00	0.805	
White proportion (%)	128.94	186.77	3976.00	0.002	1 < 2
Proportion of children under 15 years old (%)	183.46	180.73	5761.50	0.882	
Proportion of seniors 65 years and older (%)	212.22	177.54	4726.00	0.058	1 > 2
(3) Socio-demographics					
Median household income (US$)	109.89	188.88	3290.00	<0.001	1 < 2
Uninsured rate for health insurance coverage	251.01	173.24	3329.50	<0.001	1 > 2
Poverty rate (%)	240.13	174.45	3721.00	<0.001	1 > 2
Unemployment rate (%)	245.79	173.82	3517.50	<0.001	1 > 2
Supplemental Nutrition Assistance Program rate (%)	253.83	172.93	3228.00	<0.001	1 > 2
Proportion of bachelor's degree or higher (%)	113.93	188.43	3435.50	<0.001	1 < 2
(4) Air pollutant and health risks					
Ambient diesel particulate matter (PM) (μg·m^3)	265.17	171.68	2820.00	<0.001	1 > 2
Respiratory hazard index (incidence·million^{-1})	234.89	175.03	3910.00	<0.001	1 > 2
Diesel PM hazard index (incidence·million^{-1})	262.67	171.95	2910.00	<0.001	1 > 2
Cancer risk index (incidence·million^{-1})	229.03	175.68	4121.00	0.004	1 > 2

1 denotes sub-areas in the NAFTA corridor and 2 denotes Non-NAFTA corridor area in Bexar County.

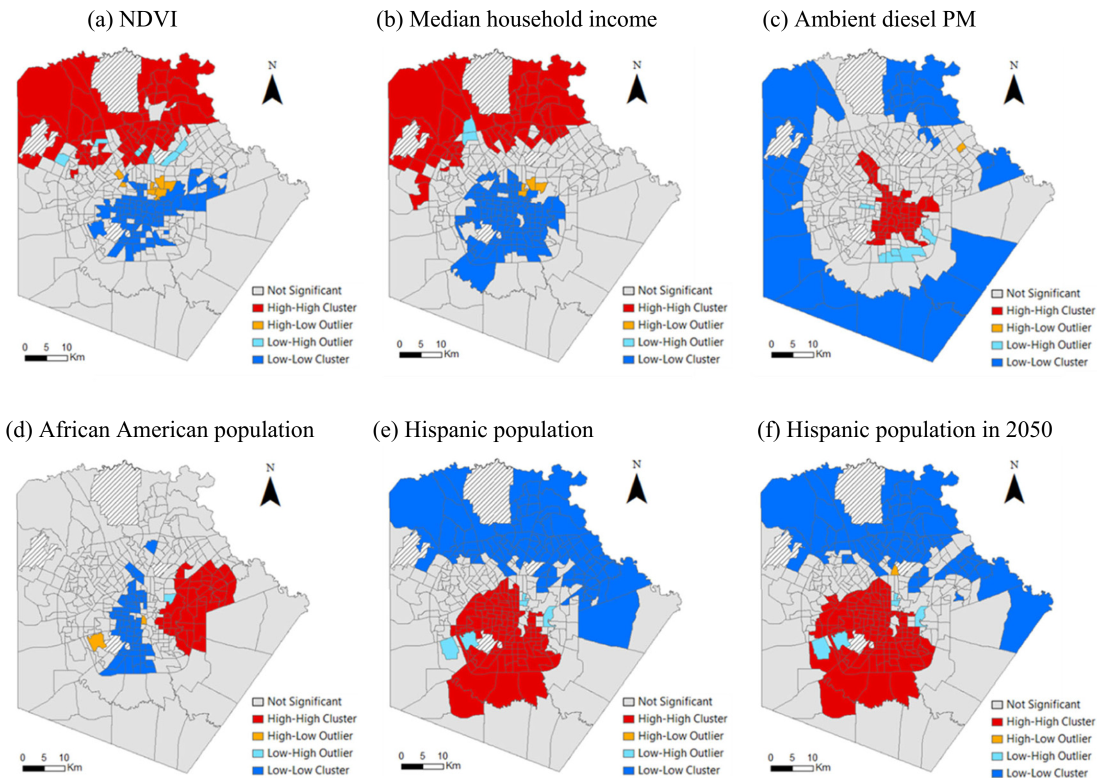

Fig. 4. Local Moran's *I* cluster and outlier analysis for the NDVI and independent variables. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

2001); these findings suggest a strong need for new institutional design for moving toward sustainability to incorporate the change in the city's governance structures (Bai et al., 2016). Such a change would include implementation of inclusive policies and strategies through which urban residents reform the rules or practices in the urbanizing social-ecological systems in which they belong (Farley, 2012; Ostrom, 2008).

While numerous studies have focused on the provision of ecosystem services, relatively little attention has been directed toward the disaggregation of benefits in terms of the institutional aspects of unequal social allocation of the supply of ecosystem services (Daw et al., 2011). Furthermore, while there are studies on the effects of hazardous air pollutants on biodiversity and ecosystem services (Grantz et al., 2003; Lovett et al., 2009), due to methodological or empirical challenges for integrated analyses, few of these have addressed the EJ implications of economic development-driven spatial disparities in ecosystem services and economic disservices (Marshall and Gonzalez-Meler, 2016). The research presented in this paper addresses that knowledge gap. In addition, because the methodology illuminates the EJ implications of disparate relationship among racial groupings in urban spaces and the delivery of ecosystem services and economic disservices, the findings are relevant for other urban regions characterized by segregated racial distribution patterns.

The findings point to persistent 'social-ecological divide (SED)' or disparities among Hispanic and African American minorities and low-income neighborhoods in Bexar County due to the derivation of fewer ecosystem services benefits, socio-economic disadvantages and greater exposure to development-related health risks. The results of spatial regression models show heterogeneous social-ecological associations between the NDVI, as an indicator of urban ecosystem services, and socio-environmental variables, including the proportion of Hispanic

Table 6
Results of OLS and GWR models based on 2010 data.

	OLS			GWR			
	Coefficient	Std. coefficient	VIF	Coef. Mean	Coef. minimum	Coef. maximum	Std. deviation
Intercept	0.384			0.406	0.248	0.573	0.103
Hispanic proportion	−0.001	−0.227	2.717	−0.001	−0.002	0.001	0.001
African American proportion	−0.002	−0.213	1.386	−0.002	−0.006	0.001	0.002
Median household income	1.183×10^{-6}	0.441	2.766	1.288×10^{-6}	0.229×10^{-6}	2.274×10^{-6}	0.637×10^{-6}
Ambient diesel particulate matter	−0.038	−0.183	1.257	−0.049	−0.077	−0.005	0.018
Condition number				23.942	17.894	29.971	3.729
Local R-squared				0.554	0.338	0.679	0.068
Multiple R-squared	0.569			0.662			
Adjusted R-squared	0.564			0.643			
Akaike's Information Criterion (AICc)	−1149.067			−1215.616			
Moran's *I* index of standard residual	0.073*			0.013			
z-score (*p*-value) of global Moran's *I*	6.154 (<0.001)*			1.323 (0.185)			

* $p < 0.01$.

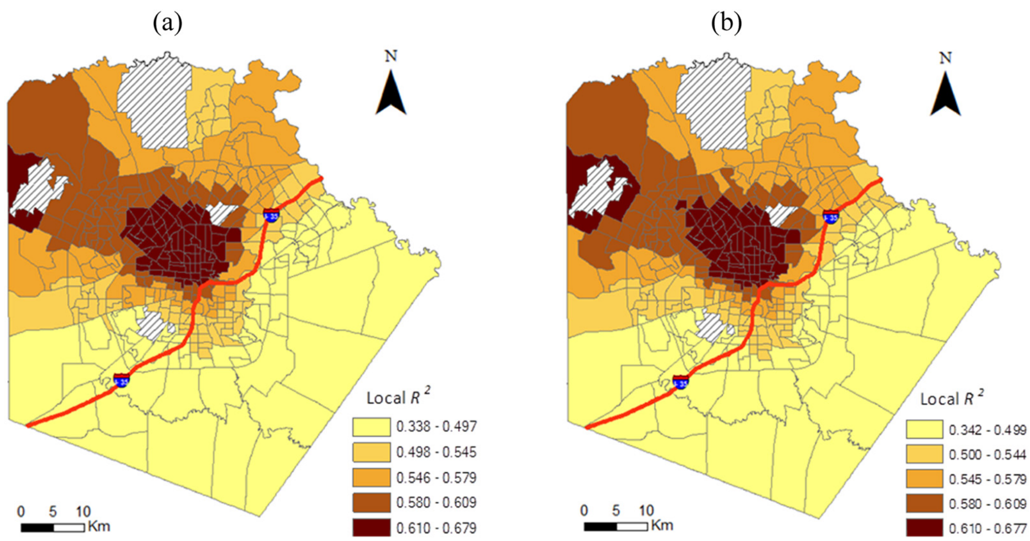

Fig. 5. Quantile maps of local R^2 in Bexar County for 2010 (a) and 2050 (b).

and African American residents, median household income, and ambient diesel PM. Furthermore, the GWR prediction for 2050 suggests the spatially fixed and reinforced racial inequality in terms of SED will likely be amplified leading to greater environmental injustice due to the path dependent and institutionalized residential patterns in the San Antonio region.

This study links historical institutionalized patterns of residential segregation to the socio-ecological outcomes and the racial disparities in the San Antonio region, an urban social-ecological system (Ostrom, 2009) that is strongly tied to economic globalization through NAFTA. For example, diesel PM is recognized as national pollutant for its detrimental effects on human health as well as ecosystem conditions and climate change (Grantz et al., 2003; USEPA, 2015). It has become increasingly recognized that pollution hazards may disproportionately affect racial and ethnic minorities and underrepresented communities (Houston et al., 2004; Oyana et al., 2004; Jephcote and Chen, 2012). In addition, air quality is affected by international trade as well as local air pollution (Zhang et al., 2017), which is increasing concerns in the San Antonio region in terms of ground level Ozone, NO_x, and other air toxics from diesel PM (CEC, 2010; AACOG, 2018). Furthermore, air pollutant emissions from the Eagle Ford shale development south of San Antonio are predicted to increase ozone concentrations in Bexar County (Pacsi et al., 2015). Thus, the combined effect of the NAFTA corridor and the Eagle Ford Shale development since 2011 indicates the serious air quality concerns for quality of life and EJ issue in the region.

The findings suggest that current trajectory of racial residential segregation will continue to hinder moving toward sustainability in San Antonio through 2050. The institutional mechanism responsible for this is exemplified by the spatial and temporal practices and policies of the HOLC going back almost a century and the NAFTA that has led to a legacy and path dependence of environmental injustice in San Antonio. For example, the HOLC redlining maps reveal that the racial concentrations are congruent with the grades of residential security and the lending practices in urban areas in the U.S. (Crossney and Bartelt, 2005; Grove et al., 2018). Likewise, NAFTA or, potentially, new United States-Mexico-Canada Agreement as an international trade institution will continue to affect the pathways to urban sustainability within the San Antonio region (Yi et al., 2018).

The results revealed uneven distribution of ecosystem services in San Antonio. Predominantly White and wealthier communities are primarily located in the upstream segment of San Antonio near the environmentally sensitive Edwards aquifer recharge zone, whereas the minority communities with lower socio-economic status are located in the south and west of the city with less favorable socio-ecological characteristics. Additionally, the results indicate significant intra-regional disparities along the NAFTA corridor that divides Bexar County into two sections to the southeast and northwest, in which contemporary 'new redlining of ecosystem service benefits' persist. This paper found that NAFTA corridor-related health risks are significantly greater in census tracts that intersect with the corridor where Hispanics form the dominant portion of the population.

Furthermore, as minority neighborhoods are increasingly exposed to environmental risks and less likely to benefit from ecosystem services under the expanding NAFTA-related development, these neighborhoods are more likely to be exposed to further negative social-ecological outcomes and less likely to benefit from the positive socio-ecological outcomes in the San Antonio region. Therefore, the environmental injustice in the region will likely become even more skewed and will aggravate the social vulnerability of certain neighborhoods. For example, the social vulnerability index (USCDC, 2018; https://svi.cdc.gov/) indicates that downstream residents in the southeast of San Antonio are more vulnerable to natural hazards and disaster compared to the upstream residents in northern San Antonio. Notably, the 2010 index indicate that more census tracts in south side are exposed to higher overall vulnerability index compared to the 2000 index.

The findings also indicate a negative correlation between the lack of health insurance rates and hotspots of ambient diesel PM, which coincides with the 'inverse care law' indicating medical care and health inequality by market forces (Hart, 1971; Talen, 1998). Likewise, the results suggest the 'inverse allocation of ecosystem service benefits' in that the distribution of urban ecosystem services is inversely related to the socio-economic conditions of neighborhoods. These findings bring attention to inter-generational inequity (Chetty et al., 2014). For example, children in a northern census tract (1821.01) come from predominantly White households with $121,809 median income and that are located away from the NAFTA corridor, compared to an urban census tract (1708) where children come from predominantly Hispanic households with $16,078 median income and that are located near NAFTA corridor.

These two residentially segregated groups of children have considerably different pathways for social mobility due to different socio-environmental conditions in 2010, which are likely to extend to the next generation. The results also demonstrated intra-generational inequity in that seniors 65 years and older tend to be more exposed to air pollutant-related health risks. These findings suggest, in order for San Antonio to develop in a sustainable and inclusive manner, it will face great challenges in the next few decades to manage trades-offs between the short-term economic benefits and long-term external ecosystem costs as well as the polarized delivery of ecosystem services that is being exacerbated by NAFTA-related rapid urban development.

In this regard, ecosystem service-based institutional transformations should be first designed to motivate urban neighborhoods to engage in civic participation or collective action for greater equity at multiple scales (Ostrom, 2000). Second, sound urban planning policies for urban green infrastructure is critical in that urban green spaces play an important role in sustaining biodiversity and ecosystem services, improving air and water quality, mitigating urban heat island effects and natural disasters, and regulating storm water runoff (USEPA, 2017). Third, regional transportation policies should consider the walkability and the connectivity to facilitate compact urban space needed for the long-term sustainability (Huh, 2018).

The analyses include uncertainty stemming from the lack of comprehensive understanding of interactions among socio-environmental parameters. More sophisticated methods with various indicators should be considered to reduce this uncertainty. For example, a finer scale of analytic unit could be considered to address the issue of modifiable area unit problem to integrate the NDVI and census data (Fotheringham and Wong, 1991). Incorporation of cultural ecosystem services (Jennings et al., 2016; Plieninger et al., 2013) and qualitative interviews (Chetty et al., 2016), demand of ecosystem services (Wolff et al., 2015) as well as sensitivity analysis (Kreuter et al., 2001; Yi, 2017; Yi et al., 2017) could reveal more nuanced multi-faceted spatial associations. Finally, dynamic models that include future scenarios for direct or indirect impacts of human-induced land and climate change could enhance the robustness of forecasts (Norgaard, 2010).

5. Conclusion

The novel empirical study of ecosystem services disparities among racially segregated residential areas demonstrates the historical legacy and path dependence of EJ linked to the 1930s racial concentration and residential security maps of the Home Owners' Loan Corporation, and continued racial segregation in and around San Antonio under NAFTA. The overall results indicate that Hispanic and African American minorities derive fewer ecosystem services benefits and face greater pollution-related health risks and socio-economic disadvantages. The forecasts of EJ highlight the spatially fixed and augmented likelihood of 'social-ecological divide (SED)' through 2050 driven by the path dependent institutional inertia under NAFTA and, potentially, new United States-Mexico-Canada Agreement.

The findings provide insights of ecosystem service-based EJ research and suggest that current trajectory of racial residential segregation will likely intensify the uneven distribution of ecosystem services in the San Antonio region through 2050. Notably, health risks from transportation-related air toxics are the most significant for the Hispanic population along the NAFTA corridor, in which contemporary 'new redlining of ecosystem service benefits' will persist in San Antonio over the next few decades. Institutional transformations should be implemented to mitigate entrenched environmental injustice and to reverse growing social-ecological inequities in the San Antonio region under the continued NAFTA-driven urban development. Furthermore, by incorporating the supply of ecosystem services when addressing EJ and sustainability issues in the rapidly urbanizing regions, the paper contributes more broadly to science-based planning and better environmental decision-making to mitigate urban SEDs resulting from historic racially segregated development patterns and globalization effects both in the U.S. and around the world.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2019.02.130.

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