Calculating a gentrification metric across UWIN sites

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The metric I think we should use

So, I had to go back to the drawing board a few times in order to generate a gentrification metric that could be applied to the 20 different UWIN cities in this study. Initially, we were going to hitch our wagon to the metrics provided in Freeman (2009). However, after collecting all the necessary census data and calculating these metrics it became apparent that the Freeman (2009) paper quantified city-level segregation, not gentrification. Instead, Freeman's 2009 paper actually used a gentrification metric they proposed in a 2005 paper of theirs to identify gentrifying areas. The general 'rules' tied to this metric are that a census tract must (Freeman 2005):

- 1. Be located in the inner city.
- 2. Have a median income less than the 40th percentile of the metropolitan area at the beginning of the intercentennial.
- 3. Has a percentage of housing built over the past 20 years that is below the 40th per centile for the metropolitan area.
- 4. Has a percentage increase in educational attainment that is greater than that of the metropolitan area.
- 5. Housing prices increased during the decade.

Unfortunately, when using these rules most UWIN sites within cities were not located in 'gentrifying' areas. As a result, this metric made gentrification so rare that it would be impossible to make comparisons in gentrifying vs non-gentrifying areas.

Because of this, I scoured through the literature again to find some other metrics that we could use to identify gentrifying areas within a city. From this, it became apparent rather quickly that there is a lot of disagreement on what 'rules' should be used to identify gentrification. This is good news, in some regards, as it gives us a little bit of wiggle room. After some searching, I decided to give a slightly modified version of the gentrification metric used by Chapple et al. (2017). This metric uses a two-step process to identify gentrifying areas. First, for an area to be gentrifying, it must be vulnerable to gentrification at the start of the study (in this case that is 2010). For a census tract to be vulnerable to gentrification it must:

- 1. Have at least 500 residents in year 1.
- 2. Have at least two of these three qualities.
- a. The median income of residents in the census tract must be lower than the city's average income.
- b. The proportion of college-educated residents in the census-tract must be lower than the proportion of college-educated residents across the city.
- c. The proportion of nonwhite residents in the census tract must be greater than the proportion of nonwhite residents across the city.

After calculating the census tract vulnerability, I created a 500m radius buffer around each camera trapping location within a city and intersected that buffer with the census tract level vulnerability index. This buffer was chosen because many sites were close to the edge of a given census tract and I wanted to capture the general area around each site that easily fell within the home range of the species we'll be modeling.

Of 962 UWIN sites across 20 cities, 459 (47.7%) were considered vulnerable to gentrification (see more below).

Following this, a census tract was considered gentrifying if at the end of the study (in this case that is 2019) if the census tract:

- 1. Was vulnerable to gentrification in 2010.
- 2. The change in median income was greater than the average change across the city, after correcting for inflation.
- 3. Had at least one of these two qualities.
- a. The change in the proportion of college educated residents was greater than average change across the city.
- b. The change in the proportion of non-hispanic white residents was greater than the average change across the city.

Of the 459 sites that were vulnerable to gentrification, about half of them of them (n = 251) are gentrifying, though there is a substantial amount of variation among cities. For example, Urbana only had one site near a gentrifying census tract (of 35 sites) while Phoenix had exactly half of their 96 sites in gentrifying areas.

Calculating change across census datasets is unfortunately not simple, because census tracts can (and often do) change every ten years. To rectify this issue, I rasterized the 2010 census data at a 500m resolution and then extracted the data with the 2019 census tracts. If census tracts did not change, this would provide a direct comparison. If census tracts did change, then this technique is similar to performing areal interpolation.

The rest of this document has some summary tables for each level of the classification process (for those that are interested, otherwise just skip passed them). However, at the end of the document I generated some plots for each city. Based on these, it appears we may need to correct some spatial clustering in our alpha and beta diversity analysis, given that lots of sites are that gentrifying are nearby one another. Please look over the plot for your city and let me know if it passes a 'smell test.'

How I got the data

The objective of this analysis is to determine how historical patterns of gentrification are associated to patterns of urban biodiversity. As such, we needed to compile census data from multiple years. To do so, I used the tidycensus package in R to query census data from the year 2010 and 2019. The 2010 data came from the 10-year decennial census whereas the 2019 data came from the 5-year American Community Survey (ACS).

Across these years I compiled data the aforementioned variables for all census tracts that were within the general area of a UWIN transect. To figure that out, I created a bounding box around the camera trap locations for each city, added 500m to each edge to make it a little larger, and then cropped the census data to that bounding box. Because of this we are making the assumption that the metropolitan area is "the general area that a UWIN partner samples," which I think is appropriate given standard UWIN study designs.

Step 1. Figuring out which areas are vulnerable to gentrification

Step 1.1 Household income in 2010 less than regional median.

After cropping the census tracts to an area around a cities sampled location, I calculated the regional median (i.e., median income across census tracts) and identified census tracts that fell below that number.

Here is a table that shows how many sites are above (FALSE) and below (TRUE) the regional median income.

Table 1: The number of sites below the median income in 2010 for each city.

	FALSE	TRUE
ahga	14	14
autx	15	17
boma	20	3

	FALSE	TRUE
chil	62	49
$_{ m deco}$	19	20
inin	29	16
ioio	28	9
${f jams}$	26	20
lrar	17	10
\mathbf{mawi}	12	10
naca	42	29
\mathbf{phaz}	43	44
poor	18	5
\mathbf{rony}	10	10
\mathbf{scut}	128	18
sewa	19	14
${f slmo}$	26	12
tawa	18	24
uril	19	16
\mathbf{wide}	17	12

Step 1.2. Educational attainment less than regional median in 2010.

This was calculated in the same way as the income data. I simplified the census data into two categories for educational attainment: those with a college degree and those without a college degree.

Here is a table that shows how many sites are below (TRUE) and above (FALSE) the regional median in educational attainment in 2010.

Table 2: The number of sites below the median educational attainment 50th percentile of educational attainment (i.e,. college degree) between 2000 and 2019.

	FALSE	TRUE
ahga	19	9
autx	18	14
\mathbf{boma}	16	9
\mathbf{chil}	59	52
$_{ m deco}$	14	25
inin	29	16
ioio	15	22
${f jams}$	30	16
lrar	14	13
mawi	12	10
naca	39	34
\mathbf{phaz}	46	43
\mathbf{poor}	13	10
\mathbf{rony}	13	10
\mathbf{scut}	132	14
sewa	16	17
${f slmo}$	29	9
tawa	28	14
uril	12	23
\mathbf{wide}	19	10

Step 1.3: The census tract must have at least 500 people.

The education data from above also has information on the number of people in each census tract, so I just used that to create a binary metric for whether or not a census tract in 2010 had at least 500 people living in them (almost all of them did).

Step 1.4: The proportion of non-white people in a census tract is greater than the city median.

Calculated same as above. I compiled the total number of people in a census tract as well as the number of non-hispanic white people living in a census tract to get this number (i.e., 1 - (number of non-Hispanic white people in a census tract / total number of residents in a census tract)).

Table 3: The number of sites over with more non-white people than the city average.

	FALSE	TRUE
ahga	15	13
autx	18	14
\mathbf{boma}	17	10
\mathbf{chil}	60	51
$_{ m deco}$	21	18
inin	28	17
ioio	19	18
${f jams}$	31	15
lrar	20	9
\mathbf{mawi}	12	10
naca	42	33
\mathbf{phaz}	40	52
\mathbf{poor}	15	8
\mathbf{rony}	13	10
\mathbf{scut}	130	16
sewa	19	14
$_{ m slmo}$	27	11
tawa	28	14
uril	21	14
wide	9	20

Step 1.5: Combining the vulnerability metrics.

The site MUST have > 500 people and at least two of the other qualities to be considered vulnerable to gentrification.

Table 4: The number of sites that reside in census tracts we identified as vulnerable to gentrification.

FALSE	TRUE
11	17
16	16
15	12
43	68
11	28
26	19
	11 16 15 43 11

	FALSE	TRUE
ioio	24	13
${f jams}$	23	25
lrar	19	10
\mathbf{mawi}	5	17
naca	31	44
${f phaz}$	33	63
poor	13	10
\mathbf{rony}	11	12
\mathbf{scut}	125	21
sewa	18	15
${f slmo}$	25	15
tawa	27	17
uril	15	20
wide	12	17

Step 2. Determine if a vulnerable location has undergone gentrification.

Step 2.1. Has a percentage increase in educational attainment that is greater than that of the metropolitan area.

Here is a table that shows how many sites are above (TRUE) and below (FALSE) the average change in in educational attainment.

Table 5: The number of sites where the increase in educational attainment (i.e., a college degree) between 2010 and 2019 was greater than the city average.

	FALSE	TRUE
ahga	15	13
autx	17	15
\mathbf{boma}	18	7
\mathbf{chil}	64	49
${ m deco}$	21	18
inin	17	28
ioio	14	23
\mathbf{jams}	21	25
lrar	18	9
mawi	12	10
naca	45	29
\mathbf{phaz}	53	34
poor	15	8
\mathbf{rony}	7	16
\mathbf{scut}	118	28
sewa	16	17
$_{ m slmo}$	17	21
tawa	25	17
uril	26	9
wide	18	11

Step 2.2: The proportion of white people living in a census tract is greater than the city average.

Table 6: The number of sites where the change in the proportion of white people was greater than the city average.

	EVICE	TDIIE
	FALSE	TRUE
ahga	18	10
autx	17	15
\mathbf{boma}	12	13
\mathbf{chil}	72	41
${ m deco}$	22	17
inin	20	25
ioio	20	17
\mathbf{jams}	28	18
lrar	18	9
\mathbf{mawi}	10	12
naca	42	32
\mathbf{phaz}	33	54
\mathbf{poor}	16	7
\mathbf{rony}	17	6
\mathbf{scut}	87	59
sewa	11	22
${f slmo}$	11	27
tawa	19	23
uril	8	27
\mathbf{wide}	17	12
-		

Step 2.3: The change in median income was greater than the city average between 2010 and 2019.

Calculating this is similar to educational attainment within a given census tract. However, we also need to account for inflation in these calculations. I went to the [U.S. Bureau of Labor Statistics website] (https://www.bls.gov/data/inflation_calculator.htm) and used their inflation calculator to determine how much the price of \$1 has changed between January 2010 and January 2019 (it is \$1.17). Thus, I multiplied the dollar values of median housing prices in 2000 by 1.17 before comparing changes in housing prices.

Here is a table that shows how many sites reside in census tracts that have increased in price (TRUE) over time and those that have not (FALSE)

Table 7: The number of sites that reside in census tracts where median income increased more than the regional median.

	FALSE	TRUE
ahga	17	10
autx	14	16
boma	14	9
\mathbf{chil}	61	51
${ m deco}$	20	19
inin	21	24
ioio	10	27
${f jams}$	28	18
lrar	11	16

	FALSE	TRUE
mawi	11	10
naca	46	25
\mathbf{phaz}	45	40
\mathbf{poor}	13	10
\mathbf{rony}	13	7
\mathbf{scut}	57	89
sewa	20	13
${f slmo}$	14	24
tawa	12	30
uril	24	11
wide	19	9

Step 2.4: Combining the gentrification metrics.

Table 8: The number of sites that reside in census tracts we identified as vulnerable to gentrification.

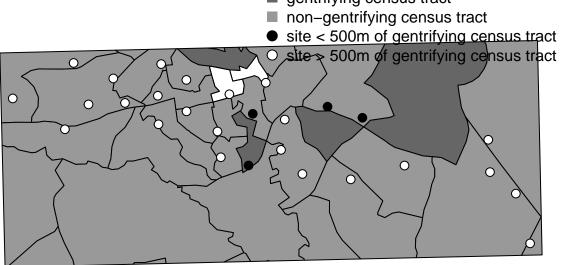
	FALSE	TRUE
ahga	24	4
autx	21	11
\mathbf{boma}	19	8
\mathbf{chil}	72	39
${ m deco}$	23	16
inin	31	14
ioio	34	3
${f jams}$	37	11
lrar	25	4
\mathbf{mawi}	17	5
naca	50	25
\mathbf{phaz}	48	48
\mathbf{poor}	17	6
\mathbf{rony}	18	5
\mathbf{scut}	136	10
sewa	26	7
${f slmo}$	31	9
tawa	31	13
uril	34	1
\mathbf{wide}	17	12

Plotting out the results across cities

Here is a plot for each city, it's pretty self-explanatory, though the legend does get overlaid on some cities a bit. Sorry!

Athens, GA

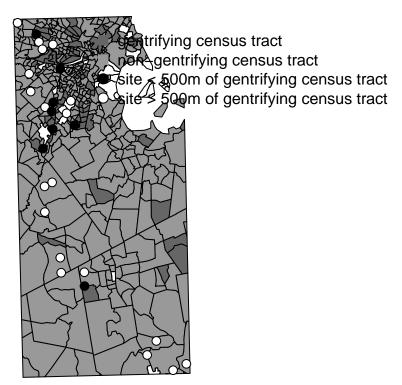
- gentrifying census tract



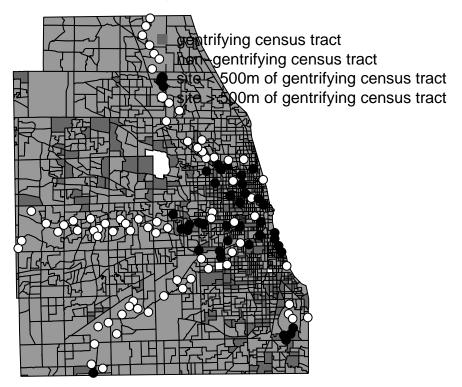
Austin, TX



Boston, MA



Chicago, IL

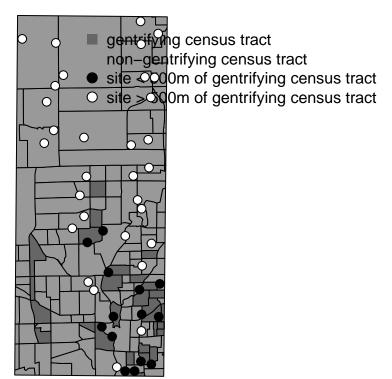


Denver, CO

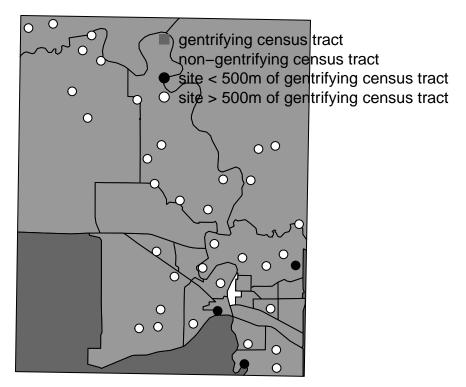
- gentrifying census tract
- non-gentrifying census tract
 site < 500m of gentrifying census tract
- O site > 500m of gentrifying census tract



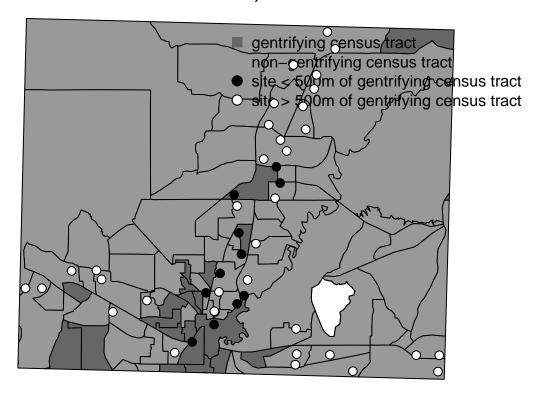
Indianapolis, IN



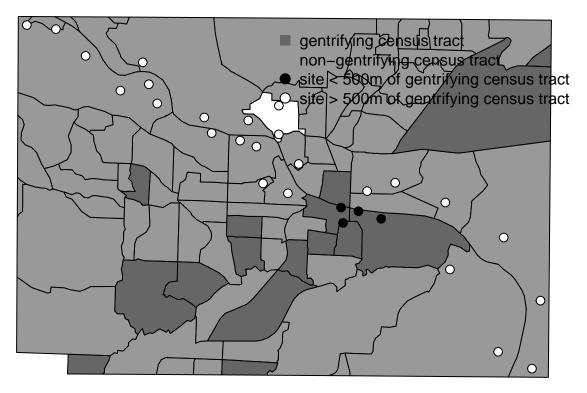
Iowa City, IA



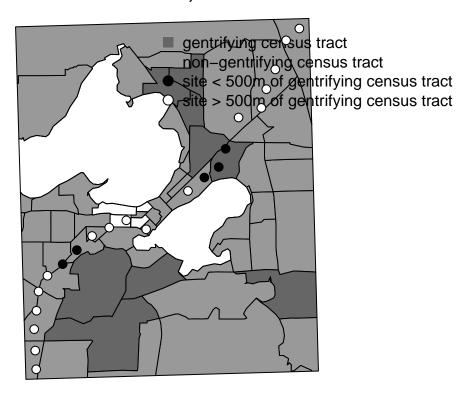
Jackson, MS



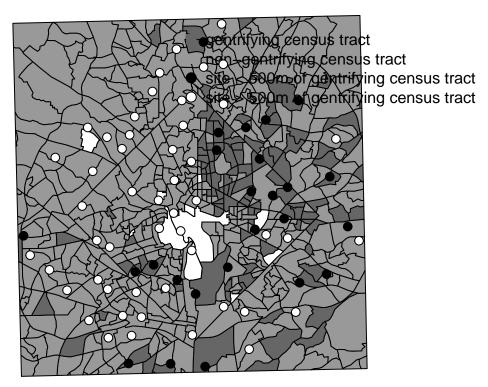
Little Rock, AR



Madison, WI

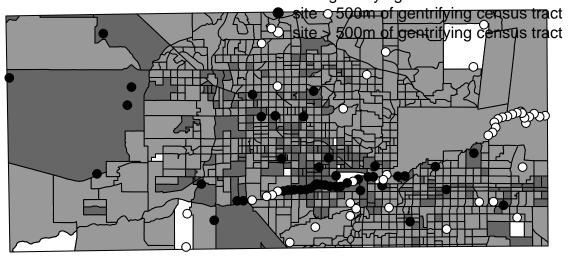


National Capital



Phoenix, AZ

- gentrifying census tract
- non-gentrifying census tract

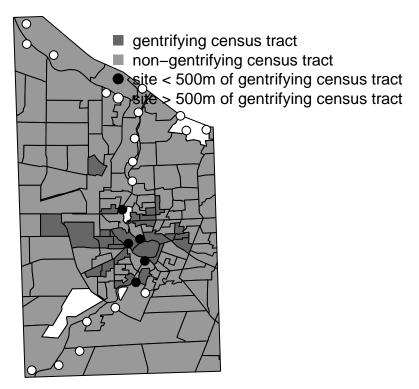


Portland, Oregon

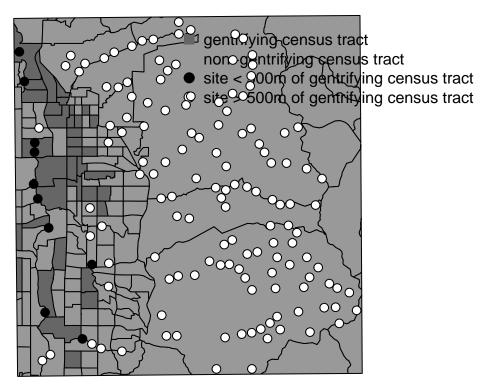
- gentrifying census tract
- non-gentrifying census tract
 site < 500m of gentrifying census tract O site > 500m of gentrifying census tract



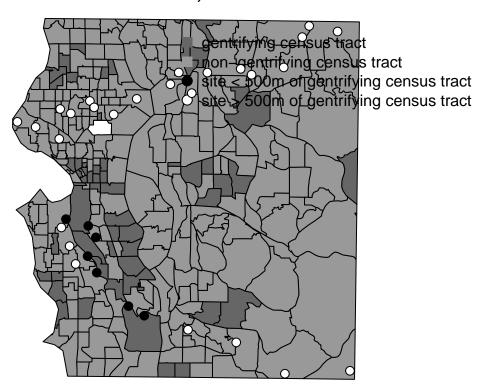
Rochester, NY



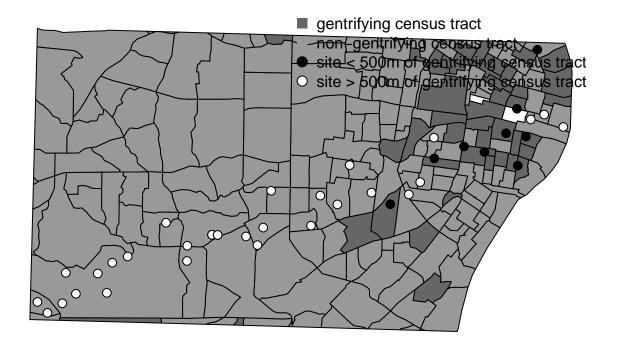
Salt Lake City, UT



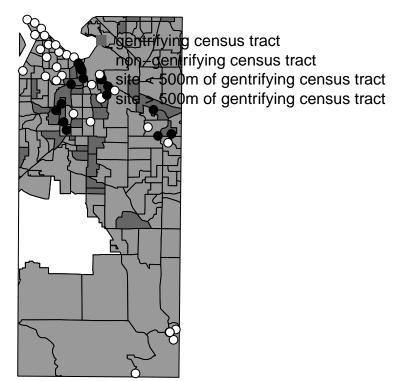
Seattle, WA



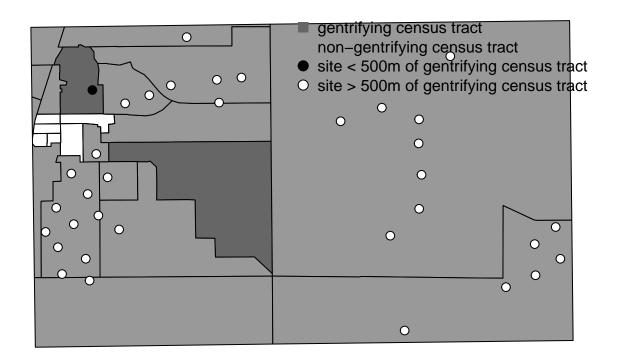
Saint Louis, MO



Tacoma, WA



Urbana, IL



Wilmington, DE

