# Optimal Greenery

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## 1 Introduction

It has been well studied and well taught that parks increase the value of surrounding properties. In traditional economic theory, parks' value comes from the land they are on - public space that is not directly paid for by the individual. In reality, their true utility extends far beyond that. Parks are characterized primarily by green space - from pastures to dense forests - which end up being the primary source of their value. Foliage has been shown to have psychological and environmental effects, increasing peoples' mental well being [van den Berg et al., 2010] while fighting urban heat island effects and lowering the level of pollutants for neighboring blocks [Feyisa et al., 2014], even noticeably decreasing cooling costs in surrounding buildings.

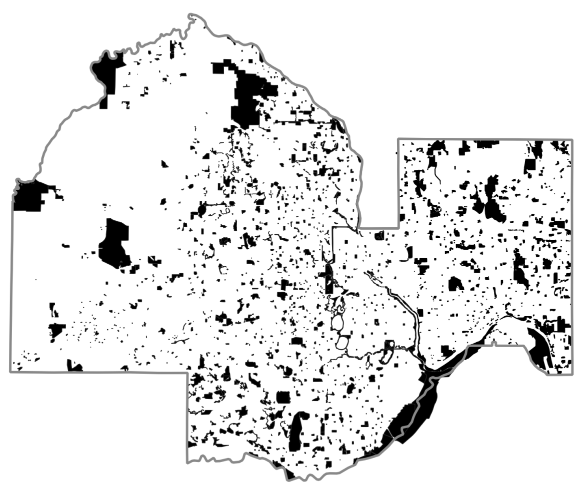

Figure 1: Parks in Hennepin and Ramsey counties

Most previous studies measure the value of parks by way of surrounding home prices. This paper continues the study of the influence of park distance on housing costs, while introducing tree cover and aggregate park land measures to control for the effects of non-public-land greenery. I find that tree cover is a better indicator of home price in urban areas than park distance and aggregate park land, suggesting that the primary benefit of parks are the plants contained within them.

Further, I use demographic controls to estimate how the need for parkland and greenery change due to the needs of the neighborhood, and find that the interaction between population density and tree cover is highly correlated with higher latent home values.

To find these results, I look at the relationship between measures of park and greenery saturation and home price in the Twin Cities metropolitan region in Minnesota, specifically Hennepin and Ramsey counties. This area is notably in particular for having an especially robust park system. Over the past six years since they were both included in the Trust for Public Lands' Parkscore ranking, Minneapolis and St. Paul have remained in the top three[202, ] out of more than 70 major U.S. cities studied.

This area, which can be seen as park-saturated, represents a unique chance to study the marginal effects of greenery measures in places not starved for public land. In this way, the Twin Cities serves as an excellent testing ground for the continued discussion over what makes a city great to live in, or economically stated, where city governments and citizens should focus their ecological investments.

We will first summarize important findings on park distance and home value from the literature, with an emphasis on work involving tree cover and park distance. Then, I'll itemize the data sources for my own research, outline how the aggregate measures were calculated, and explain why these are sufficient. I'll explain the empirical model used to find my results. Then, a more extensive explanation of these results will be accompanied by tabulated summarizes to conclude the paper. Finally, in Appendix B, visual representations of key variables are included as an optional accompaniment to the reading.

## 2 Literature Review

There is longstanding consensus that parks increase the value of nearby homes. In research aggregated by I-Hui Lin [Lin, 2016], this relationship has been studied as far back as the 1800s.

Most of this research has been focusing on raw distance from a park, finding that the closer a home is to park, the higher valued it is[Lutzenhiser and Netusil, 2001]. This result squares with the historical theory and is generally unsurprising.

That being said, parks are not a monolithic good. As congregating spaces, under the wrong circumstances with little supervision, they can become breeding grounds of crime[Putnam and Quinn, 2007], where lack of ownership leads neighbors to ignore festering social issues. A study of urban neighborhoods in Baltimore found that parks served as a neighborhood good up until a crime threshold was crossed, in that paper determined to be between 406 and 484% of the national average incidence[Troy and Grove, 2008].

This further enhances the importance of the possibility of augmenting public land with public greenery, which may have violence calming effects in and of itself [Donovan and Prestemon, 2012].

Much of the more nuanced literature on park distance effects point to this latent "tree effect." Lutzenhiser notes that

> Homes located within 1,500 feet of a natural area park, where more than 50% of

> the park is preserved in native and/or natural vegetation, are found to experience, on average, the largest increase in sale price.

The key here being that the most valuable public areas contain an abundance of natural greenery, as opposed to golf courses, which were found to be *negatively* correlated with home value. On the environmental side, a study of Kenyan neighborhoods [Feyisa et al., 2014] found that

> Cooling effects of green spaces mainly depended on species, canopy cover, size and shape of parks.

Again pointing to the fact that a large tree canopy packs the biggest punch in combating urban heat island effect. Research even points to the value of urban trees as a civic rallying point [Dwyer et al., 1991].

Compared to literature on the effects of parks, studies of tree canopies' effects on home prices are relatively hard to come by. However a 2000 study, similarly in Minnesota, generated ground cover statistics at five distance levels ranging from 100 to 1000 meters. This study used a hedonic pricing model to derive a significant and positive relationship between tree cover in the 100 and 250 meter radii and home price[Sander et al., 2010]. Interestingly, they also noted that this effect only held true up until the 40-60% tree cover range, at which point the returns to trees became negative.

It should be noted that this study was conducted in Ramsey and Dakota counties, the first of which is shared but the second of which is much more rural than both Hennepin and Ramsey counties. As the authors of that paper note, their results indicate "neighborhood externalities." By including Hennepin as opposed to Dakota county, this paper investigates more the "neighborhood" aspect of this, as opposed to rural areas with large lot sizes where externalities are less apparent.

In this vein, a meta-analysis of tree cover in fifteen cities around the country found that returns to tree cover leveled out after 30%[Siriwardena et al., 2016]. Siriwardena referenced [Cho et al., 2008], whose team found that the value of forested regions increases in density. This paper continues in this trend by studying the interactions of each greenery statistic and demographic measures, including density.

# 3 Data

This study uses data from Hennepin and Ramsey counties in the Minneapolis-St. Paul metropolitan area. To answer the question of green space vs. tree value, I needed to compile both individual and aggregate park data as well as granular tree cover data and controls for demographic factors. I pull these figures from four main sources:

1. From Hennepin and Ramsey counties' tax data
2. Ground cover data from the University of Minnesota's Geospatial Analysis Laboratory
3. From Hennepin and Ramsey counties' park

land maps

4. From the US Census' American Community Survey *ACS*

### 3.1 Tax Data

The dependant variable, land price, is taken from the public tax records of Hennepin and Ramsey counties. This data comes from each of the cities' assessors and is re-assessed every year. For the most part we can assume this data is consistent at the county level: while there may be differences in each city's valuation strategy, the incentive is constant for cities to accurately value homes, and for home owners to appeal this valuation if it is too high. Further, while value is assessed by the city, it is collected by the city, the county, the watershed district and the school district. Due to the combination of stakeholder interests, we can rely on the valuation data provided to be unbiased.

It should be noted that this study breaks from previous literature, which mostly uses home sale prices and structural controls, by observing latent housing demand via land price per meter. This decision is informed by the nature of the data available. Both Hennepin and Ramsey counties' tax datasets contain clearly labeled total value, building value and land value measurements. The additional data they provide for use as control variables, however, is inconsistent. Ramsey county, for instance, tracks and provides the invaluable information of floors, living and bed rooms and even exterior style of each home, while Hennepin does not. These were omitted for consistency. Instead, common fields in both datasets were used: school district, parcel size (meters), city name and land use.

After combining, the dataset of all parcels in the two counties numbered over 600,000. From this I selected small residential parcels, ultimately choosing land use classifications whose means were normally distributed around the median home price in the Twin Cities metro, around $300,000[Med, ] as of 2020. This process resulted in slightly over 500,000 data points. The exact data-cleaning process and associated charts is codified in the linked Github repository.

It should be noted that this abundant data, courtesy of transparency initiatives and localities' thirst for property tax revenues, provides a rare opportunity for the study of a whole population. I passed on this for processing power reasons, instead using a random sample of 25,000 parcels. Finally, for purposes of attributing other spatial data to these parcels, each parcel's "geometry" value - originally a polygon - was converted to the center of that polygon.

### 3.2 Ground Cover

The data on ground cover: tree cover, building cover and pavement cover, comes from the University of Minnesota Geospatial Analysis Lab's Twin Cities Metro Area Land Cover Classification. This dataset is a classification of every square meter of land in the seven-county metro area, generated by compiling various satellite imagery. Previous research [Sander et al., 2010] indicates that treecover within 100 and 250 meters of a home is a significant indicator of home price. To that end, I derive ground cover values by sampling 900 points in a 300 by 300 meter grid centered at the representative point of the parcel. This is generated by the avgGrndCoverAtPoints method, available in aggregator.py on Github.

'TCMA 1-meter' is re-created every few years, most recently in 2015. It includes 12 categories of ground cover - from which I pull "Coniferous Trees", "Deciduous Canopy", (combined in this paper), "Roads/Paved Surfaces", "Lakes/Ponds" ("water" in the associated dataset) and "Buildings". In later regressions, only tree cover is used. This is due to preliminary examination of the dataset, which showed that building cover is highly colinear with density and water is above zero for a very small percentage of the homes studied.

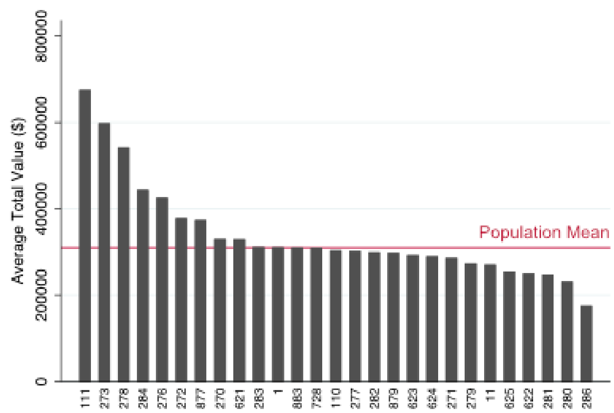


Figure 2: Home price variation by school district

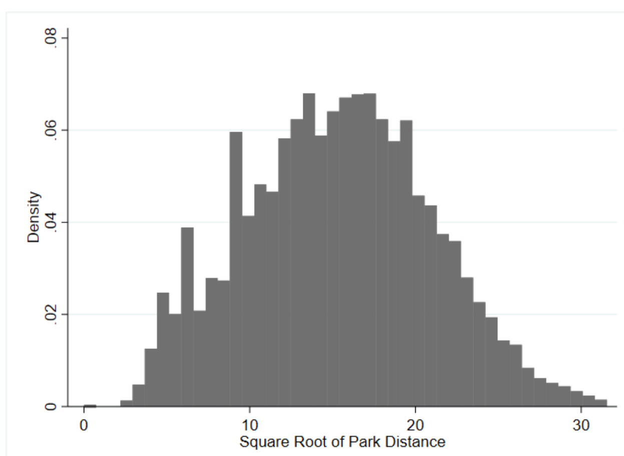


Figure 3: Histogram of normalized park distance

### 3.3 Parks

The data on parks comes from Hennepin and Ramsey counties' GIS portals. I compiled these shapefiles and generated two values from them: first, a raw "distance from park" measure, the number of meters (up to 1.5km) a house is from the nearest park. Second, an aggregate measure of the percentage of land in a Census Tract covered by parks (note, different from the Census Block Group level used for demographics). This larger area was chosen to represent a rough neighborhood size - while there is about one park per Census Block Group in the Twin Cities, a Tract encompasses the nearest set of parks, generally in the mid-single digits. Effectively, this aggregate measure seeks to answer the question "how many green space options does a homeowner have?" It should be noted that in rare cases this percentage value exceeds one - an artifact of the Tract size values available. While the Census tracks area as land area, some parks include large amounts of water in their area statistics. This measure was preserved despite this, as it is generally still an accurate measure of park saturation.

### 3.4 American Community Survey

The data on population density and average age come from the American Community Survey's 5 year estimates, pulled from the dataset updated in 2018. The American Community Survey, a service of the U.S. Census, offers this information for a variety of geographies, from Census Block Group to State. For this paper the smallest unit, Census Block Group, was used. The exact size of this unit varies by region, with a more dense clustering in the urban core and larger Groups in rural areas. The decision for this size specifically was made with theory in mind: many dense communities in the Twin Cities metro region are scattered throughout suburbs - i.e. a condominium development on the periphery of a mall, or packed housing on a lake shore. This project seeks to understand how the need for public spaces and greenery changes in these neighborhoods, not just in the urban core; thus a more granular measure was chosen.

The actual values were derived by a Python script which, given our set of representative parcel-points, determined which block each point was in and queried the Census' API for total population and average age figures. Finally, density was derived from this and total population was discarded.

### 3.5 Crime

Previous studies find a significant link between the value of parks and crime levels in surrounding neighborhoods. Unfortunately, compiled and geo-tagged crime data is only freely available for Minneapolis. The data I use to control for this effect comes from the "Police Incidents 2019" dataset available on Open Minneapolis' website. To achieve aggregate statistics, each incident was grouped into the census tract where it occurred. Finally, I normalized this data by dividing the raw count by the population of each Tract.

### 3.6 Other notes

One of the more unique normalizations in this paper is the use of the square root of park distance. Despite its obscurity, this method fits theory: since park distance scales on a two dimensional plane, the number of home radius $r$ from a park is proportional to $r^2$. While this makes interpretation slightly harder, it allows us to be more accurate in our inference. See figure3 for a visual defense.

As for the primary dependant variable, log land value per square meter was chosen as I believe it approximates accurately the same latent demand for homes as home sale price. The goal is to approximate the proportion of each home's value due to environmental factors. While home sale price is excellent as a timely and precise market value, it takes into account the value of the structure, which may be independent of its location. Since structural characteristics aren't available to us, we instead use land value per meter as a indicator of the underlying desirability, and take the natural log to rectify this with by its distribution.

Finally, the use of build year may jump out to the reader, as I claim to use no structural data. Build year, in this paper, is classified into three eras: before 1935, between 1935 and 1975 and 1975 to present. Instead of being used as a structural value it is used as a proxy for the development pattern of the neighborhood, and the cost / benefit ratio of building new. For instance, land values dip in the the middle era due to the fact that they are often too new to justify tearing down or significant remodeling, but too old to fetch new-house prices.

## 4 Empirical Model

The empirical analysis in this paper follows the previous literature in using a hedonic regression model, a measure of property price as a function of various property attributes. This is generalized in the formula given by [Siriwardena et al., 2016]:

$$P = f(PC, SC, LC, EC : \beta) + u$$

Where P is the price (normally sale price, in this case assessed value), PC is property characteristics, SC is structure characteristics, LC location characteristics, EC environment characteristics and $\beta$ is a vector of coefficients. As noted in (3), this paper does not take into account structural characteristics. Instead, I rely on property characteristics, specifically lot size, to normalize prices. Since land value varies linearly in lot size 4, my model divides both sides by lot size to yield a final dependant variable of log land value per square meter. See Data(3) for more information.

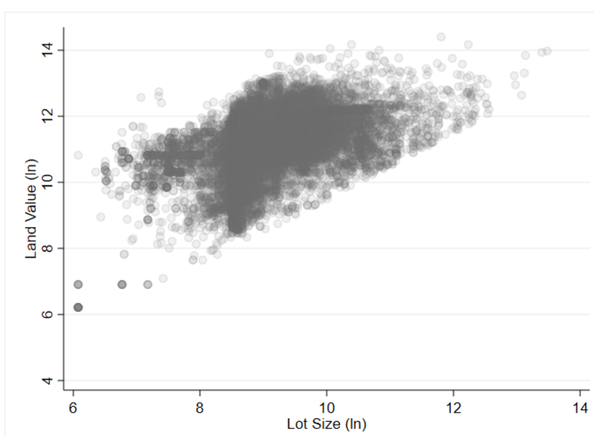


Figure 4: Land Value vs. Lot Size

The *implicit price*, $IP_i$ of any characteristic $C_i$ is
simply the derivative of price with respect to that characteristic. As we use a log value for price to match both the data and theory [Benford, 1938], each implicit price in my model is given as

$$IP_i = \frac{\partial ln(P_i)}{\partial C_i}$$

And thus are interpreted as the effective percentage increase of land value per square meter. School district and density are the primary location characteristics in my model specification, while all of the greenery indicators (tree cover, census tract park percentage, and distance from parks) are the primary environment characteristics.

This investigation specifically uses a fixed-effects approach to isolate land price variation within school districts. Using fixed effects allows us to see how home price deviates from the school district's mean based on its greenery characteristics. Mathematically, our model looks like:

$$\frac{ln(P_iS)}{m^2{}_iS} = \beta X_{iS} + \alpha_i + u_{iS}$$

Before compensating for the location characteristics, where S is an indicator for each school district. Using the de-meaned approach of fixed effects shows us how the each parcel's land value varies relative to the average for its school district. Our final model looks like this:

$$\frac{ln(P_{iS})}{m^2{}_{iS}} - \overline{\frac{ln(P_{iS})}{m^2{}_{iS}}} = \beta(X_{iS} - \overline{X_i}) + (\alpha_i - \overline{\alpha_i}) + (u_{iS} - \overline{u_i}) \Rightarrow \ddot{y}_{iS} = \ddot{X}_{iS}\beta + \ddot{u}_{iS}$$

Where $X$ is the set of environmental characteristics we are testing and $\alpha_i$ is the effect due to school district. I apply this model to various combinations of environmental characteristics and their interactions in the results section below.

# 5 Results

First, we observe the effects of each greenery metric - distance from park, percentage of parkland in census tract, and tree cover on log land value per square meter. Then, to answer our query of how each of these changes based on demographics, introduce the log of density and average age at the census tract level. Our hypothesis being that high population density or many young children would increase the value of public land. Finally, I assess the effects when controlling for the era of the homes construction to isolate for urbanist vs. car-centered development patterns.

## 5.1 Estimates for greenery values

Table 1 shows the effect of each greenery measure on the land value per meter of properties, in terms of percentage change. Due to the large $n$, all of these coefficients are significant at the .1% level. The magnitude of each coefficient is notable however: while distance from a park has a negative coefficient on land value, as expected, this effect gets *smaller* when interacted with density, and smaller still when interacted with average age. This contrasts my initial intuition, as well as [Cho et al., 2008]'s findings. Controlling for the era of the home yields an insignificantly different number.

On the other hand, tree cover % has larger coefficients associated with its impact on land prices. A 1% increase in surrounding tree cover can, before adjusting for other factors, be seen as increasing the value of the value of each square meter of land by .3%. Again, when interacted with density this effect gets smaller, but remains positive, and again the interaction with average age is the smallest of the three coefficients.

Panel C can be interpreted on a similar basis as panel B; a percentage increase in park cover in a census tract yields a 0.07% increase in home values. The sign of this change is consistent with theory and the previous literature, however because its effect on home prices is much smaller than tree cover's. Park cover's effect on land values is interesting as it is the only one which changes significantly when controlling for the era of the home. Presumably, this can be attributed to low cost, mid-century developments sharing census tracts with large boundary parks.

### 5.2 Estimates for tree cover and interactions

Distance from park's relative significance is the basis for its role as our primary independent variable in our regression. Results of these regression are shown in 3. Here we can see that once density is controlled for by itself, the interaction between tree cover and density/ average age becomes positive and much bigger than all other interaction coefficients. The progression of these results mirrors previous results of [Cho et al., 2008]. At first, controlling for era built but not density or average age, neighborhood tree cover is a significant positive predictor of land value per meter. However, once density and its interaction with tree cover is included, tree cover has a much larger but *negative* influence on latent home prices. In this second frame, a one percent increase in density is correlated with a .5% decrease in home values, but the interaction between these two negative terms is positive. A one percent increase in both density and tree cover is correlated with a 1.4% increase in land value per square meter. In summary, home buyers want the best of both worlds: very urban areas are not worth it without trees, very suburban areas are boring without people.

Note that when average age is included, for continuity, it has little effect. While its coefficients are significant at the .1% level, they are small, especially compared to log density and percent tree cover. Average age dulls the effects of other coefficients but not enough to make this author question our previous result.

### 5.3 Estimates controlling for crime

To do justice by the literature, we must attempt to reconcile the crime rate in and near parks with their value. Again, it should be noted that at the time of writing, spatial crime data was only available for the city of Minneapolis. Figure 11 shows this extent in context. The results of fixed effects regression tests interacting crime incidents with greenery statistics are shown in figure 4. Clearly, crime per capita has very negative correlation with latent home value: one more incident per person per year decreases nearby land value per meter by about 5% to 6.5%. For the most part, the rest of the results from these tests are similarly unsurprising. What is of note in this set of regressions, however, is the coefficients' lack of significance. Once density and average age are controlled for, only tree cover, average age and crime per capita have coefficients with any significance at all. This is a stark contrast from our previous large-$n$-induced results, and re-affirms this paper's result that tree cover is the best predictor of land value of the three greenery statistics studied.

# 6 Conclusion

Parks are valuable, but they're claiming a lot of credit that isn't all theirs. In this paper I examined the percentage of neighborhood tree cover and two separate indicators of park proximity and their effects on home prices. After controlling for the significant location characteristic of school district, I find a positive correlation between these metrics and latent home price. In a relatively low population density, high park density metropolitan area like the Twin Cities, tree cover is the best predictor of home prices 5. This result points to the transcendent effects of foliage on human well being as well as urban micro-climates.

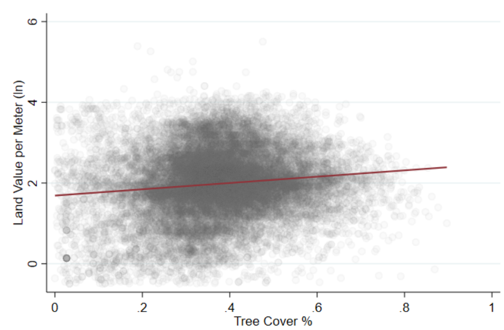


Figure 5: Parks in Hennepin and Ramsey counties

Further, unlike previous studies, I reject a threshold of decreasing returns to tree cover. While in table 3, a negative coefficient on tree cover is shown in the second panel, the more important result is the positive correlation on the interaction between density and tree cover. By interpreting these results from a Market Urbanist lens, I draw the inference that home value is jointly dependant on the amenities density provides [Rappaport, 2008] and the psychological benefits of greenery.

These results have a battery of policy implications. First, while parks are valuable, they too often are conflated with the value of the foliage within them. Cities and citizens would do well to invest more in maintaining their street trees and encouraging planting initiatives. Second, these findings refute Le Corbusier-derivative planning goals: these modernist ideals focus on the *separation* of dense space cities and green space, as well as push for the parks that are built to be stark, grassy spaces surrounding their densely-packed patrons. Instead, I suggest an integrative approach of many small buildings and many small parks.

**Percentage land value increase for each greenery unit**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *Panel A: park distance* | | | | |
| Distance from park | -0.00437*** | | | -0.00470*** |
| $\sqrt{m}$ | (0.000940) | | | (0.000941) |
| Distance from park | | -0.000564*** | | |
| × density (ln) | | (0.000112) | | |
| Distance from park | | | 0.000181*** | |
| × average age | | | (0.0000214) | |
| Control for era | - | - | - | Yes |
| $N$ | 21890 | 21850 | 21850 | 21877 |
| $R^2$ | 0.001 | 0.001 | 0.003 | 0.002 |
| *Panel B: tree cover* | | | | |
| Tree cover (%) | 0.319*** | | | 0.335*** |
| | (0.0449) | | | (0.0463) |
| Tree cover (%) | | 0.0511*** | | |
| × density (ln) | | (0.00562) | | |
| Tree Cover (%) | | | 0.0140*** | |
| × average age | | | (0.000890) | |
| Control for era | - | - | - | Yes |
| $N$ | 21890 | 21850 | 21850 | 21877 |
| $R^2$ | 0.002 | 0.004 | 0.011 | 0.004 |
| *Panel C: park percentage* | | | | |
| C.T. park cover (%) | 0.0726*** | | | 0.0849*** |
| | (0.0142) | | | (0.0143) |
| C.T. park cover (%) | | 0.00866*** | | |
| × density (ln) | | (0.00175) | | |
| C.T. park cover (%) | | | 0.00297*** | |
| × average age | | | (0.000327) | |
| Control for era | - | - | - | Yes |
| $N$ | 21888 | 21848 | 21848 | 21875 |
| $R^2$ | 0.001 | 0.001 | 0.004 | 0.003 |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1: Effects of each greenery statistic

**Key variable summaries within school district**

| Variable | | Mean | Std. Dev. | Min | Max | Observations | |
|---|---|---|---|---|---|---|---|
| Land value | overall | 1.982106 | .8250138 | -.49923 | 5.50299 | N = | 21890 |
| (ln, per $m^2$) | between | | .7590099 | -.29706 | 2.974332 | n = | 27 |
| | within | | .7609936 | -1.478739 | 5.654963 | T-bar = | 810.741 |
| | | | | | | | |
| Tree cover | overall | .3707125 | .1329608 | 0 | .8966666 | N = | 22862 |
| % | between | | .0859441 | .1834794 | .5283242 | n = | 27 |
| | within | | .1176607 | -.093879 | .9154884 | T-bar = | 846.741 |
| | | | | | | | |
| Park area | overall | .4227204 | .3905544 | 0 | 2.67952 | N = | 22860 |
| % of C.T. | between | | .1693946 | .1145288 | .6999918 | n = | 27 |
| | within | | .3692484 | -.1959205 | 2.728993 | T-bar = | 846.667 |
| | | | | | | | |
| Park distance | overall | 15.29209 | 5.603212 | 0 | 31.55975 | N = | 22862 |
| square root | between | | 3.673976 | 12.97298 | 31.55947 | n = | 27 |
| | within | | 5.498342 | -.1866554 | 32.80225 | T-bar = | 846.741 |
| | | | | | | | |
| Year built | overall | 1959.599 | 31.06022 | 1850 | 2019 | N = | 22783 |
| | between | | 15.79527 | 1929.903 | 1994.503 | n = | 27 |
| | within | | 22.5732 | 1838.472 | 2047.578 | T-bar = | 843.815 |

Table 2: Within/between S.D.

| Percentage land value increase for tree cover | | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| | lnLVperMet | lnLVperMet | lnLVperMet |
| Tree cover (%) | 0.307*** | -10.52*** | -8.730*** |
| | (0.0465) | (0.372) | (0.522) |
| C.T. park cover (%) | 0.0666*** | 0.0482*** | 0.0123 |
| | (0.0146) | (0.0145) | (0.0143) |
| Park distance | -0.00359*** | -0.00317*** | -0.00257** |
| ($\sqrt{m}$) | (0.000956) | (0.000938) | (0.000920) |
| Control for era built | Yes | Yes | Yes |
| Density | | -0.518*** | -0.412*** |
| (ln) | | (0.0185) | (0.0195) |
| Tree cover (%) | | 1.368*** | 1.283*** |
| × density (ln) | | (0.0467) | (0.0498) |
| Average age | | | 0.0339*** |
| | | | (0.00216) |
| Tree cover (%) | | | -0.0316*** |
| average age | | | (0.00535) |
| $N$ | 21875 | 21835 | 21835 |
| $R^2$ | 0.006 | 0.044 | 0.081 |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Effects of tree cover and associate controls on land price

**Percentage land value increase, accounting for crime levels**

| | (1) | (2) | (3) |
|---|---|---|---|
| | lnLVperMet | lnLVperMet | lnLVperMet |
| Distance from park | -0.000275 | -0.0750* | -0.0408 |
| | (0.00325) | (0.0325) | (0.0369) |
| Crime per capita | -5.618*** | -5.332*** | -4.752*** |
| | (0.790) | (0.791) | (0.753) |
| Distance from park | -0.0515 | -0.0641 | -0.0357 |
| × crime per capita | (0.0460) | (0.0461) | (0.0440) |
| C.T. park cover (%) | 0.198*** | 0.129** | -0.0165 |
| | (0.0397) | (0.0410) | (0.0392) |
| Tree cover (%) | 3.707*** | 3.532*** | 2.992*** |
| | (0.150) | (0.152) | (0.146) |
| Density (ln) | | -0.280*** | -0.0653 |
| | | (0.0644) | (0.0641) |
| Distance from park | | 0.00853* | 0.00460 |
| × density (ln) | | (0.00371) | (0.00366) |
| Average age | | | 0.0436*** |
| | | | (0.00499) |
| Distance from park | | | -0.0000416 |
| × average age | | | (0.000293) |
| $N$ | 4750 | 4742 | 4742 |
| $R^2$ | 0.253 | 0.259 | 0.339 |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Effects of crime on park desirability

# References


[202, ] 2020 parkscore index — the trust for public land.

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# Appendix A

## Links to data sources

- Github repository used for compiling and cleaning
- Hennepin County GIS portal
- Ramsey County GIS portal
- Minneapolis Crime Data

# Appendix B

## Getting a lay of the land

Urban economics is best done visually. To that end, this appendix includes maps of the homes studied in this paper, color coded according to various attributes. Enjoy.

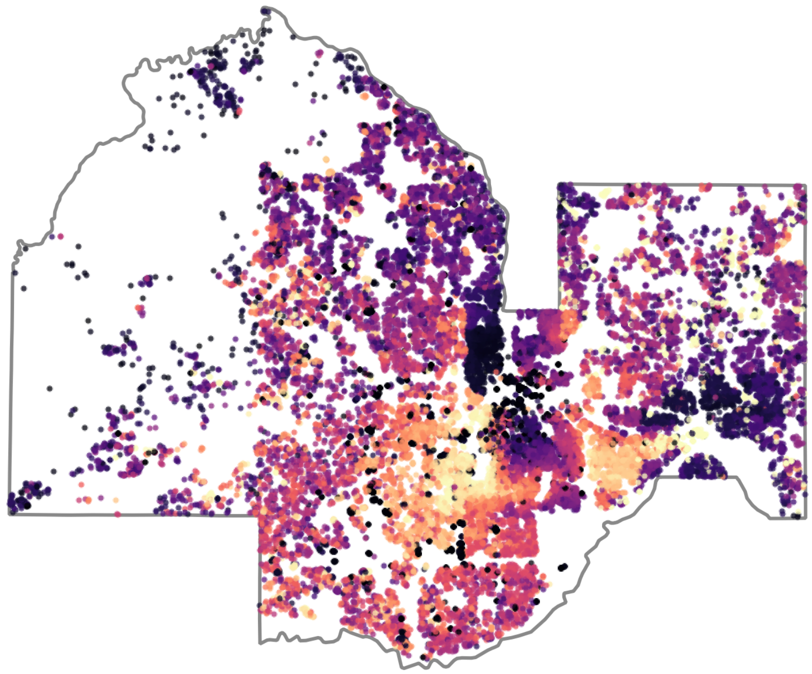

Figure 6: Land value per meter

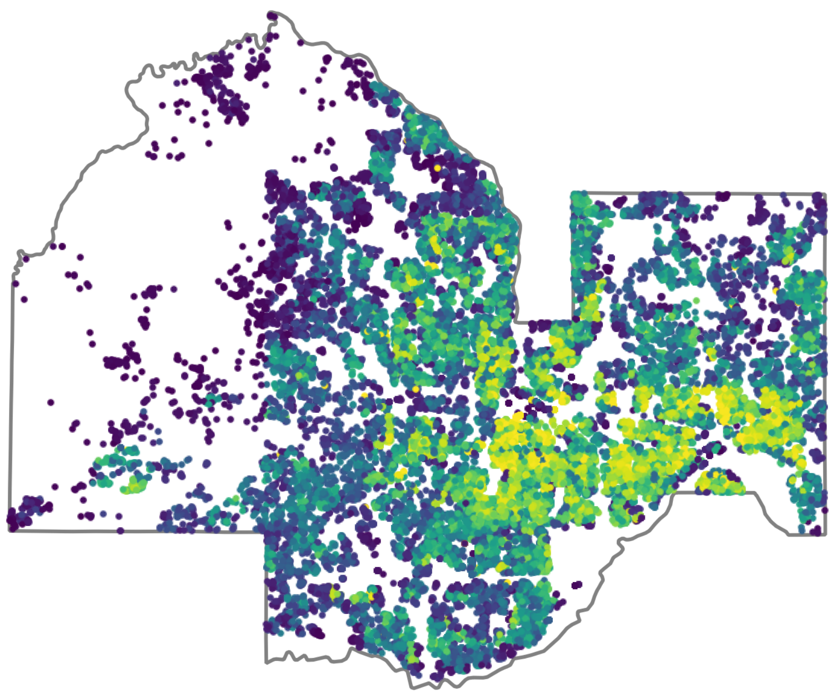

Figure 7: Tree cover × density

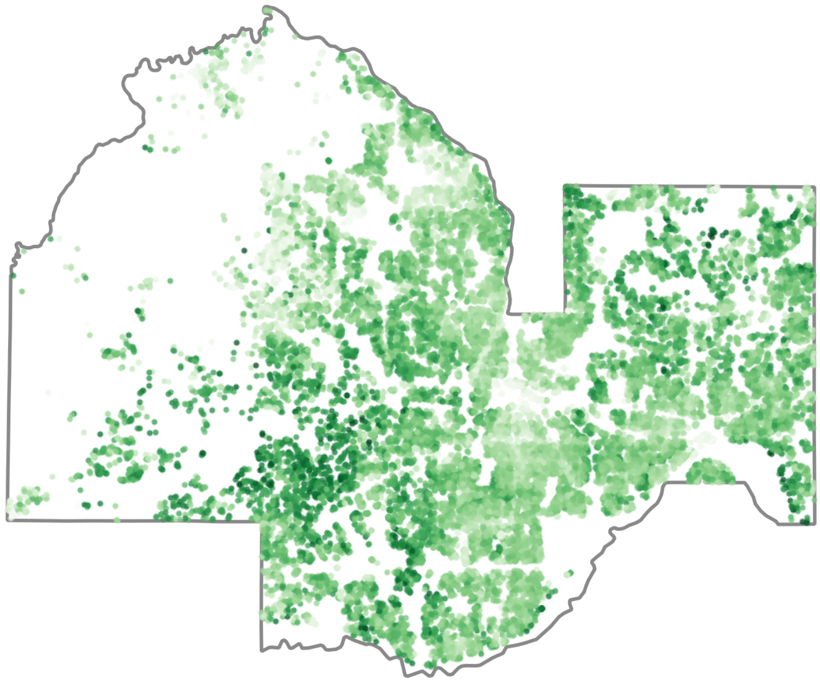

Figure 8: Tree cover %

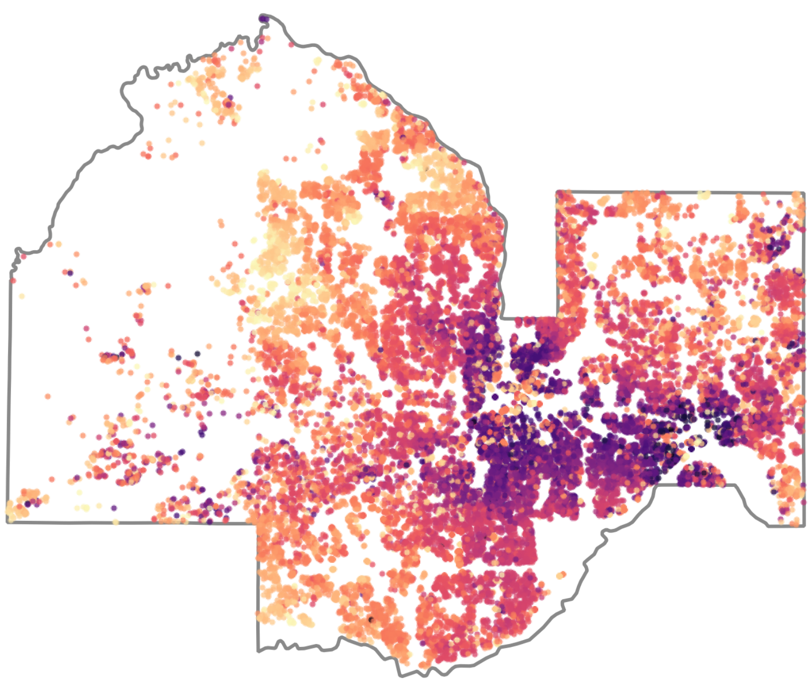

Figure 9: Year built

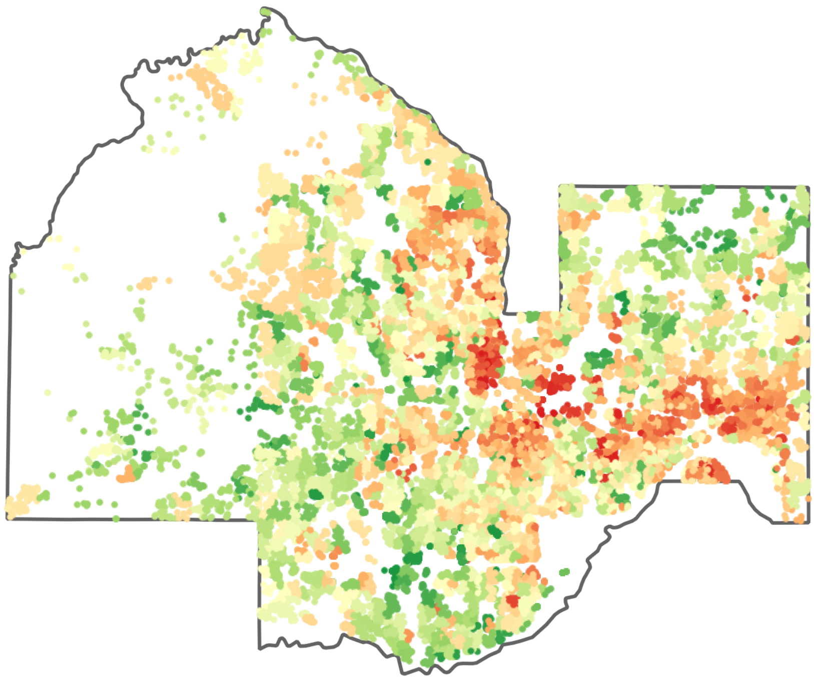

Figure 10: Average age (red as youngest)

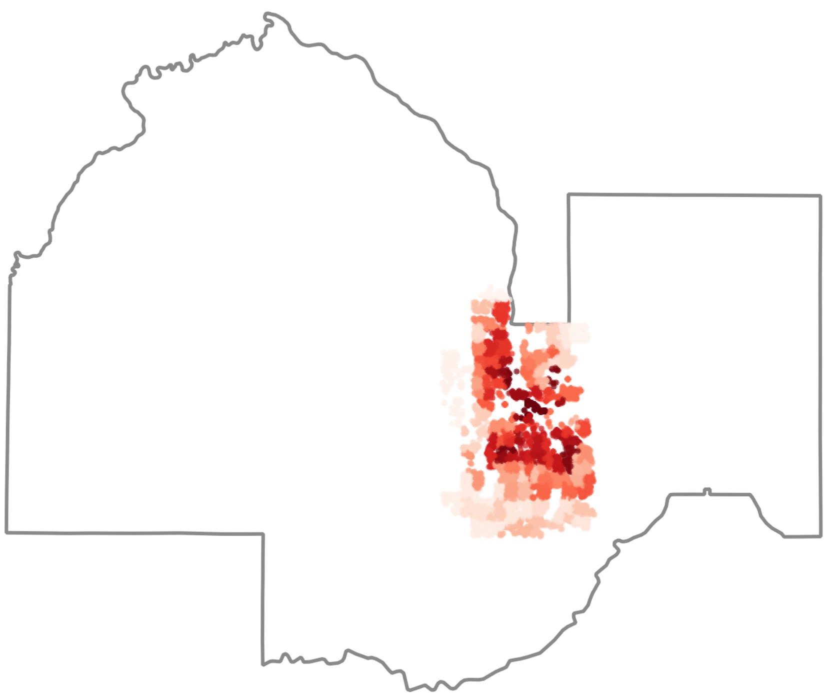

Figure 11: Crime per capita