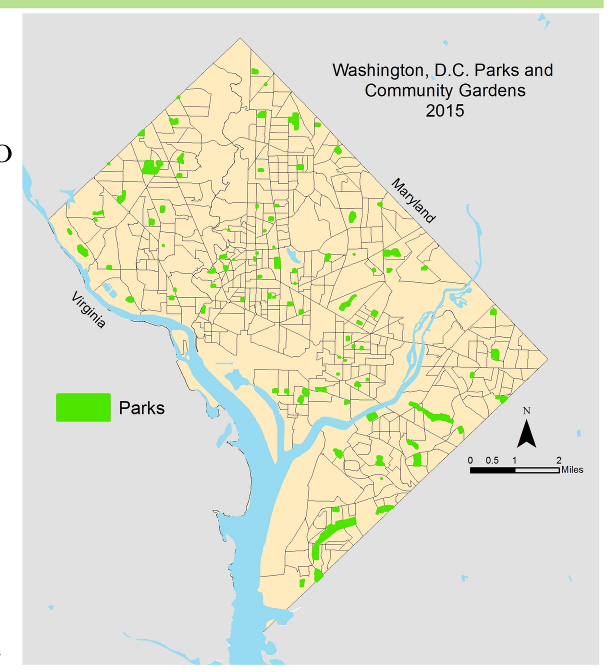
Green Gentrification in Washington, D.C.

Does distance to parks predict gentrification?

Introduction

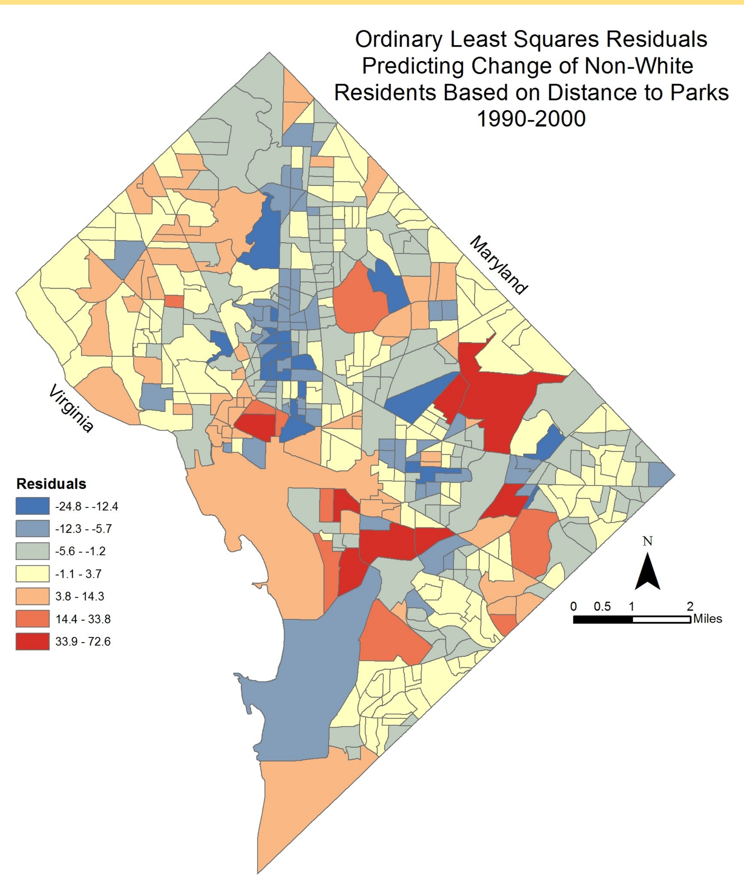
Urban green space is widely regarded as a valuable resource and a key element of a healthy and sustainable city. Yet, there are large disparities in the distribution of and access to green space, which reflects already existing income and socio-economic disparities (Wolch, Byrne, and Newell 2014; Jennings, Johnson Gaither, and Schulterbrandt Gragg 2012; Heynen, Perkins, and Roy 2006). Environmental gentrification, characterized by environmental or sustainability initiatives that lead to the exclusion, marginalization or displacement of the residents in the surrounding community, has been extensively documented in the literature. From this concept emerges the idea of the "green paradox:" interventions intended to reduce the disparities in green space access lead to the displacement of the very residents the project was meant to benefit (Wolch et al. 2014). The following research questions serve to better explore this phenomenon in Washington, D.C., where gentrification has been a pervasive force since the 1950s, with acute acceleration in the last couple decades.



1. Does the introduction of green space cause gentrification? Does it lead to an increased level of spatial segregation?
2. Are certain indicators of gentrification more highly correlated with distance to parks?

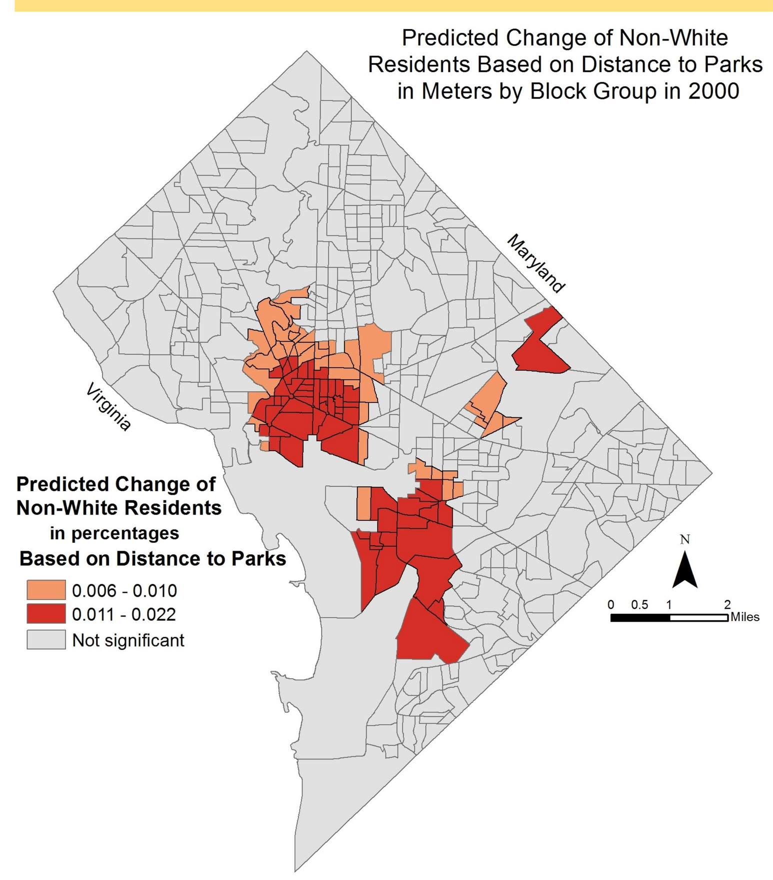
2000 OLS Results

Percent Non-White



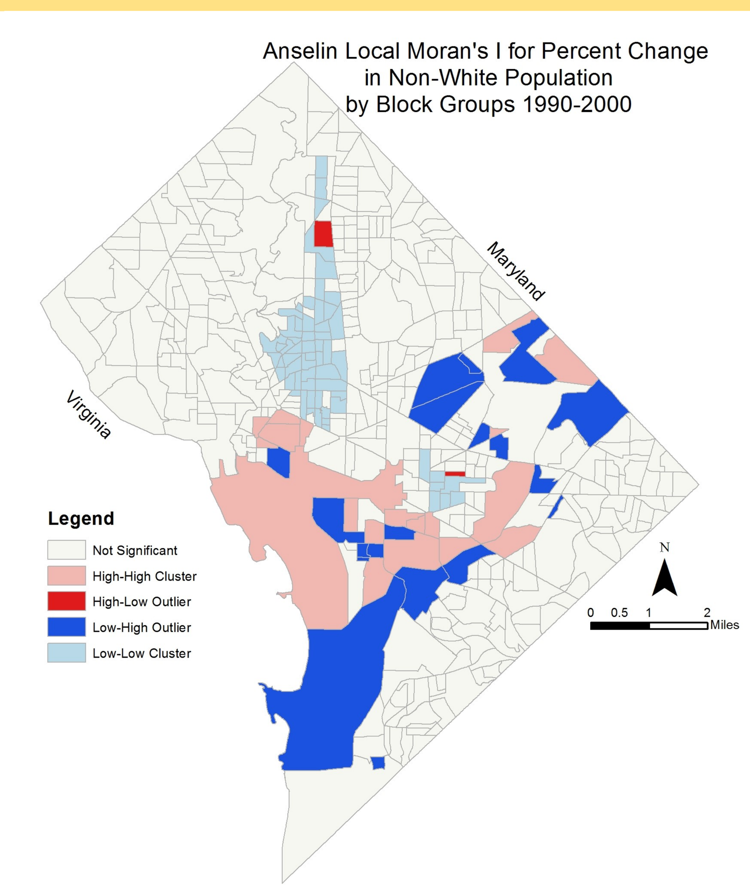
2000 GWR Regression

Percent Non-White

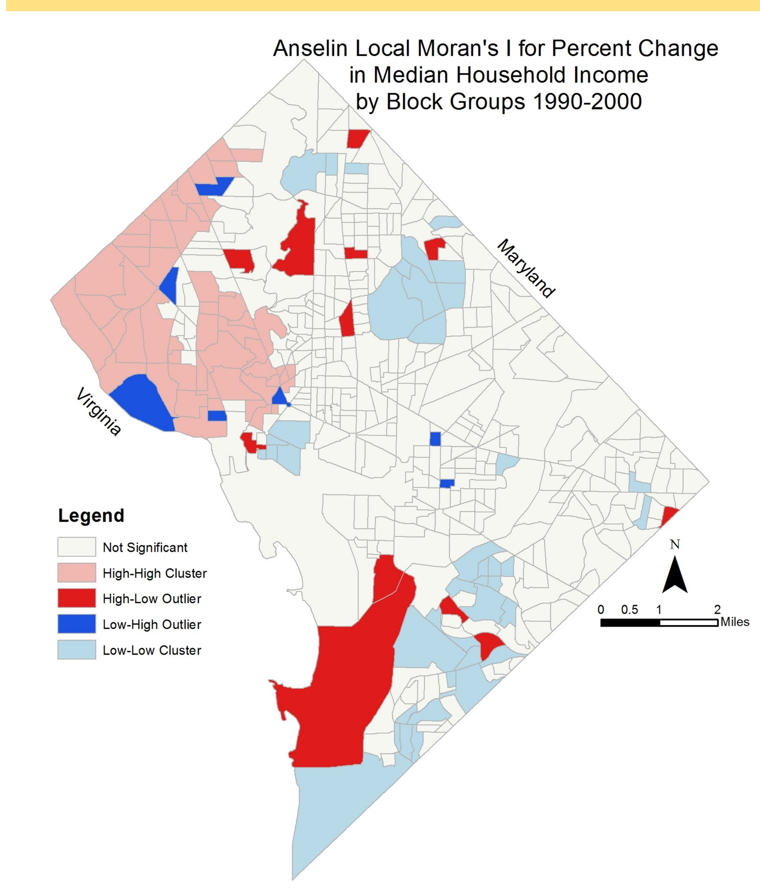


2000 Anselin Local Moran's I

Percent Non-White



Median Household Income



Data

Demographic and housing data comes from the U.S. Census and American Community Survey data at the block group level from 1990, 2000, 2010 and 2015. Indicators of gentrification include: Median Household Income in 2015 Inflation Adjusted Dollars; Percentage of Households with Public Assistance Income; Median House Value for all Owner-Occupied Housing Units; and Percentage of Non-White. The values from each decade were subtracted to calculate change over time. The parks data comes in vector format from the DC government open data portal and are filtered by year acquired. All data are projected to NAD 1983 UTM Zone 18N.

Methods

In an effort to replicate the methods from the Anguelovski et al. (2017), distance to parks was used as the independent variable and the sociodemographic indicators were used as the dependent variables. The first step was to do data consolidation and organization. Due to changing census boundaries over time, the geographic boundaries had to be standardized to the 2010 block groups to compare across years. Areal interpolation was used for each of the four selected variables for all years (1990, 2000, 2015) to create comparable datasets. From there, the variables were joined into two layers, one for 1990 and one for 2015, and compared with the field calculator.

To calculate the distance to green space, the Euclidean Distance tool was used in ArcGIS to calculate the Euclidean distance to the closest park. Next, zonal statistics was employed to result in the mean distance to the closest park for each block group based on 2010 boundaries. Finally, the results were joined with the sociodemographic data to create two final layers for each target period of time.

The spatial analyses were conducted in GeoDa and ArcGIS for each variable using the Anselin Local Moran's I, ordinary least squares regression, and geographically weighted regression. The weights matrix used in GeoDa was Queen's Contiguity of the first order, and in ArcGIS was Contiguity Edges Corners.

Results

Univariate and bivariate Local Moran's I were run in GeoDa using Queen's contiguity and distance to parks as the independent variable. Results showed significant clustering for all variables, indicating spatial autocorrelation. Next, regressions were run in both GeoDa and ArcGIS. The results in GeoDa did not yield any significant results except percent Non-White for 1990-2000. With an R^2 value of .126 and a coefficient of .003, the results indicate that for every percent increase in non-white populations, the distance to parks increased by .003 meters. Mapping the residuals results of the Ordinary Least Square regressions in ArcGIS also revealed spatial dependency. Given the spatial dependency of the variables, geographically weighted regression in ArcGIS was run to show the variation in significance and coefficients over space. Block groups were mapped that had a t-score of 2 or higher.

OLS Results from GeoDa with Distance to Parks as independent variable

	2000		2015	
	R^2	Coefficient	R^2	Coefficient
Percent Non-White	.126	.003	.460	.002*
Median Household Income	.015	-6.226*	.184	-5.17*
Percent Public Assistance Income	.003	.001*	.041	.0009*[+]
Median House Value	.002	15.41*	.418	-22.255*

*Insignificant results, [+]lambda is significant

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UEP 294 Advanced GIS, Urban & Environmental Policy and Planning
Data Sources: American Community Survey 2015, 2010; U.S. Census 1990, 2000; DC Open Data
Map Projection: NAD 1983 UTM Zone 18N
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Conclusions and Limitations

Given the lack of significant models, there are few policy conclusions to draw. While it appears that distance to green space can be predicted by changes in percentage of non-white population, the majority of conclusions stem from limitations in data and methodology. First of all, sociodemographic data from the census do not adhere to the same boundaries over time, making measuring temporal changes challenging. The interim solution to do an areal interpolation was also problematic, producing inaccurate values based only on estimations. Future research may need to change the scale to the census tract. Additionally, given that all the variables were spatially dependent, this analysis does not account for edge effects of bordering states. Another limitation is the incomplete dataset for green space. The only parks included were those with an available date, when really there are many more existing parks. Future research includes switching the independent and dependent variables to result in a multivariate model.

Sources

Anguelovski, Isabelle, James J. T. Connolly, Laia Masip, and Hamil Pearsall. 2017. "Assessing Green Gentrification in Historically Disenfranchised Neighborhoods: A Longitudinal and Spatial Analysis of Barcelona." *Urban Geography 0 (0):1–34. https://doi.org/10.1080/02723638.2017.1349987.*

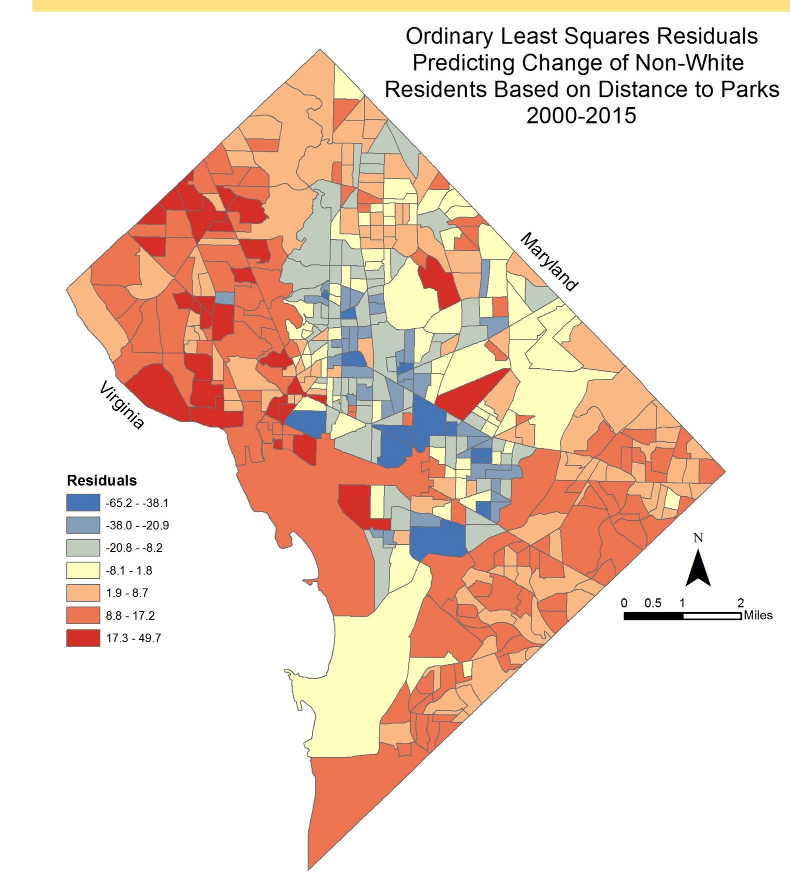
Heynen, Nik, Harold A. Perkins, and Parama Roy. 2006. "The Political Ecology of Uneven Urban Green Space: The Impact of Political Economy on Race and Ethnicity in Producing Environmental Inequality in Milwaukee." *Urban Affairs Review 42 (1):3–25. https://doi.org/10.1177/1078087406290729.*

Jennings, Viniece, Lincoln Larson, and Jessica Yun. 2016. "Advancing Sustainability through Urban Green Space: Cultural Ecosystem Services, Equity, and Social Determinants of Health." *International Journal of Environmental Research and Public Health 13 (2):196. https://doi.org/10.3390/ijerph13020196.*

Wolch, Jennifer R., Jason Byrne, and Joshua P. Newell. 2014. "Urban Green Space, Public Health, and Environmental Justice: The Challenge of Making Cities 'just Green Enough.'" *Landscape and Urban Planning 125 (May):234–44. https://doi.org/10.1016/j.landurbplan.2014.01.017.*

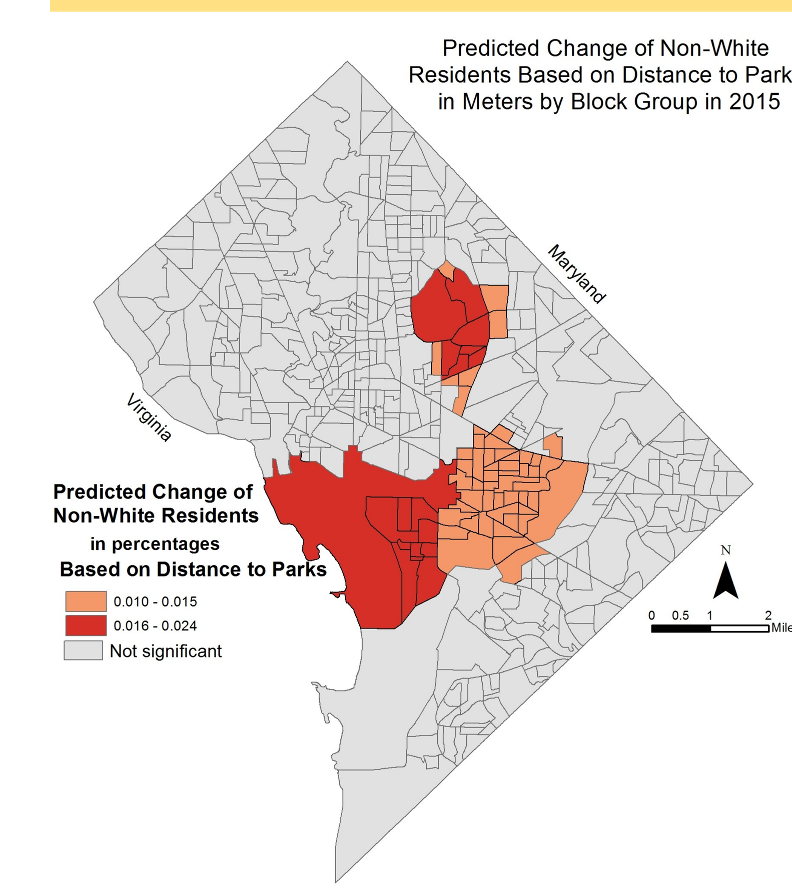
2015 OLS Results

Percent Non-White



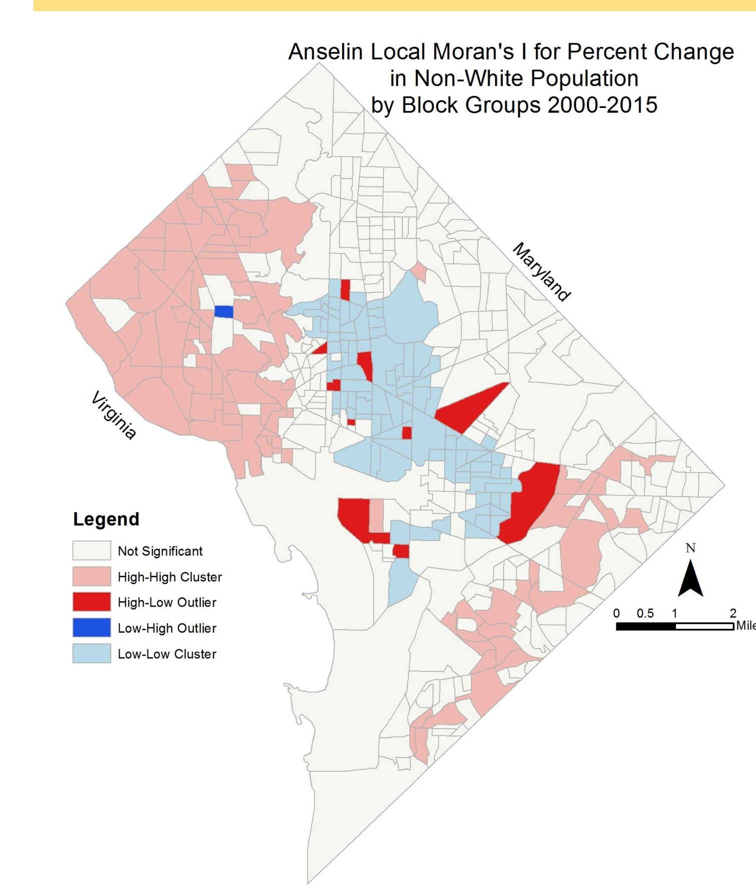
2015 GWR Regression

Percent Non-White



2015 Anselin Local Moran's I

Percent Non-White



Percent Non-White