DOES MOVING IN MEAN GETTING OUT?

An Assessment of Boston's Gentrifying Neighborhoods and Change in Voter Turnout Over Time

INTRODUCTION

Some literature on "social capital" in changing neighborhoods suggests that lower income residents in neighborhoods attracting wealthier new residents will benefit in various ways with their arrival. Such research argues that new residents who tend to receive higher levels of education may encourage long-term residents to be more politically engaged. The findings of another body of research, centering political displacement, conflicts with this theory. Political displacement posits that neighborhoods with existing political structures experiencing an influx of new residents of a different socio-economic background may have those structures undermined, diluted, or interrupted by these new residents. This can result in feelings of political inefficacy, therefore decreasing the political participation of residents who had previously felt represented.

Research Questions

1. **What neighborhoods of Boston are vulnerable to gentrification?**
2. **Does gentrifying pressure impact voter turnout in vulnerable Boston neighborhoods?**

METHODS

The methods used include three different processes. The first was to execute a vulnerability assessment by census tract for neighborhoods in Boston for both 2005 and 2015. The second was to measure voter turnout by precinct for those same years. The last process was to evaluate, using a linear regression, whether there is any relationship between populations' vulnerability to gentrification and their likelihood of voting. Data from the years 2005 and 2015 was chosen in part because 2005 was the oldest accessible data with the specificity required. Additionally, these are both years of municipal elections. Despite expected low turnout rates in these election cycles, this model assumes participation in municipal elections is more directly tied to feeling empowered to participate in local political channels.

Seven variables were used o perform the vulnerability analysis; these were built off of Eliana Golding's prior work in this area ("Surviving the Development Boom: A Suitability and Vulnerability Analysis of Boston's Neighborhoods", 2018). These variables, all at the census tract level, included distance from MBTA T stops, distance Boston's designated Main Streets Districts (MSD), percent nonwhite population, percent renters, percent population who obtained a B.A. or higher schooling, density of housing value/square foot, and percent census tracts with low median household income. MBTA and MSD raster layers were created using Euclidean Distance. Demographic tabular census data was joined by attribute to TIGER census tract polygons. Using the Field Calculator different percentages were calculated, incorporated into the tables, and rasterized. A random sample of about 5,000 was selected from assessor's parcel data, the centroid of the polygon data was determined, and the polygons were converted into point data. Property value/square footage values were interpolated from the sample using IDW. All of the above raster layers were fuzzified and inputted into the Fuzzy Overlay tool, resulting in the final output for both 2005 and 2015.

Tabular data was joined to a precinct polygon layer to calculate voter turnout by precinct. Local Moran's I evaluated whether and where the data was clustered. Global Moran's I was used to determine whether there was clustering and if it was statistically significant.

Zonal Statistics generated a precinct polygon layer with a mean gentrification vulnerability score by precinct to maintain a uniform spatial unit. The Ordinary Least Squares tool was used to execute a linear regression, designating the mean gentrification vulnerability score as the independent variable and voter turnout as the dependent variable.

DATA

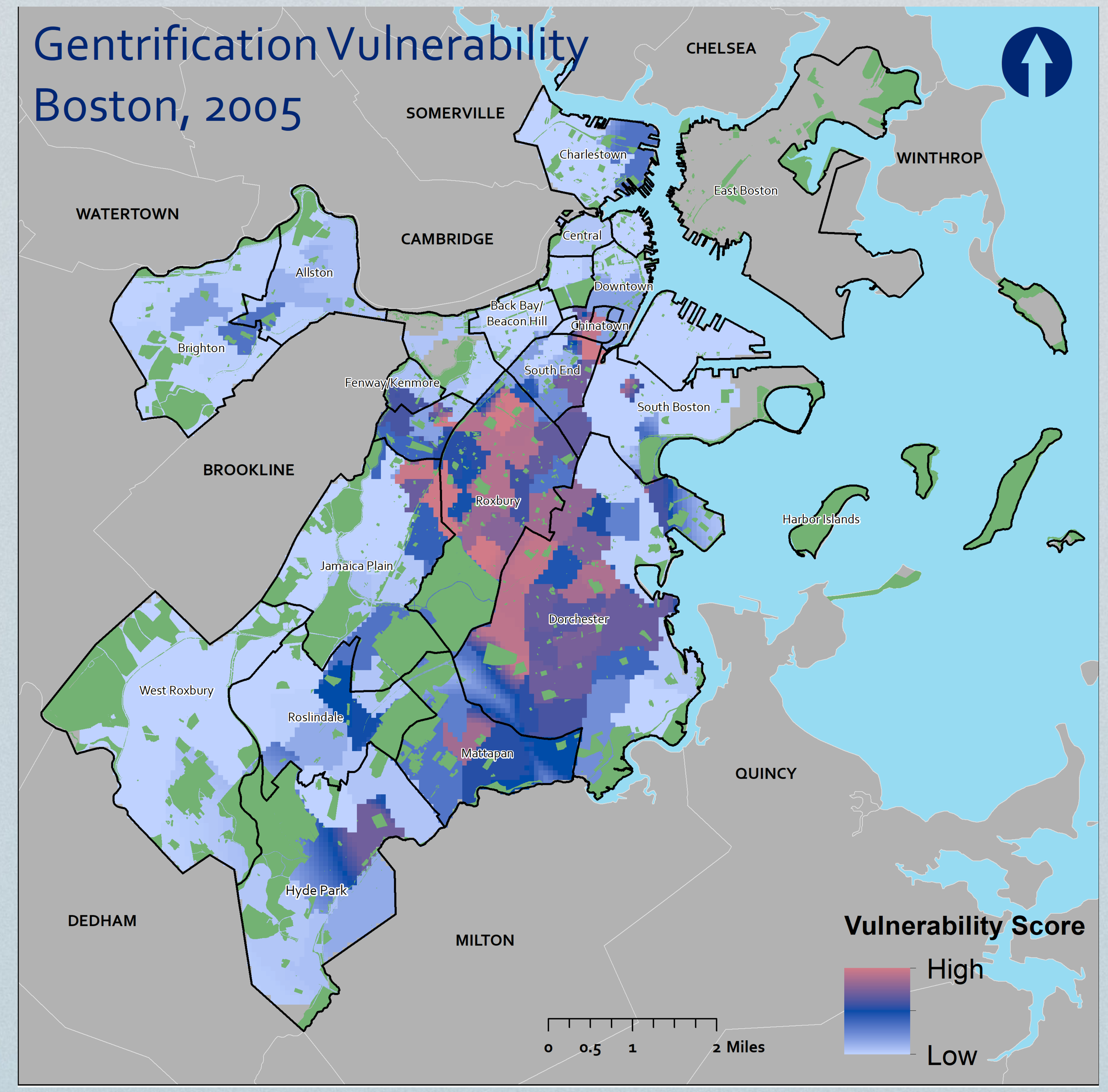
American Community Survey (5 year): Demographic Data

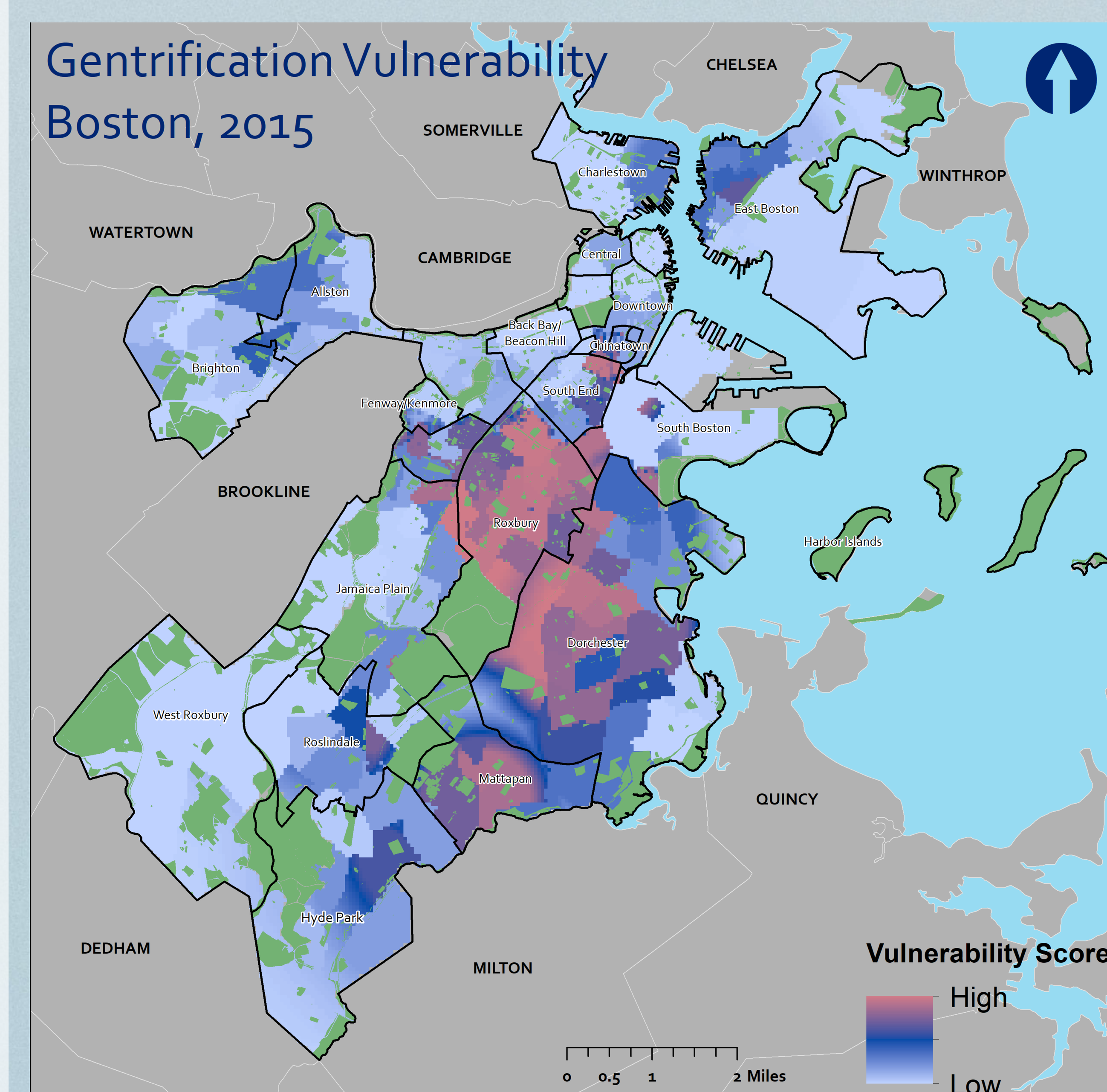
TIGER Shapefiles

MassGIS: MBTA Routes and Nodes, Assessed Housing Values and Parcels

AnalyzeBoston: Main Streets Districts, Voter Precincts, Voter Turnout by Precinct

Tufts UNIVERSITY





INFO

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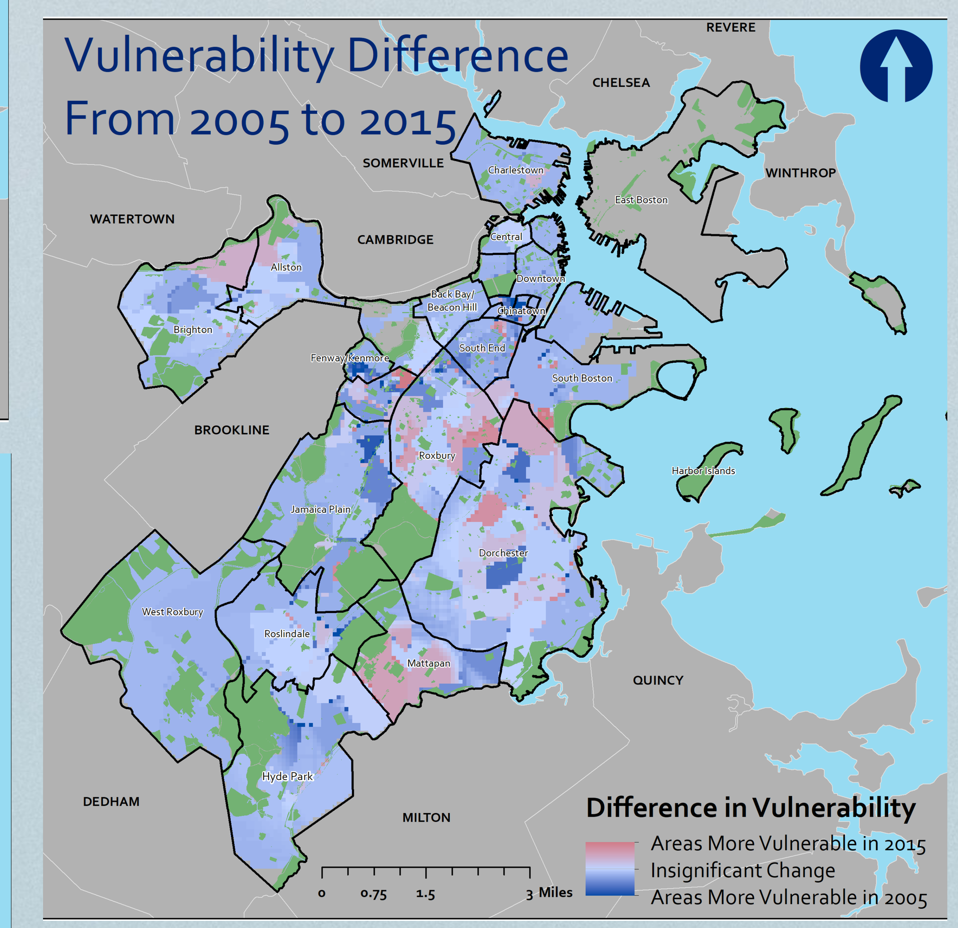
Projection: Lambert Conformal Conic
Coordinate System: State Plane MA Mainland FIPS 2001

Image: Jeffrey Czum from Pexels

RESULTS/DISCUSSION

In both the 2005 and 2015 gentrification vulnerability layers there is clustering of areas of high vulnerability in parts of Dorchester, Chinatown, Roxbury, and where Jamaica Plain meets Roxbury. Large portions of these and surrounding neighborhoods are marked in transitional shades of dark blue and purple. The Raster Calculator generated a difference layer, displayed below. Areas in pink show were more vulnerable in 2015, areas in dark blue were more vulnerable in 2005. This layer demonstrates the dynamic nature of gentrification as a process as well as the movement of people and resources over time. Neighborhoods with significant vulnerability score difference areas include Dorchester and a portion of South Boston where it abuts Dorchester, Mattapan, the northeast corner of Mission Hill, Roxbury, and Brighton.

A Global Moran's I of **0.157** and **0.191** for 2005 and 2015 respectively indicated that both years of voter turnout data were highly clustered with a P-value of 0.000*.



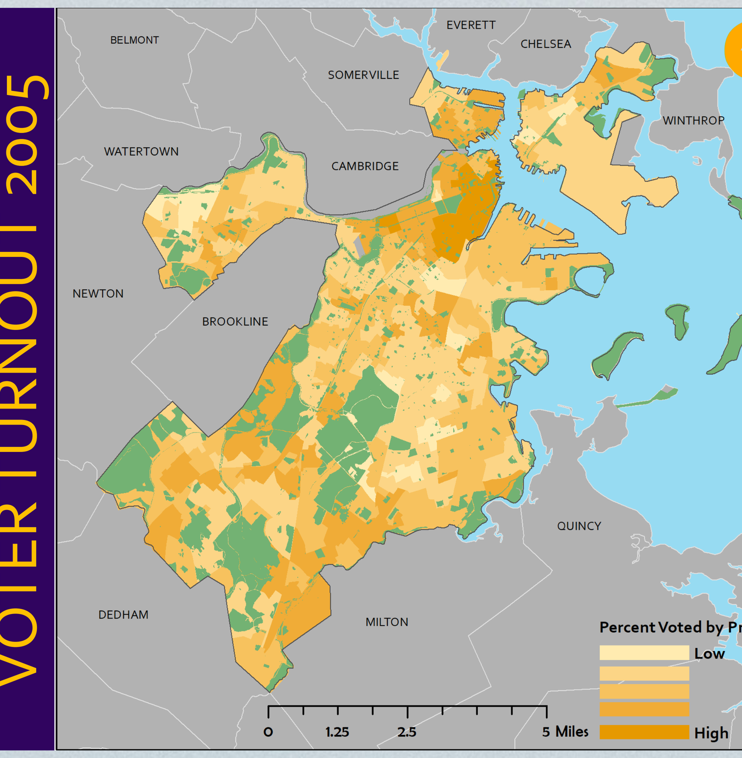
The OLS tool rendered a Gentrification Coefficient of **–0.1257** for the 2005 data and **–0.16** for 2015 data. The P-values were 0.00083* and 0.014* respectively. These numbers indicate that there is a slight negative correlation between gentrification vulnerability and voter turnout as defined here. This project presented several hurdles that impacted the shape and accuracy of my analysis. First, I wanted to include an eighth variable in the gentrification index that I feel would have made it more comprehensive- density of old housing stock- but was unable to acquire parcel data that included year built for the 2005 set. Many of the difficulties this analysis presented revolve around a dearth of voting data that has not been aggregated by state. Protecting voter privacy is necessary, but there is a need for more voter data at localized spatial units. The data I found was provided by the city of Boston, but there was no description of how the voting counts were collected. It is difficult to discern the accuracy of these numbers. In addition, my regression analysis was fairly limited. I only incorporated one explanatory variable- the gentrification vulnerability score- but there are other variables worth considering when thinking about influencers of voter turnout. Availability of information and resources on voting and registration, voter ID laws and other exclusionary policies, age break-down of voting population, and the number of accessible voting locations to name a few. A fuller analysis would consider these other factors.

I ran a Geographically Weighted Regression on both the 2005 and 2015 data with limited significant results. In addition to the above limitations, GWR best performs when there are several hundred data points, my sample falling far short.

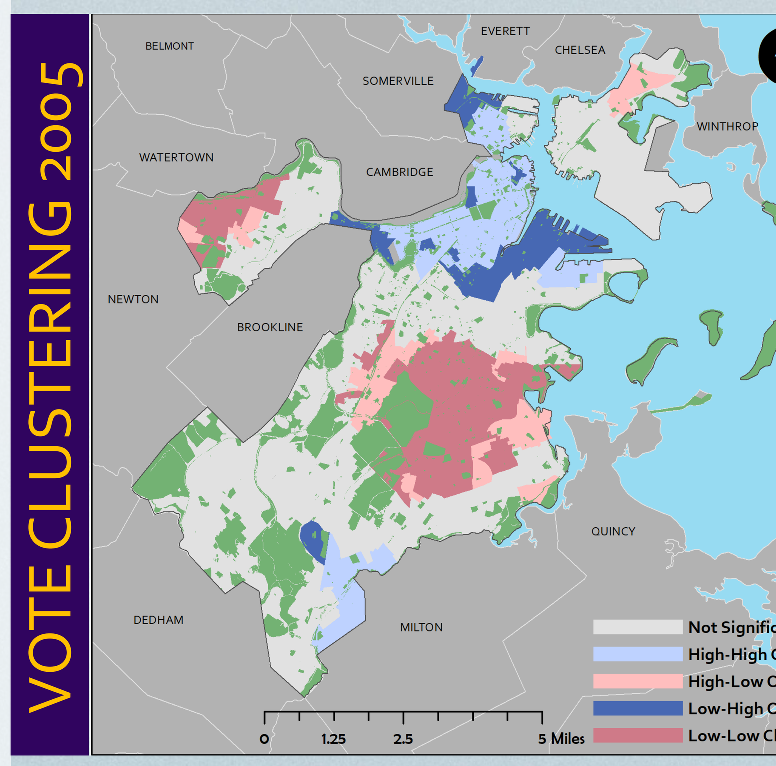
By centering voter turnout, I chose to measure political participation in a narrow way. My choice to do so was for lack of access to other kinds of survey data that spoke to communities' feelings of political efficacy, non-electoral political participation, and empowerment over time. More research and access to the collection of input in this area is needed.

I used a fuzzy vulnerability model to avoid introducing uncertainty from weighting and creating "classes" in output raster layers. It is hard to account for values that close to the end of one class and the beginning of the other. Classifying these values as one or the other seems in some sense arbitrary and I believe using fuzzy overlay allowed for more confidence in the vulnerability analysis. That said, since gentrification has no established definition, the variables I chose do not account for the varying research on measuring gentrification. Their selection reflects some level of personal bias.

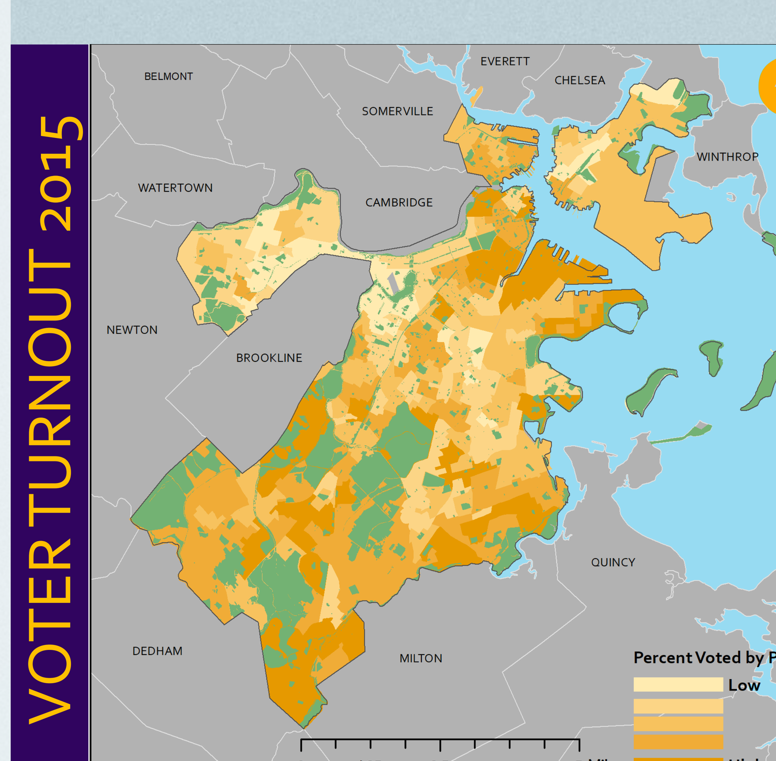
VOTER TURNOUT 2005



VOTE CLUSTERING 2005



VOTER TURNOUT 2015



VOTE CLUSTERING 2015