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Urban green space distribution in Oklahoma City: A spatial analysis of bio-physical and socio-economic characteristics

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Urban green space distribution in Oklahoma City: A spatial analysis of bio-physical and socio-economic characteristics

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BY THE COMMITTEE CONSISTING OF

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Abstract

Oklahoma City, Oklahoma (OKC) is a fast-growing city undergoing urbanization. Rapid urbanization can lead to neighborhood construction where impervious surfaces are prioritized over urban green space (UGS). Urban green space can be defined as green vegetation on housing parcels not just parks and recreational areas. Housing properties are funded through banks and socio-economic status. Creating an efficient UGS without proper funding can make UGS unsustainable. Redline districts are districts that are financially hazardous to fund. National Agriculture Imagery Program (NAIP) offers high spatial resolution imagery (1m) that is used to create land cover classification map consisting of trees and grass in Google Earth Engine (GEE). Comparing percentage of trees (dependent) to socio-economic status variables and bio-physical variables told us that the spatial autocorrelation with a financially hazardous neighborhood exhibited higher tree percentages and higher Normalized Difference Vegetation Index (NDVI) in comparison to neighborhoods declared desirable. Financially hazardous neighborhoods do show a higher percentage of vacant lots which leads to overgrown vegetation. Overgrown vegetation will help the remote sensing camera detect a pure vegetation pixel compared to a sparce environment where the camera may detect the soil instead of vegetation. Much more research is still needed to bring down the number of variables that have an effect on vegetation growth.

Chapter 1: Introduction

1.1 Urban Green Spaces

Rapid urbanization has led to higher densities of impervious surface land cover in cities across the United States (Bounoua et al., 2018). One way to respond to the increase of impervious surface is by aiming for compact urban development. Compact cities respond to accommodate the population growth of metropolitan areas by maximizing land use for new houses and infrastructure, often resulting in high-density housing and infill development (Obiakor et al., 2012). The latter can result in reduced inner-city vegetation which has a detrimental effect on air quality and extensive precipitation surface runoff (Baldauf et al., 2008; Sanders, 1986).

Given the rapid urbanization in metropolitan areas in the U.S. over the past decades and the a resulting reduction of both urban and rural vegetation to accommodate a growing population (Bounoua et al., 2018; Colding et al., 2020), cities need to emphasize urban green spaces (UGS) as a way to balance the negative impacts of ongoing urbanization processes. Urban green space can be defined as “urban land use classified by any type of vegetation” (EPA, 2022). Public spaces such as parks or recreational areas in an urban setting are excellent examples of UGS that can create opportunities for interactions among residents and ways to foster a sense of community (Jennings and Bamkole, 2019). Private urban green spaces such as yards of residential housing can help with the general aesthetic of neighborhoods and lead to higher property values (Anderson and Cordell, 1988).

1.2 Urban Green Spaces Effects on Microclimate

Urbanization – and the corresponding change in land cover - has led to increased temperatures in cities, also known as an urban heat islands (UHI; Grimmond, 2007). Impervious surfaces like concrete, asphalt and roofing tile possess higher heat capacities in comparison to areas covered by vegetation (Sekertekin and Zadbagher, 2021). Impervious surfaces retain heat from the incident solar radiation during the day and slowly re-emit longwave radiation throughout the afternoon and evening. Vegetation, soil and water act as a natural cooling mechanism to convert water to water vapor (Wu and Zhang, 2019). This process of evapotranspiration takes in a large amount of energy from the nearby environment and cools down the surrounding microclimate. Hence, UGS can reduce the ambient and surface temperature of the microclimate of neighborhoods or cities (Clinton and Gong, 2013).

1.3 Urban Green Spaces Effects on Mental and Physical Health

Urban green spaces benefit humans' physical and mental health. For example, using UGS for recreation provides a break to the overstimulating environment of the urban landscape by alleviating stress, anxiety or other mood disorders (Tsai et al., 2018). Hunter et al. (2015) found an increase in physical activities of middle-aged adults in the presence of UGS, in part due to the aesthetically pleasing effect vegetation can have on a person. Moreover, aesthetically pleasing neighborhoods encourage getting outside and being physically active (Tzoulas et al., 2007). Urban green spaces also benefit the respiratory health of humans by purifying air pollution (Villeneuve et al., 2012).

Donovan et al. (2011) found that pregnant mothers can be positively stimulated by "feel good" factors of UGS and Hipp et al. (2016) found that well-kept campus UGS was associated with a calmer attitude in students compared to students in un-kept UGS.

1.4 Impact of Urban Green Spaces on Community Revitalization

Urban green spaces improve neighborhood aesthetics by introducing a green environment, which provides communities with a place to come together for recreational activities or social gatherings (Jennings and Bamkole, 2019). A united community will help increase a sense of togetherness along with pushing for increased housing prices when selling property in the neighborhood (Clarke and Freedman, 2019). Increased property value is linked to UGS by having a pleasant aesthetic, community unity and environmental benefits (Bolitzer and Netusil, 2000). As a result, municipalities have used UGS to revitalize lower-income neighborhoods (Anguelovski et al., 2018). Oklahoma city has revitalized a lower-income neighborhood through the MAPS project in the Oklahoma City metropolitan area that resulted in the implementation of Scissortail (OKC, 2009). While these revitalization efforts can improve the livability in neighborhoods, they also have the potential to create gentrification dynamics, e.g. via increased property values and the influx of a more affluent population ultimately leading to a displacement of the original occupants of neighborhoods (Cole et al., 2019).

1.5 Socioeconomic Factors and Urban Green Spaces

In the U.S., UGS are typically implemented through cooperation between neighborhoods and municipalities. Socio-economic factors (e.g., population numbers, household income, whether a house is occupied or vacant (Dawson et al., 2018; Pearsall and Christman, 2012) are frequently use to represent varying priorities, values, and opportunities among the urban populations. Neighborhoods closer to downtown areas typically meet limitations to establishing a greener landscape as population density near downtown areas tends to be much higher as compared to suburban neighborhoods. However, yards of vacant houses may have overgrown vegetation resulting in visibly greener environment (Pearsall and Christman, 2012). Residential and well as public green spaces require constant maintenance such as lawn and tree maintenance, and irrigation, to ensure vegetation remains healthy throughout the year and to keep lots up to code (Mukherjee and Takara, 2018). This requires money to help facilitate personal and neighborhood projects. Household income that is disposable for household maintenance is only achievable through high household incomes or through loans (Pearsall and Christman, 2012). Loans coming from banks require proof that you can return their investment. Households that are from the lower class may not have the proof that they can pay back the loan or the bank will not allow a loan for certain neighborhoods.

1.5.1 Historical Maps of Redlining – Shaping Urban Landscapes

Redlining is a practice used by federal, local, and private organizations in the 1930s to discriminate against people of color and suppress minorities and citizens in low-income neighborhood from obtaining goods and services through the use of racial mortgage appraisal practices established in the 1930s (Nardone et al., 2021). The federal government created the Home Owners' Loan Corporation (HOLC) as part of rescue effort to help home owners from defaulting on their home loans (Hillier, 2003). Mortgage companies used these boundaries to denote neighborhoods of "financial risk," withholding those neighborhoods from accessing home loans for revitalizations or renovations. Redline practices are known to exacerbate segregation of neighborhoods by promoting black ghettoization and from developing heterogeneous neighborhoods (Faber, 2020).

1.6 Case Study – Urban Green Spaces in Oklahoma City

Research on UGS and their correlation to socio-economic drivers has been conducted around the world in different cities including American cities Chicago, Detroit, Philadelphia, and Porto, Portugal, and Beijing, China (Dawson et al., 2018; de Vries et al., 2020; Hoffimann et al., 2017; Liu et al., 2014). There are two major clusters of studies on green spaces in urban areas. A large body of literature exists that focuses on public UGS, such as parks, and their relevance in the environmental justice context, evaluating the association among greenness and socio-economic characteristics (Balram and Dragićević, 2005; Dawson et al., 2018; Pearsall and Christman, 2012). Research in the field of remote sensing frequently analyses greenness indices across urban areas (including public as well as residential vegetated areas), for example to understand the impact of vegetation on surface temperature or urban heat islands (Gomez-Martinez et al., 2021; Mohajerani et al., 2017; Onishi et al., 2010; Zipper et al., 2016). However, fewer studies exist to combine the evaluation of socio-economic factors focusing on residential green spaces, such as yards, and their association to socio-economic characteristics.

The city of Oklahoma City (OKC) has not received much research attention in general and is especially understudied regarding the analysis of the association among greenness as a proxy for urban greenspaces and socio-economic characteristic. Moreover, to my knowledge, no study exists that evaluates the association among greenness and redlining in OKC. This research focuses on Oklahoma City residential areas, examining the correlation between greenness values and socio-economic characteristics. As such, this research aims to close the research gap identified above and start growing environmental justice related research with a focus on the understudied OKC metropolitan area.

1.7 Research Questions, Hypothesis, and Objectives

The objective of this study is to examine the spatial distribution of UGS in the OKC spatial extent and analyze the spatial distribution of greenness values at the parcel spatial level. Examination of spatial distribution of greenness values at the parcel level will help researchers, homeowners and urban development officials find the socio-economic and bio-physical drivers that correlate to higher greenness values on properties and UGS. Strong correlation between median income and urban greenness is observed in other studies from urban areas such as Chicago, Detroit, and Philadelphia (Dawson et al., 2018; de Vries et al., 2020; Hoffimann et al., 2017). I hypothesize that higher median income neighborhoods will show a stronger correlation to high greenness values. The research questions the study examines are:

1) Do we find the same general patterns in OKC as in other cities across the US?
2) What is the relationship between greenness and socio-economic factors?
3) Is there a difference in the relationship between greenness and socioeconomic factors inside formerly redlined areas of OKC as compared to non-redlined areas?

In section 2, I provide an overview of the literature relevant to interpret and contextualize my findings. Section 3 introduces the methods applied in this study along with the statistical analysis applied to the methods. Section 4 presents the results of the study with maps and tables. Section 5 I discuss the results in extensive detail and contextualize it to my research questions. Section 6 wraps the study up with a brief description of the results, study limitations and future study adaptations.

Chapter 2: Background

2.1 Green Spaces in Urban Areas

There is a general trend that can be observed between population density and proximity to city centers; the closer a neighborhood is to a city center, the smaller amount of space available to use for individual lots (Delmelle et al., 2014) , whereas suburbs tend to have larger lots in comparison. Urbanization has led to both urban sprawl and urban densification and infill in city centers (e.g., Meentemeyer et al. 2013). Vertical growth in downtown regions will increase the population density while suburban regions growing in a horizontal direction will lead to smaller population density.

A common way to develop UGS in downtown regions is to create what is known as a green roof design. This green roof design is meant to minimize the urban heat island effect by preventing concrete roofs from absorbing too much incident radiation (Asadi et al., 2020). Incident radiation is the incoming shortwave radiation produced from the sun. Incident radiation absorbed by concrete will be held on to longer through specific heat of the concrete. Higher specific heats will hold onto incident radiation longer throughout the night causing an increased ambient temperature in the urban landscape. Green roof designs have vegetation on the roof that will absorb the incident radiation but will not hold onto that energy as long throughout the night. Energy reemitted in the nighttime will result in cooler temperatures in the morning. Cooler temperatures in the morning will result in the sun not being able to heat up the soil and vegetation to even higher temperatures throughout the next day.

Suburban population density is typically much lower due to the horizontal growth of neighborhoods (Guo and Zhang, 2021). Large parks and recreational areas are more prevalent in suburban regions due to the lower population density. The number of UGS in suburban regions is much higher compared to UGS in downtown regions due to the access to more land. Properties in suburban regions has the availability to create vegetated landscapes on their own property whereas downtown regions do not have the luxury.

Measuring greenness is conducted through remote sensing methods. Remote sensing platforms like the United States Geological Survey (USGS) Landsat program, National Agriculture Imagery Program (NAIP), or European Space Agency (ESA) Sentinel program give snapshots of the land surface in the form of pictures. The images captured will provide a spectral analysis of what is happening at the point. Greenness of the vegetation can be calculated based on different mathematical combinations of spectral band measurements from remote sensing platforms (Xue and Su, 2017). Common spectral vegetation indices are Normalized Difference Vegetation Index (NDVI), Near-Infrared vegetation (NIRv), and Normalized Difference Water Index (NDWI) (Xue and Su, 2017). The bands present in most common spectral vegetation indices are red and near-infrared which tie close to vegetation cell-structure (Peñuelas and Filella, 1998).

2.2 Greenness and relationship to socioeconomic factors

Greenness in neighborhoods do not come naturally as there are Homeowners associations (HOA) or Neighborhood associations (NAS). Homeowner associations and NAS have guidelines on lawn heights and tree canopies exceeding property lines (Morera et al., 2020; Sisser et al., 2016; Turner and Stiller, 2020). Lawn height and making sure trees do not cross property lines comes at a price (Kuo et al., 2018). Socioeconomic factors like median household incomes is highly correlated to greenness in neighborhoods. Lower income households that do not abide by HOA and NAS guidelines are more likely to make the choice of not having grass lawns or trees to save income. Keeping lawns healthy requires extensive amounts of water and may not be as effective as shading from tree canopies (Wang et al., 2016). Higher income households have the opportunity to water their lawns on a regular basis due to availability to disposable income. Lower income households will not have the excess money to allocate to irrigation for lawncare.

Houses that were built decades earlier have the time to produce mature trees and result in higher NDVI values. Families with more children tend to plant or move to neighborhoods that contain higher percentages of tree canopies (Lowrie et al, 2012). Lifestyle behaviors such as households containing families have a strong statistically significant association but weak positive correlation with greenness on properties (Orban et al., 2017). Families tend to promote physical activity instead high stimulus activity like indoor entertainment technology (television, social media, video games, etc.) (Saelens et al., 2003). Urban green spaces can reduce stress and promote mental health by reduced urban noises like traffic. Downtown cities have a higher population density and lower greenness values in comparison to houses in the suburbs. The lower greenness values in downtown regions are correlated to an increase in impervious surfaces (Onishi et al., 2010). Families that want to move out to the suburban regions want larger properties with higher percentage of grass and trees to impervious surfaces.

2.3 Tree and grass ecology

Trees can have a significant impact on the quality of life by providing natural shade for residents and vegetation, reducing the ground surface temperature on the property, and purifying the air. Trees contain a higher leaf area index due to the multiple layers of leaf development in the canopy. The higher the leaf area index the more significant shading available for the property. High leaf area index will result in higher NDVI values due to the sensor picking up more vegetation area (Johnson, 2003). Trees improve air quality by absorbing air pollutants through their stomata and depositing the resultant pollutant onto the leaves and branches (Vos et al., 2013). Properties that possess high percentage of concrete create large amounts of storm runoff due to lack of soil absorbing water. Cities have neglected maintenance on storm drainage systems, and this has caused neighborhoods to flood during higher precipitation storms. Trees are useful for preventing large storm runoffs by absorbing water through transpiration and stemflow (Gotsch et al., 2018). Water that would normally flow over the concrete or bare soil into the storm drainage systems, are instead reused for vegetation growth.

Urban grasses (lawns) are characterized by being constantly manicured and being uniform throughout a neighborhood. This differs from natural grasslands where natural grasslands have tall vegetation. Lawns are aesthetically pleasing to the community when they are manicured to low grass heights. Manicured lawns can reduce the vegetation structure and composition by removing the ability for grasses to flower. Plant diversity is reduced with manicured lawns through the lack of pollination and an increase in pest species is seen (Watson and Lovelock, 1983). Manicured lawns are only useful for aesthetic reasons in the neighborhood. Keeping lawns well-manicured also requires an abundance of water to make sure vegetation stays healthy. Dry regions like neighborhoods in California that are prone to droughts will have to receive more irrigation to ensure lawn vegetation stays healthy throughout the year.

Trees have a more significant impact on air quality through shading and lack of maintenance required compared to lawns (Norton et al., 2015). Lawns absorb rain runoff preventing large discharge into the urban storm drains. Rain runoff that cannot be absorbed through roots or leaves have the availability to be absorbed through the soil. Soil absorption of rainwater will be able to increase the natural water table in the environment. Increasing the water table has significant benefits for natural irrigation of vegetation in the environment instead of relying on water companies. Environments with more availability to water will show a more consistent diurnal temperature fluxuation due to the specific heats of water and vegetation (Wang et al., 2016). Neighborhoods containing more concrete and dry environments will have larger temperature swings throughout the day and night (Onishi et al., 2010).

Environments control what type of vegetation that can integrate into the ecological balance of the geography. Ecoregions are geographical regions of ecosystems that share similar regional ecological patterns (Omernik, 1987). Similar biotic and abiotic species will dominate an ecoregion, creating a somewhat homogeneous environment. Ecoregions like the Cross-Timbers show abiotic similarities like post oak and blackjack oak with sandy, coarse soils while ecoregions like the Central Great Plains is dominated by grasslands (Omernik, 2004).

Lawns can thrive depending on multiple environmental and ecological variables. Vegetation can be classified as C_3 or C_4 plants. The terms C_3 or C_4 denote the type of carbon dioxide fixation pathways used during photosynthesis. C_3 plants produce a 3-carbon molecule while C_4 plants produce a 4-carbon molecule (NSW, 2022). Every species possess the primitive C_3 pathway, but some grass species have evolved to use the C_4 photosynthetic pathway. Photosynthetic pathways are import to urban lawns due to the environmental and ecological requirements for healthy growth. C_3 grasses have been shown to be more abundant in shaded regions while C_4 grasses produce more biomass in well-lit environments (NSW, 2022).

2.4 Trees and socioeconomic factors

Tree patterns are often a result of municipal policy like HOA and NAS along with socioeconomic characteristics of parcels (Chalker-Scott, 2015). Municipal policies are derived from socioeconomic trends like the housing market or could come from biophysical variables like invasive tree species. Invasive tree species can be damaging to the environment by decreasing ecosystem resilience (Dyderski and Jagodziński, 2020). Municipal policies will enforce rules on what type of tree species are available for planting on the property or the neighborhood. Capita mean annual income in neighborhoods can persuade HOA and NAS to produce municipal policies for aesthetics alone with no consideration of the environmental impact invasive tree species can have (Zhai et al., 2018).

Older neighborhoods have matured trees while newly built neighborhoods will tend to have juvenile tree species. Transporting matured trees is an expensive process in comparison to planting juvenile tree species. Higher income communities have the financial resources to be able to participate in ecological programs to preserve and increase tree cover. Reforestation projects can require a substantial amount of money to implement. Homeowner associations and NAS need to plan that the neighborhood will 1) appreciate it enough for the HOA and NAS to get their money's worth and 2) neighborhoods will be able to properly take care of the vegetation (Koeser et al., 2014). Reforestation projects can lead to spatial clustering of tree distribution throughout a city. Lower income population neighborhoods can be at a disadvantage for reforestation projects to redline neighborhoods as cities tend to fund forestation projects for high income neighborhoods (Flocks et al., 2011).

2.5 Oklahoma City studies of greenness

2.5.1 Oklahoma City water consumption with population growth

Oklahoma City is the largest urban area in Oklahoma, with a 17% increase in population which proposes potential water consumption from other water sources like the Kiamichi watershed (Burch et al., 2020; Ellis and Mathews, 2019). Oklahoma City water use comes from outside sources like surrounding reservoirs and the Kiamichi watershed in the southwest. Population growth of cities result in more houses being built with green spaces added into the properties. Keeping greenness within a property throughout the year requires a tremendous amount of water consumption. Kharel et al (2018) used the ENVISION model to analyze the relationships among climate change, population growth, urban development, vegetation greenness, and residential water use for irrigation in the OKC metropolitan. Testing different population growth scenarios, Kharel et al (2018) showed that tree cover plays a larger role in urban greenness. Water consumption did not have that high of an effect on vegetation greenness but related to mean maximum temperature, building age, land value.

2.5.2 Oklahoma City spatial distribution of tree canopies

Urbanization in OKC has created an increase in population density by the destruction of forests and grasslands in favor of impermeable surfaces (Ellis and Mathews, 2019). Urban green spaces can provide significant results for physical activity as well as providing a natural air purification system, a more moderate climate, decrease urban noises (Irvine et al., 2010; Nowak & Dwyer, 2007; Wu, 2008). Ellis et al. (2018) uses lidar-derived digital terrain models (DTMs), digital surface models (DSMs), and National Agriculture Imagery Program (NAIP) to examine spatial distribution and change of tree canopies in Oklahoma City between 2006 – 2013. The image classification method Ellis et al. (2018) used was object-based image analysis (OBIA) which removes the heterogeneity of image classification. Ellis et al. (2018) showed that 9.69 km^2 of tree canopy coverage which accounts for a 2% total loss in greenness.

2.5.3 Oklahoma City urban heat island effect

Urbanization can lead to natural spaces being converted to impervious surfaces which have a positive correlation to urban heat islands (UHI). Impervious surfaces absorb and retain solar radiation causing a rise in ambient temperature while vegetation will absorb solar radiation and create evapotranspiration reducing the ambient temperature of the microclimate. Impervious surface spatial clusters can provide insight into ratio of impervious surface to urban green spaces. Cui et al. (2018) examined multiple cities (rural and urban) in Oklahoma using the Oklahoma Mesonet, remotely sensed land surface temperature, and enhanced vegetation index to look at the UHI from 2000 - 2014. Looking at rural cities will show how the difference in ratio of impervious surface to urban green spaces can contribute to the UHI. Rural cities will have less impervious surface in comparison to cities like Oklahoma City and Tulsa. Oklahoma City showed to have the highest UHI intensity with a value of 0.58°C and an increase of impervious surface by 3.19%.

2.5.4 Oklahoma City environmental and community benefits from greenness

Spatial distribution of UGS is highly dependent on socioeconomics of the space. Neighborhoods are categorized by undesirable to desirable and funding for anything based on the classification of the neighborhood is dependent on how desirable the neighborhood is. The expense of reforestation or refurbishing neighborhoods depends on the amount of risk involved with funding reforestation or refurbishing projects. Lower income neighborhoods tend to have smaller UGS that are run down while higher income neighborhoods have access to larger well-kept UGS. Delano (2015) showed in Oklahoma City that census block groups categorized with higher percentage of minority and lower income neighborhoods are in closer proximity to UGS but are smaller than UGS in higher income neighborhoods

Chapter 3: Materials and Methods

3.1 Study Area

The study area covers Oklahoma City (OKC), which is the capital of and located in the central part of the state of Oklahoma (Figure 1). Oklahoma City has a total area of 1,608 km^2 making it the largest metropolitan area in the state. Data from the U.S. Census reports a population of 620,553 people with a median age of 34.4 years for the year 2014 (U.S. Census Bureau, 2014). The economic sector in OKC consists mainly of livestock and petroleum markets; Tinker Air Force Base, one of Oklahoma's largest employers, is in the southwestern part of the OKC metropolitan area.

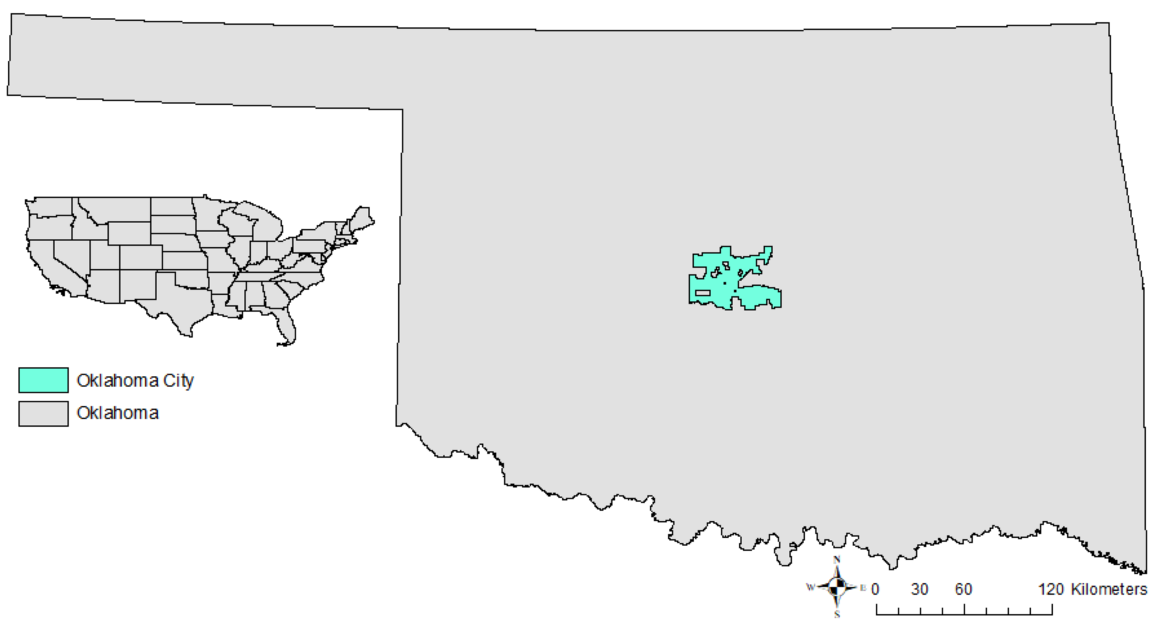


Figure 1: The study area covers the Oklahoma City spatial extent located centrally in the state of Oklahoma.

3.2 Vector Data

3.2.1 Counties

The full spatial extent of the OKC metropolitan area includes the four counties: Canadian, Cleveland, Oklahoma, and Pottawatomie. However, 99.996% of the parcels fall into Canadian, Cleveland, and Oklahoma counties (196,859 parcels), with only 0.0041% in Pottawatomie County (8 parcels) (Figure 2). Hence, I excluded the latter from the analysis to assure statistical significance to use in the analysis. The county dataset is downloaded from the US Census Bureau.

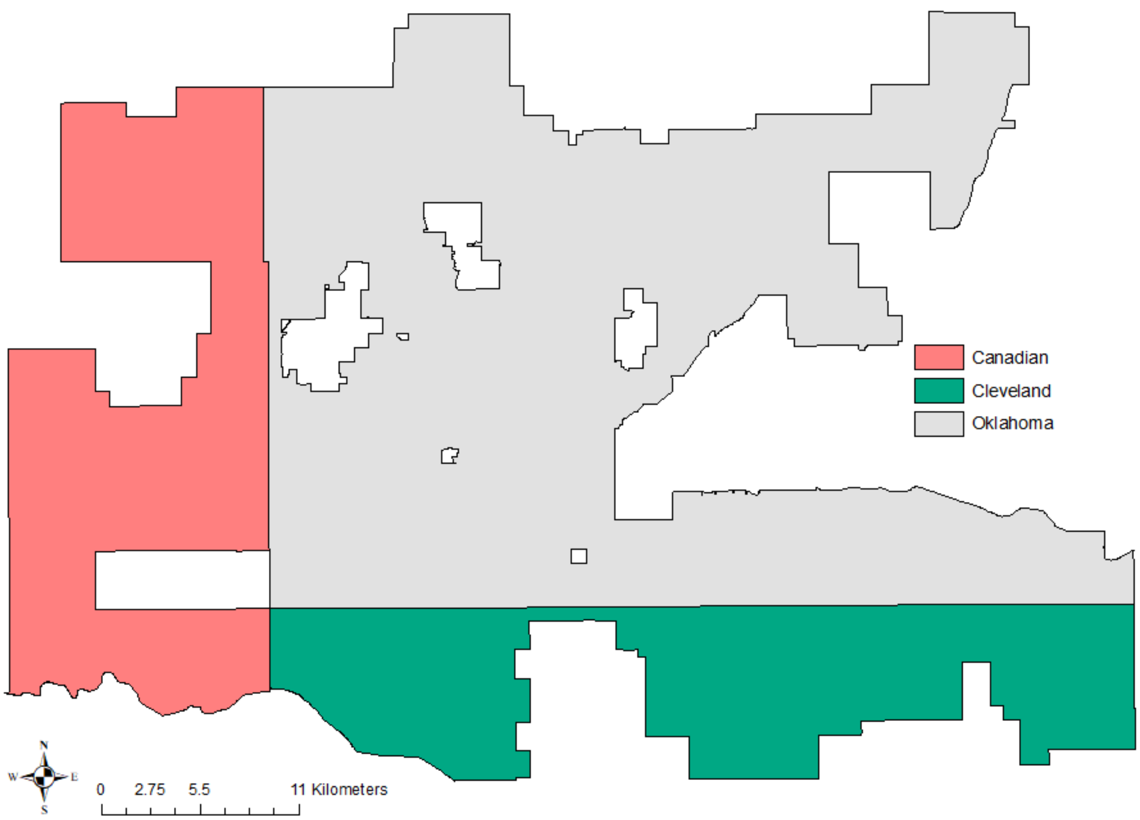


Figure 2: Counties within the Oklahoma City spatial extent.

3.2.2 United States Census Tracts

Census tracts have a total population between 1,200 and 8,000 people and are designed to be homogeneous with respect to socio-economic variables like living conditions, economic status, and population (U.S. Census Bureau, 2022) . Since the census tracts' boundaries are defined via population numbers, larger census tracts have a lower population density in comparison to smaller census tracts. As new housing developments are established, population density in the tracks increases. Every ten years the census tracts are updated because of socio-economic changes in the census tracts. Census tracts have unique identifiers (four-digit number) and sub-tracts share the four-digit identifiers with two more suffix unique identifiers. The OKC spatial extent for this study contains 253 census tracts (Figure 3).

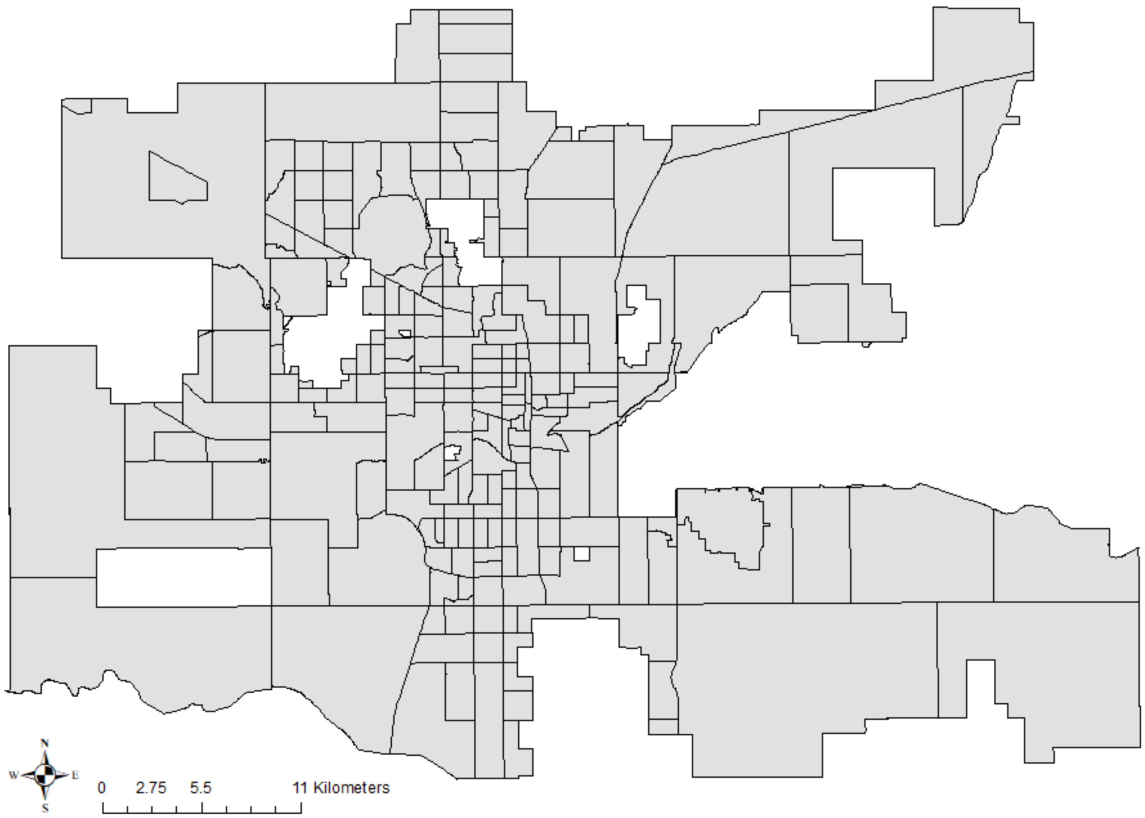


Figure 3: U.S. Census Tracts for the year 2014 of the city of Oklahoma City, Oklahoma. For spatial reference in the state of Oklahoma, please refer to Figure 1.

This study uses census tract data for the year 2014, to be in line with the parcel dataset (see below). Since the year 2014 falls between the 2010 and 2020 census surveys, I derived the socio-economic information from the American Community Survey (ACS), which provides yearly estimates of data on topics that the decadal census does not cover (e.g., education or employment) (ACS, 2017). I derived information on the census tract level (Table 3) for the year 2014 from the ACS.

3.2.3 Environmental Protection Agency Ecoregions

The climate in central Oklahoma is meteorologically influenced by the moisture from the Gulf of Mexico and dry, cold air from the jet stream in the northwest. Moist air from the south and dry air from the northwest tend to produce severe weather in the Spring and Fall (Wang et al., 2020). The moisture from the Gulf of Mexico creates natural ecological boundaries of the ecoregions that make up the OKC metropolitan area. Ecoregions are areas that have very similar biotic and abiotic species characteristic traits (Omernik, 1995). Some vegetation only grows in one type of ecoregion and cannot survive in other ecoregions, unless there are interspecific connections that benefit the relationship (Morales & Aizen, 2010).

The eastern part of the study area receives more precipitation as compared to the west due to the moisture from the Gulf of Mexico resulting in a higher density of trees on the eastern region of OKC. The Environmental Protection Agency (EPA) level three ecoregions dataset was chosen for this study due to the representation of vegetation and precipitation (EPA, 2021). Since level one and two are too broad of a spatial extent of each ecoregion (Omernik & Griffith, 2014), for this study I chose to use EPA level three ecoregion data. The study area covers two ecoregions (Central Great Plains and Cross Timbers) at the EPA level three within the OKC spatial extent (Figure 4). The OKC spatial extent is split between a transitional zone in the Great Plains. Transitional zones share similar biodiversity, especially at the dividing line of ecoregions known as ecotones. Ecotones tend to show similarities in biodiversity (Senft, 2009). The Central Great Plains, covering the western part of the study area, is a semi-arid prairie ecoregion with less dense tree canopy and higher density of grasslands. The Cross Timbers, covering the eastern part of the study area, contain a mix of prairie, savanna, and woodlands with higher precipitation accumulation than the Central Great Plains (Figure 4).

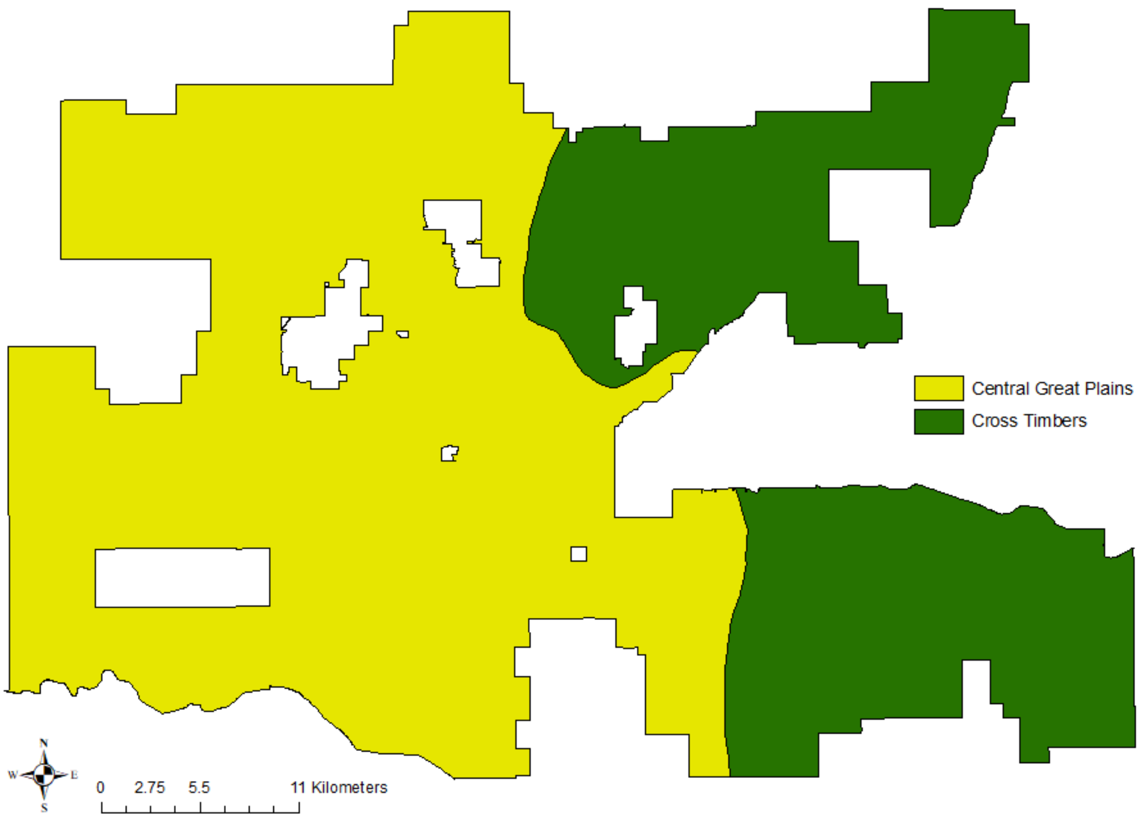


Figure 4: Oklahoma City spatial extent showing the Central Great Plains in the west (yellow) and Cross Timbers ecoregion in the east (Green).

3.2.4 Redline Districts

Redlining data was acquired from American Panorama (Nelson et al., 2016). The Homeowners' Loan Corporation (HOLC) maps are a public domain with most maps coming from the National Archives. Figure 5 shows the spatial distribution of the classified redline districts. The first thing to note is the lack of spatial distribution creating a cluster of classified redline districts in the dense urban environment of downtown OKC. The majority of classified redline districts are located on the south side of downtown OKC.

Table 1: Redline classifications reported from (Nelson et al., 2016). The best locations are classified as A and the worst locations are classified as D.

REDLINE CLASSIFICATION	REDLINE DESCRIPTION
A	Best
B	Still Desirable
C	Definitely Declining
D	Hazardous

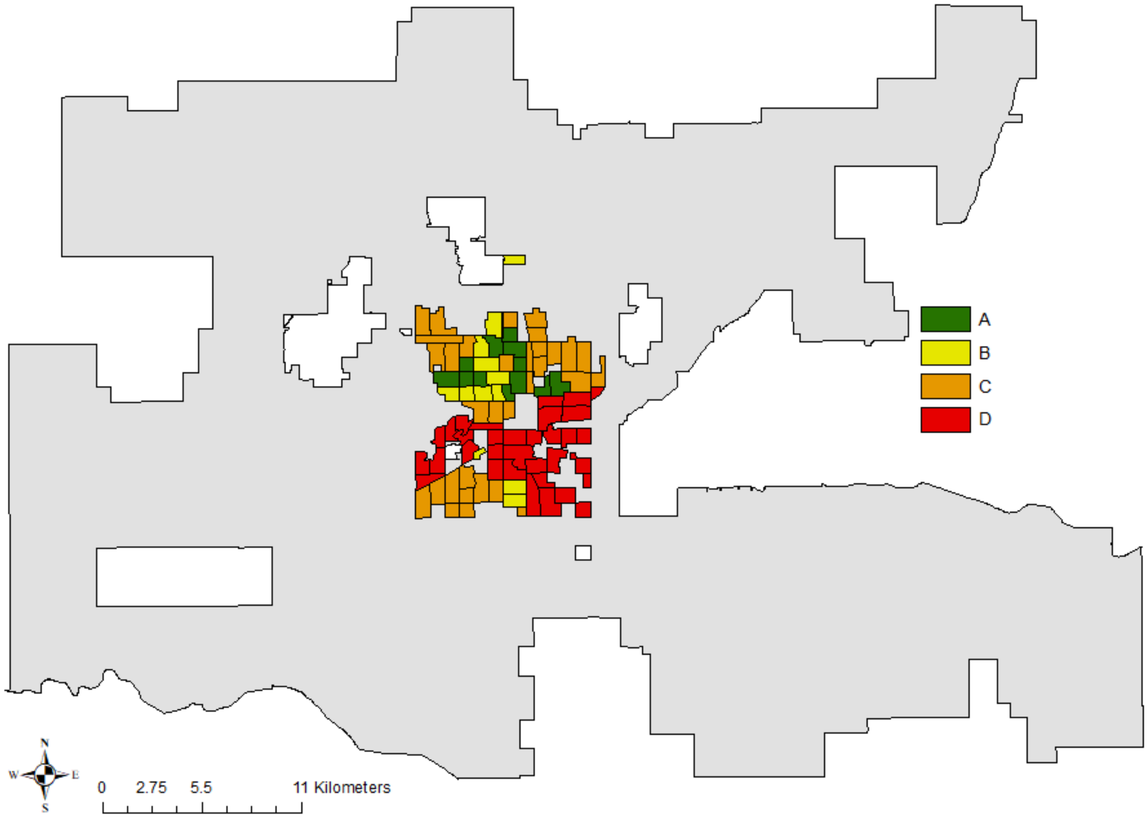


Figure 5: A map of the redline districts of Oklahoma City. The redline district grades are green (best), yellow (still desirable), orange (definitely declining), and red (hazardous).

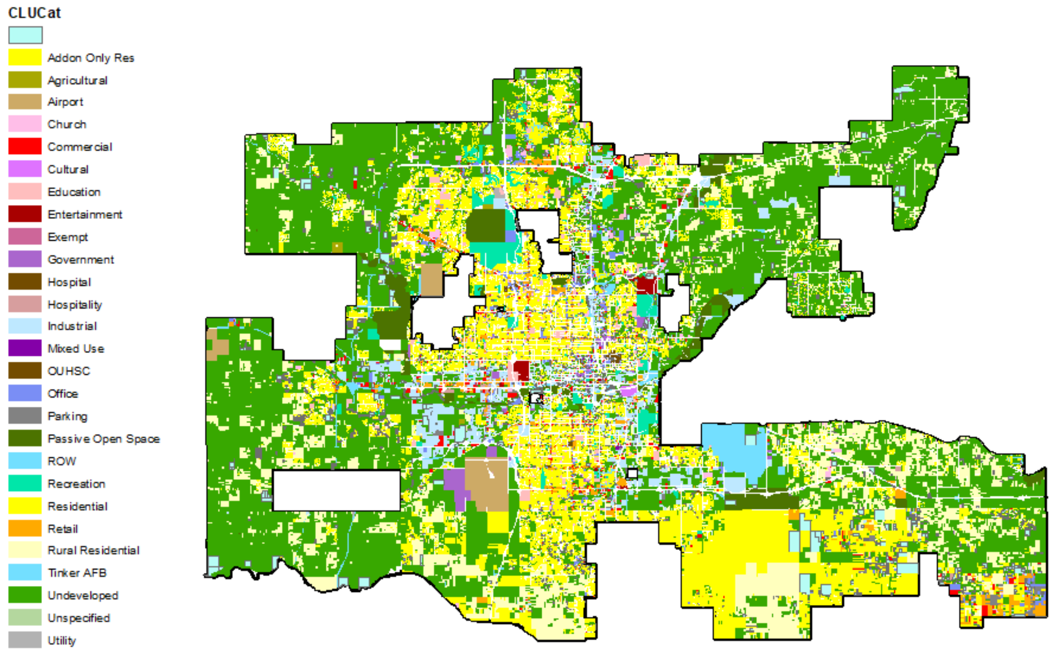
3.2.5 Tri-County Parcels

The parcel dataset contains information at the parcel scale in 2014. The parcel dataset was collected by the city of Oklahoma City Planning Department. The information used in this dataset is the current land use category (CLUcat). CLUcat is the basic level of generalization (smallest number of categories). Any parcel with a floor area ratio (FAR) (Eq. 2) below 0.01 regardless of whether or not it has improvements. Indoor floor area is a calculated value from the parcel floor plan and the area of the parcel is calculated by the total shapefile feature of the parcel.

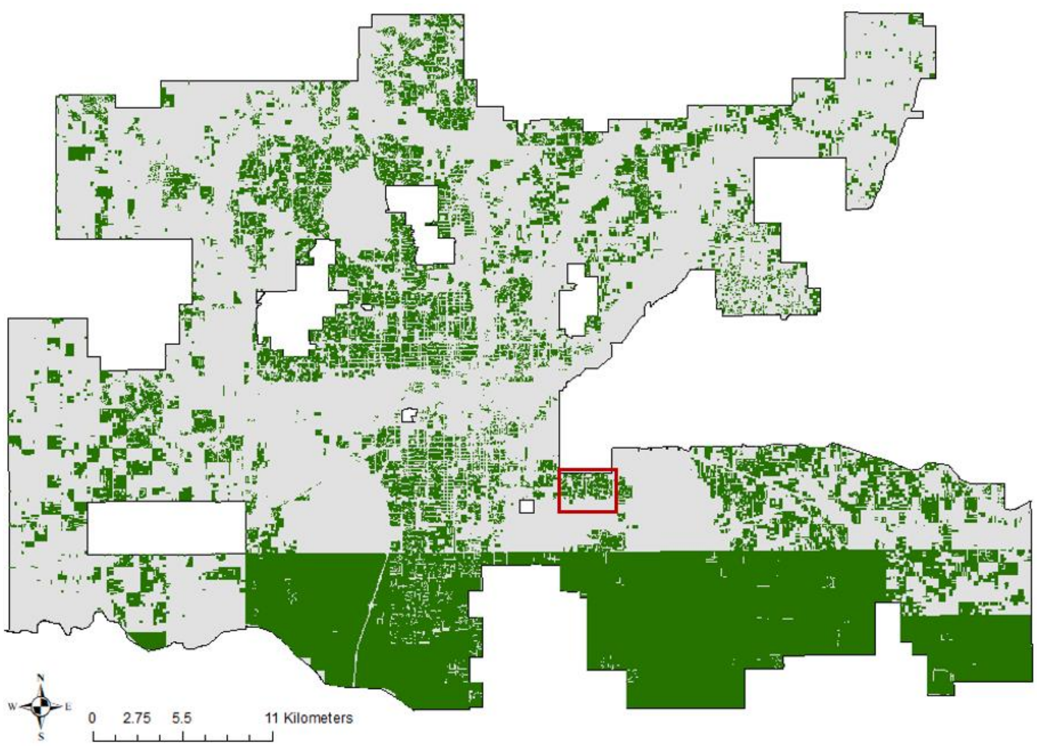
$$Floor\ Area\ Ratio\ (FAR) = \frac{Indoor\ floor\ area}{Area\ of\ parcel} \tag{2}$$

This could be from housing, apartment complexes, duplexes, residential housing, military housing, or farmland that contains a residential house. Parcels that were classified as residential or rural residential were chosen in CLUcat variable. There ended up being 197, 270 parcels after filtering out other parcel data that did not contain residential, rural residential, no census data available for the tract the parcel belonged in, or parcel contained extreme census socio-economic values. Residential parcels account for 33% of the OKC spatial extent.

a)


CLUCat
Addon Only Res
Agricultural
Airport
Church
Commercial
Cultural
Education
Entertainment
Exempt
Government
Hospital
Hospitality
Industrial
Mixed Use
OUHSC
Office
Parking
Passive Open Space
ROW
Recreation
Residential
Retail
Rural Residential
Tinker AFB
Undeveloped
Unspecified
Utility

b)


N
W
E
S
0 2.75 5.5 11 Kilometers

c)

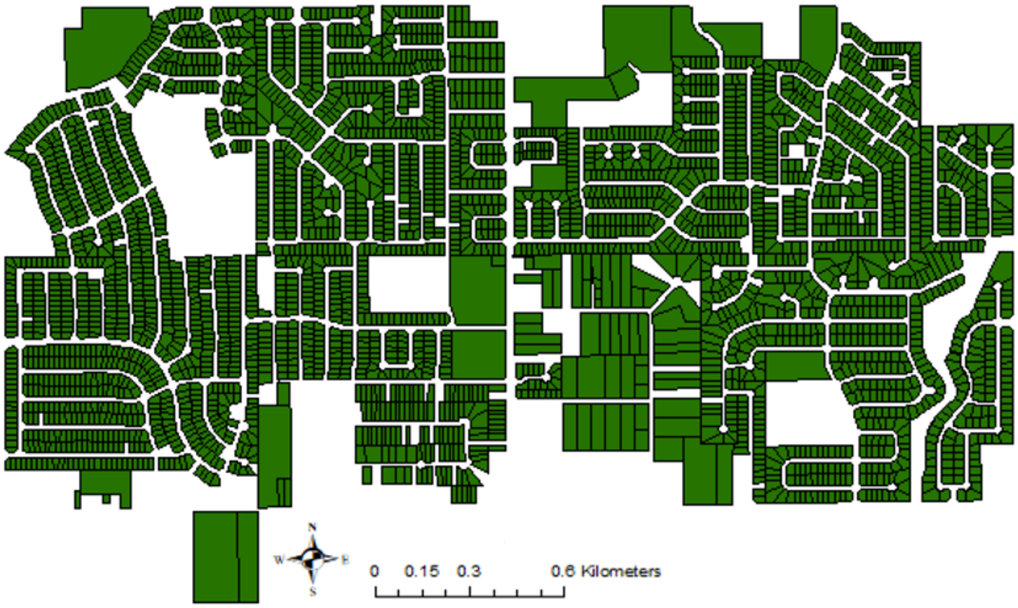


Figure 6: a) Oklahoma City spatial extent for tri-county parcel 2014 dataset containing every CLUcat unique value. b) Parcel dataset with every residential and rural residential CLUcat classification. c) Zoom in parcel dataset with only residential and rural residential and rural residential CLUcat classification.

3.3 Raster Data

3.3.1 National Agriculture Imagery Program

National Agriculture Imagery Program (NAIP) data are orthophotography images that are captures through an airplane. Each image is comprised of a multispectral representation of the surface features. Most studies examine land cover and biophysical properties using Landsat imagery. Landsat imagery uses a spatial resolution of 30m (Figure 7a) and has a temporal resolution of 16 days, which is ideal for time series analysis throughout each year. National Agriculture Imagery Program uses a high spatial resolution of 1m (Figure 7b) to create a digital ortho quarter quad (DOQQs) into a single mosaic. The temporal resolution of NAIP has a low resolution of 2 years in some states like Oklahoma (USDA, 2017). The temporal resolution of the NAIP is a downside to using it for land cover analysis but a 1m spatial resolution makes up for the lack of temporal resolution as long as there is not much land use land cover change between image acquisition dates. A spatial resolution of 1m can provide further insight into differentiating grass, trees and urban landscape.

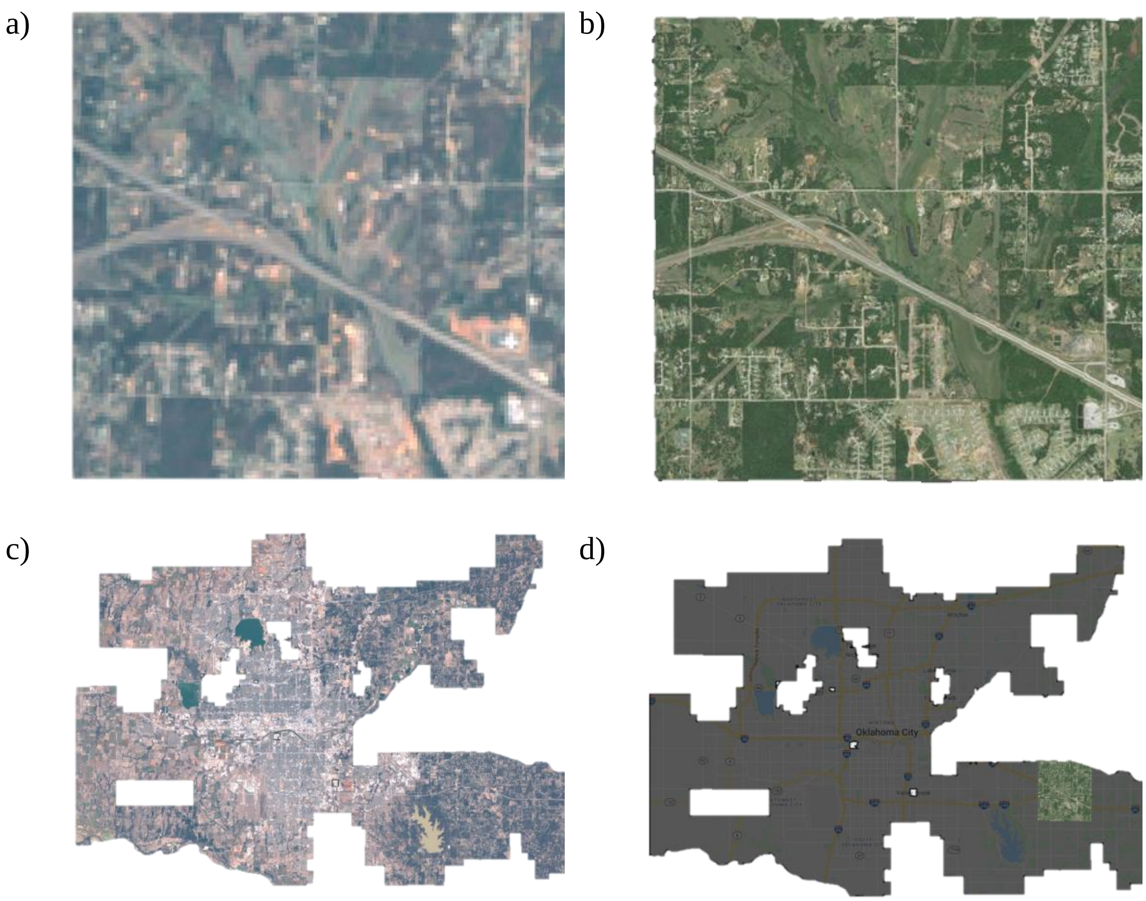


Figure 7: Landsat 8 top of atmosphere and b) National Agriculture Imagery Program images at the same location and spatial extent of the National Agriculture Imagery Program image. Shows how the resolution makes a significant impact on the quality of pixel classification. c) Landsat 8 top of atmosphere tile and d) National Agriculture Imagery program quarter-quad tile in comparison to the spatial extent of the study area.

National Agriculture Imagery Program schedules flight plans for remotely sensed orthophotography during days that have atmospheric stable conditions less than ten percent cloud cover. These images are necessary for the agricultural leaf-on season to observe vegetative growth the year of image acquisition to crop rotations (Maxwell et al., 2017). The leaf-on season is related to biological plant phenology transitioning from fall to winter brown dehydrated leaves in the dormant season to spring to summer healthy green leaves in the growing season (Maxwell et al., 2017). Central Oklahoma has a vast range of leaf-on season, but an average growing season for tree canopies is from March to September each calendar year (Wagle & Kakani, 2014).

This study uses the years 2013 and 2015 for a total of 146 images. National Agriculture Imagery Program started with real-color images of Oklahoma with a spatial resolution of 1m till 2007 and in 2010 the program changed the cameras by installing a multispectral camera that includes the near-infrared band (Maxwell et al., 2017). A Google Earth Engine (GEE) script was created to avoid having to download a terabyte worth of images and reduce image processing time. The GEE script filtered out images that were outside of 2013 to 2015, did not have the red, green, blue, and near-infrared (NIR) spectral bands, and clipped each image to the OKC spatial extent. Once the images were filtered and clipped to the study area, the median function was used to create a single pixel that would represent 2014 for each overlapping pixel was calculated to produce a mosaic of NAIP imagery for OKC representing 2014.

3.3.2 Vegetation Indices and Land Cover Classification

Vegetation index NDVI is a measure of the greenness of vegetation using the red and NIR bands (Pettorelli et al, 2005). Chlorophyll absorbs visible light in the red spectrum and the internal spongy mesophyll will reflect light in the NIR spectrum. When vegetation becomes diseased, the internal composition loses structure and begins to absorb NIR light and the vegetation will begin to heat up (Pettorelli et al, 2005). The values of NDVI are between -1.0 and 1.0.

$$NDVI = \frac{NIR - Red}{NIR + Red} \tag{2}$$

Vegetation index NIRv is mainly used for detection of solar-induced chlorophyll fluorescence and gross primary production (GPP) of vegetation (Badgley et al, 2017). This study uses NIRv to make a clear separation of vegetation from impervious surfaces and water bodies in the study area. Grass and tree canopies have a very high value in comparison to impervious surfaces (Badgley et al, 2017). Impervious surfaces have a value closer to the minimum range of the product (Badgley et al, 2017).

$$NIRv = NDVI * NIR \tag{3}$$

Vegetation index NDWI is a measure of water bodies in the study area using the green and NIR bands (McFeeters, 1996). The primary purpose of NDWI is to source open water bodies and eliminating soil and vegetation from the image. Positive values denote water bodies and impervious surfaces while negative values denote non-flooded vegetation (McFeeters, 1996). The values of NDWI are between -1.0 and 1.0.

$$NDWI = \frac{Green - NIR}{Green + NIR} \tag{4}$$

I explored vegetation index threshold classification using vegetation index values as boundaries for different land cover classifications but ended up using a training dataset created myself (Figure 8). I used a pixel-based land cover classification using vegetation indices and spectral bands to classify trees, grass, and urban land cover. A training dataset of points were used to run through a machine learning Classification and Regression Tree (CART) to classify each pixel based on vegetation indices and spectral bands (Table 1) (Figure 8). The CART classification is chosen over threshold index classification as threshold classification produced lower accuracy in comparison to CART classification. The vegetation indices used in this study are Normalized Difference

Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and Near-Infrared Vegetation (NIRv) (Equations 2 – 4).

Table 2: Point pattern training dataset used for Classification and Regression Tree machine learning algrorithm.

RECLASSIFY VALUE	COLOR	LAND COVER CLASSIFICATION	NUMBER OF POINTS
01	Green	Trees	500
02	Lime	Grass	500
03	Black	Other	500

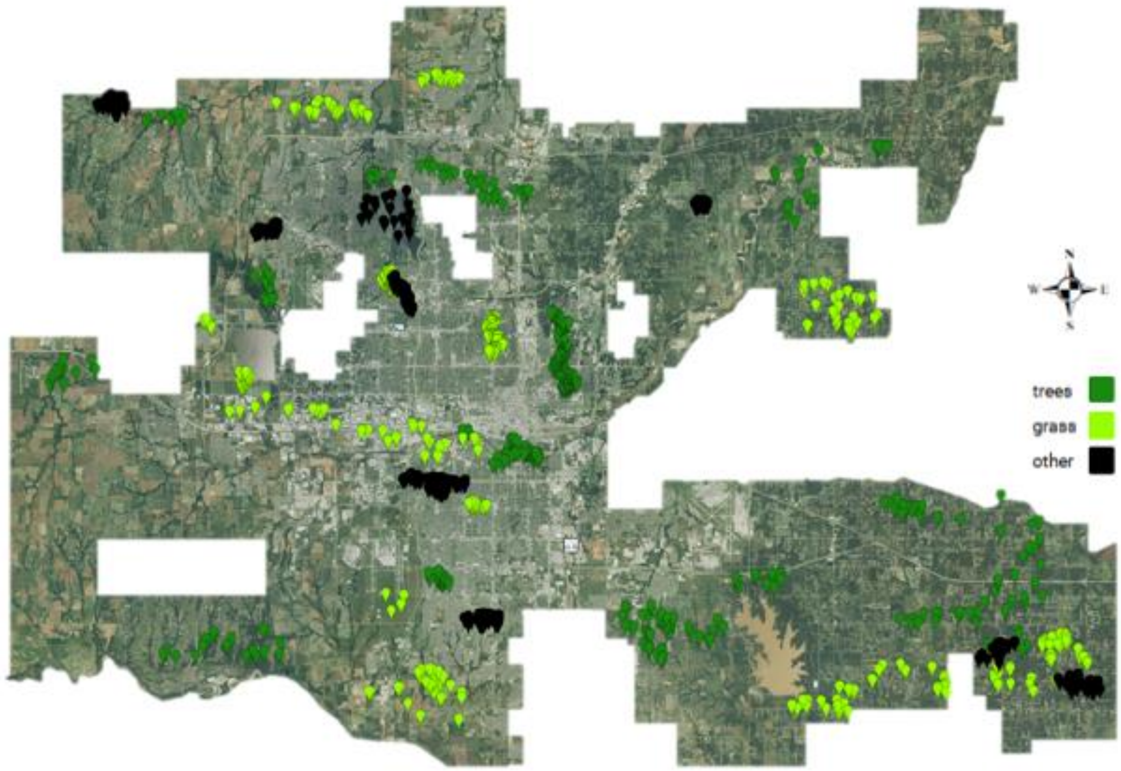


Figure 8: Distribution of training dataset throughout the Oklahoma City spatial extent. The National Agriculture Imagery Program imagery is used for reference to acquire accurate training data. Processed through Google Earth Engine using a projection of WGS84.

3.4 Study Design

This study focuses on Oklahoma City and uses open-source datasets to examine the relationship between bio-physical and socio-economic variables at the parcel level and their effects on percentage of trees in neighboring parcels. For the purpose of my study, I use spatial parcel data on neighborhoods in the OKC spatial extent and combine those with census data and NAIP imagery. National Agriculture Imagery Program uses high spatial resolution with one pixel representing one square meter in the reality (USDA, 2017). The use of high resolution NAIP imagery allows for a more accurate representation of bio-physical variables on the parcel level in comparison to platforms like Landsat. More specifically, the use of NAIP imagery as compared to the frequently used Landsat (30m), allows researchers to evaluate (1) the spatial relationship between percentage of trees versus percentage of grass on residential parcels in OKC, and (2) the spatial relation among percentage of trees/grass and socio-economic variables (e.g., educational background, travel time to work, driving habits, income, etc.) on residential parcels in OKC.

I expect a higher percentage of trees to be located in neighborhoods with higher median household incomes and older parcels, based on the assumption that established parcels and parcels with a higher median household income will have more disposable income to use on landscaping. Newer lots are expected to have mainly grass covered yards or younger trees which are harder to identify in satellite images; the lower leaf area index of younglings cause the satellite imagery to detect the ground rather than the tree itself (Xiao et al., 2004). Moreover, I expect to find a higher percentage of trees in suburban neighborhoods, based on the assumption that suburban lots are larger, and hence, have a lower fraction of impervious surface. Analyzing these assumptions and understanding the relative importance of trees versus grass versus impervious surface and the resulting greenness of parcels in OKC, which is partially located in the Cross-Timbers region (amongst others dominated by woodlands and oak-hickory forests), will contribute to a more nuanced understanding of the relationship between socio-economic characteristics and UGS.

In this study, I use NAIP imagery to derive information on NDVI, tree pixel classification, and grass pixel classification for OKC. I then combine this information with residential parcel boundary data to calculate mean NDVI per parcel, as well as percentage tree and percentage grass for each residential parcel in the study area. In the second step, I add socio-economic information from the U.S. Census to the residential parcels. The socio-economic information is essentially tract level U.S. Census information but transformed based on a parcel weighted ratio (Eq 1). The weighted parcel ratio is used to see trends at the parcel spatial level.

$$Weighted\ Ratio\ = \frac{1\ parcel}{total\ number\ of\ parcels\ in\ tract} \tag{1}$$

I include bio-physical independent variables such as mean NDVI, parcel area, and ecoregion to describe the spatial characteristic of each residential parcel in OKC. I include commuting tendencies, educational background, housing situations, financial availabilities, and demographics to describe the socio-economic characteristics of each residential parcel in OKC. After completing pre-processing of spatial data, I conducted a multiple regression analysis to find a model that best describes the influential factors on the dependent variables (first greenness, and then in a second step percentage of trees). I used the Akaike Information Criterion (AIC) to identify different independent variables in models to show the best statistical model to use. I use spatial autocorrelation with the best model to show global and local indicators of spatial clustering of parcels that have similar characteristics as neighboring parcels' percentage of trees.

3.5 Data Processing

This study is meant for replicability, thus requiring python, R, and GEE computer programming scripts used throughout the study. All shapefiles were reprojected to use the same spatial projection as the Tri-County Parcel shapefile which was the North American Datum 1983 Lambert Conformal Conic Oklahoma North in feet. Counties shapefile was used for clipping the OKC spatial extent by selecting Canadian, Cleveland, and Oklahoma counties. Counties shapefile reduced the OKC spatial extent by reducing the eastern portion of the city. Census tracts in Pottawatomie County did not possess enough tracts to make it statistically significant to keep. The census tracts dataset provide information about the entire census tract. Two census tract shapefiles were created to properly assign socio-economic census survey information down to the OKC spatial scale. Counting the number of parcels inside the full census tract shapefile and counting the number of parcels inside the OKC spatial extent are used to create the ratio used to proportionally disaggregate the socio-economic data (Equation 4). Number of parcels was used for disaggregation instead of area of tract due to the idea that tracts that are large mean that there is a smaller population density compared to small tracts which are located near the downtown regions of cities. The parcel ratio is used to transform census tract data from tract level to parcel level (Equation 5). Number of parcels gives a more accurate representation when downscaled to smaller spatial levels as census tracts are describing people and not spatial area.

$$Tract\ Ratio = \frac{Number\ of\ parcels\ in\ clipped\ tract\ shapefile}{Number\ of\ parcels\ in\ full\ tract\ shapefile} \tag{4}$$

$$Parcel\ Ratio = \frac{1\ parcel}{Number\ of\ parcels\ in\ same\ tract} \tag{5}$$

Each parcel in the parcel dataset needs a tract identifier number to assign socio-economic census survey information. The Point on Surface geoprocess in QGIS was used to transform each polygon feature in the parcel shapefile to an area-weighted centroid point. Some features of the parcel shapefile will intersect tract boundaries creating a problem for assigning tract identifier numbers but turning the polygon features into points will remove this error by using a point instead of polygons. This points shapefile was used for assigning tract identifiers, ecoregion, and redline intersections. Unique identifiers were created for the parcel shapefile that are used to match up the point shapefile attributes to the polygon shapefile attributes. The bio-physical variables (trees count, grass count, other count, and mean NDVI) were calculated in GEE and exported into a comma-separated value to be imported into the polygon shapefile attribute table. Percentages of grass and trees were calculated in the R-script.

3.6 Statistical Analysis

The statistical analysis was conducted on the parcel shapefile. The dependent variable of this study is the percentage of trees, and the independent variables are the socio-economic and some bio-physical variables (Table 3).Twenty-four parcels were removed due to having extreme outlying values across the socio-economic variables (Tracts 107500, 107808, 108404, 202106, 301410) or having no census survey information (Tracts 107101, 400101, 501003). There are 261 parcels that are removed due to containing NA values in any of the socio-economic variables. All variables (dependent and independent) that are a proportion or percentage are transformed using the arcsine square root transformation method (Ahrens et al., 1990). Arcsine square root transformation is used on proportions and percentages because as the ratios are reaching a maximum value at a proportion of 0.5 and declining to zero at proportions of boundary effects.

This study examines the ordinary least squares (OLS) of the multiple linear regression analysis. A linear regression approach is conducted due to the relationship shown between mean NDVI and percentage of trees in a parcel. Dependent variables are percentage of trees or percentage of grass on each parcel (Figure 11). Choosing the dependent variable was statistically chosen by using two OLS simple linear regression tests using mean NDVI as the dependent variable and percentage trees as the independent variable for the first test. The second test is mean NDVI as the dependent variable and percentage grass as the independent variable for the second test.

The dependent variable is percentage of trees, and the independent variables are described in table 3**.** Multiple regression analysis is useful for this study as bio-physical variables are dependent on more than on socio-economic variable to fully understand the causal effects of greenness in parcels. The independent variables are chosen based on the Akaike Information Criterion (AIC). The statistical test AIC is useful for measuring which independent variables are not suitable in the linear multiple regression model.

Spatial autocorrelation is useful for measuring how closely related the socio-economic variables are for each parcel the neighboring parcels using a first-order queens based spatial weights matrix. Zero-policy is set to true to account for the non-residential parcels filtered out of the parcel dataset and the weights style of the neighbors are set to “W” to standardize the rows. Moran’s I statistic is used for testing global spatial autocorrelation in the residuals and testing if there is a presence of spatial clustering. Local indicators of spatial association (LISA) test is used for local clustering in the residuals by reclassifying parcels based on the mean value of the OLS multiple linear regression fitted value and the mean local Moran’s-I value for the parcel being positive or negative. If the p-value of the parcel does not meet the statistical significance threshold (p-value < 0.001) in the LISA test, then a zero is assigned to the parcel. An alpha threshold of 0.001 is chosen to increase the strength of the results by removing the chance of seeing false positives in the results.

Chapter 4: Results

4.1 National Agriculture Imagery Program Classification Validation

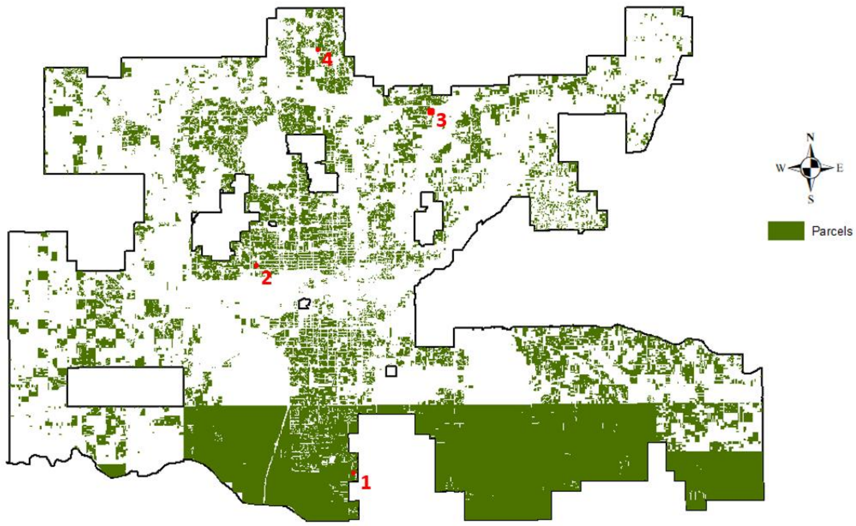
The NAIP land cover classification was tested for accuracy by examining individual parcels (Figure 9). Further systematic accuracy examining looked at the kappa coefficient that resulted in 0.99. The overall accuracy of the machine learning land cover classification produced a value of 0.99. The confusion matrix shown in table 2 shows slight variance in between training data and classified pixels. Overall this training data showed positive results in classifying NAIP pixels.

Table 3: Resubstituting error matrix for training data using 20% as a random sample of the 1500 training points used for land cover classification

		Reference Data			
		Trees	Grass	Other	Total
Classified Data	Trees	111	0	1	112
	Grass	0	96	1	97
	Other	0	0	109	109
	Total	111	96	111	318

Figure 9: Land cover classification map produced from Classification and Regression Tree machine learning algorithm using Google Earth Engine with a projection of WGS84.

a)



b)

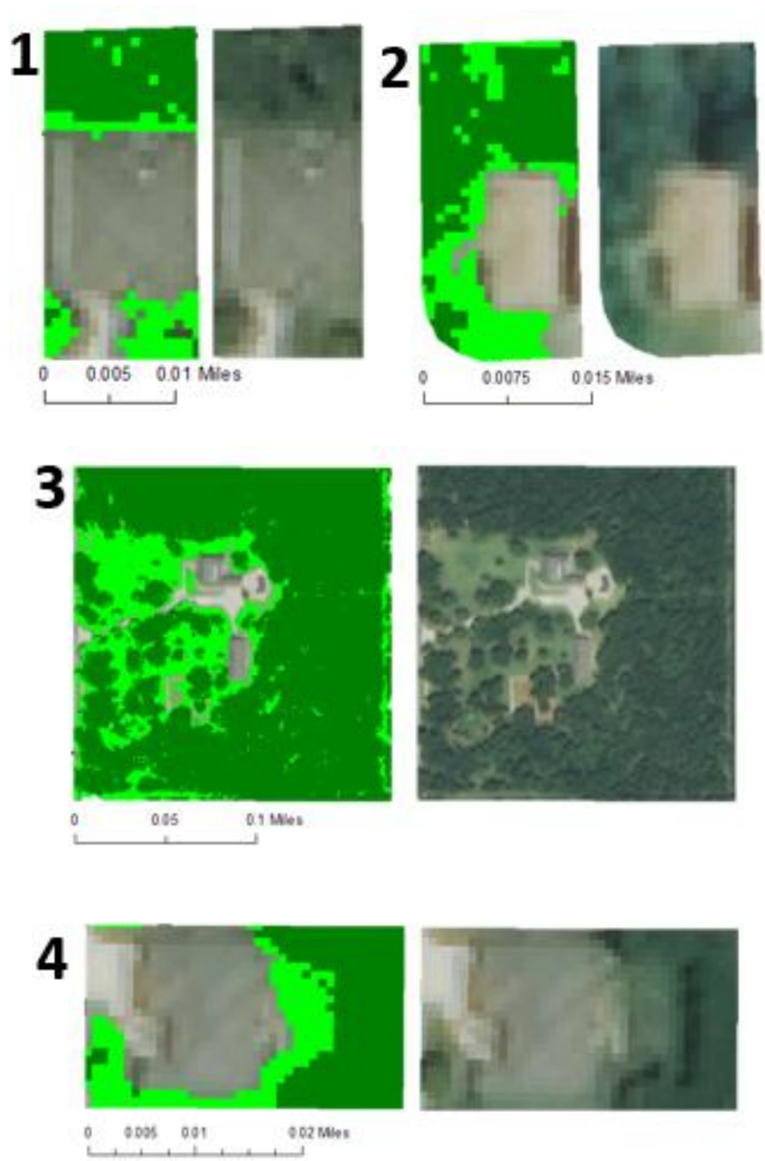


Figure 10: Subjective validation of land cover classification examining individual parcels. a) Oklahoma City residential and rural residential houses with four parcels selected for validation. b) Zoomed in National Agriculture Imagery Program true color imagery overlayed with the Classification and Regression Tree algorithm result from Google Earth Engine for that parcel using a WGS84 projection (Unique IDs: 265900, 154690, 164926, 223083 respectively). The numbers are the unique ID associated with each parcel.

4.2 Ordinary Least Squares Regressions

The original OLS test to decide the dependent variable to examine with OLS multiple linear regression model showed that percentage of trees is a more suitable variable to use (Figure 11). Percentage of grass correlated to mean NDVI only showed an adjusted R^2 value of 0.09323 and a p-value of less than 0.05. Percentage of trees correlated to mean NDVI showed an adjusted R^2 value of 0.66 and a p-value of less than 0.05. Percentage of trees was chosen for the OLS multiple linear regression model by showing a more accurate correlation of mean NDVI with a higher R^2 value.

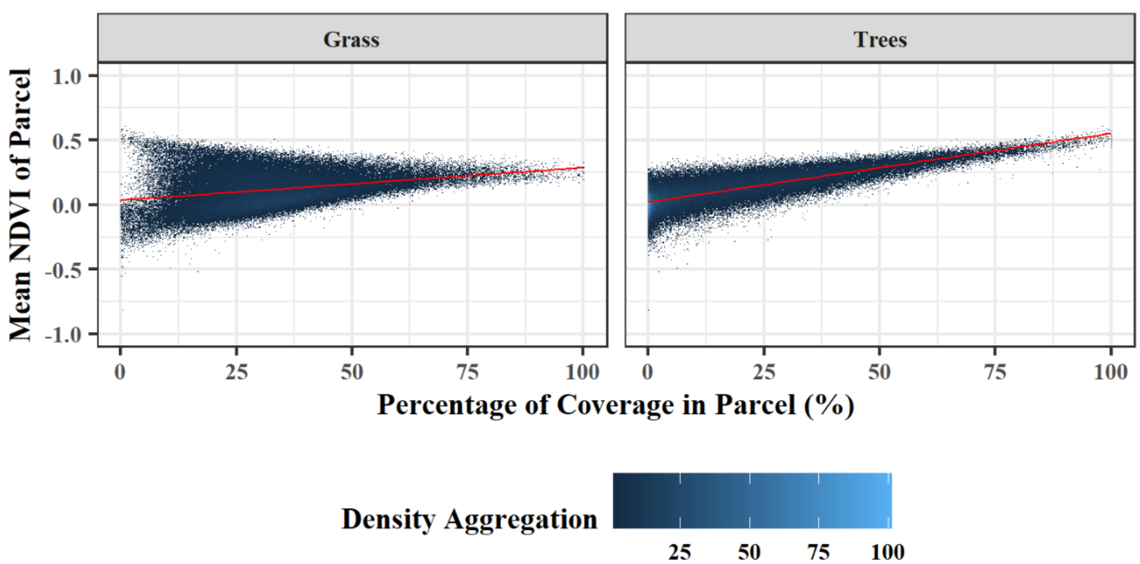


Figure 11: Density scatterplot showing the correlation between trees and grass coverage percentage in a parcel compared to the mean NDVI of that parcel. The bins were situated at 500.

The OLS multiple linear regression model was originally ran using every variable I created in the parcel shapefile for the independent variables and percentage trees used for the dependent variables (Table 3). Independent variables percentage of associates degree and percentage of vacant parcels were removed from the OLS multiple linear regression model as the variables show p-values larger than 0.05. The first and second OLS multiple linear regression models were tested to see which statistical model would be a better fit to describing the relationship to percentage of trees in each parcel. Both models were tested using the AIC method and both models produced an AIC value of -320288.4. Since both models produced the same AIC value, the model that removed independent variables associates and vacant was chosen for the spatial autocorrelation statistical method. There is a strong correlation between the statistical fitted values assigned to each parcel and greenness values based on the multiple linear OLS regression.

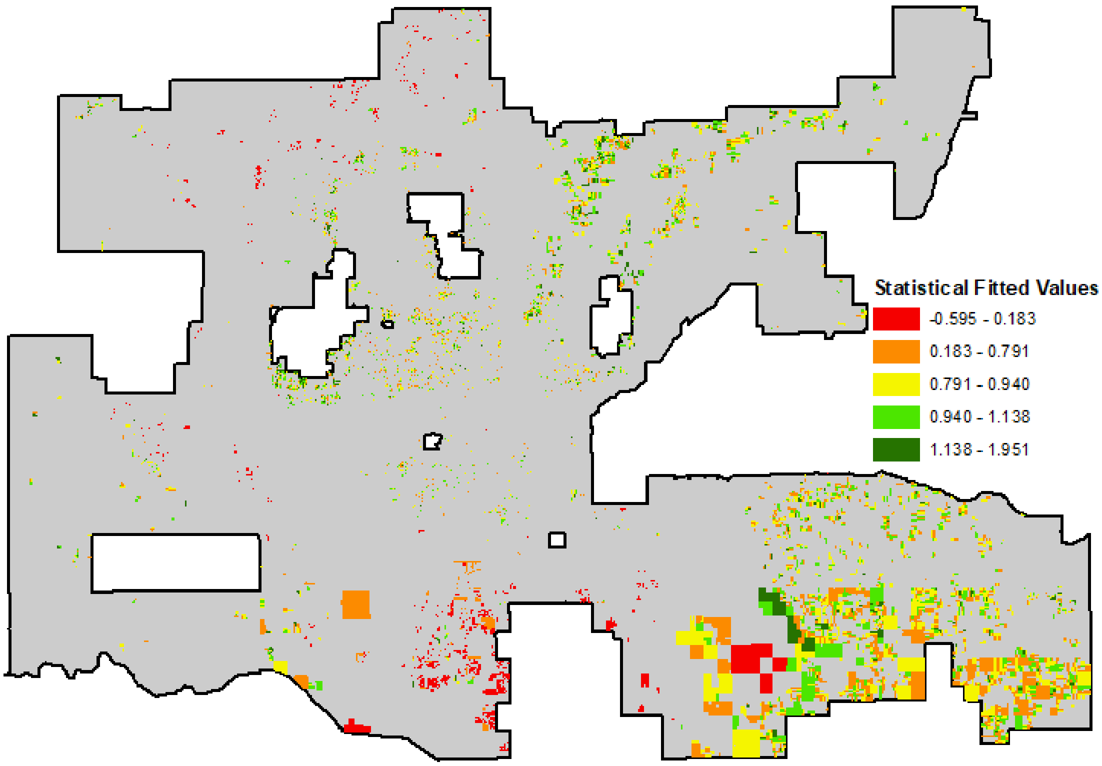


Figure 12: Choropleth map showing the spatial distribution of the statistical fitted values throughout Oklahoma City.

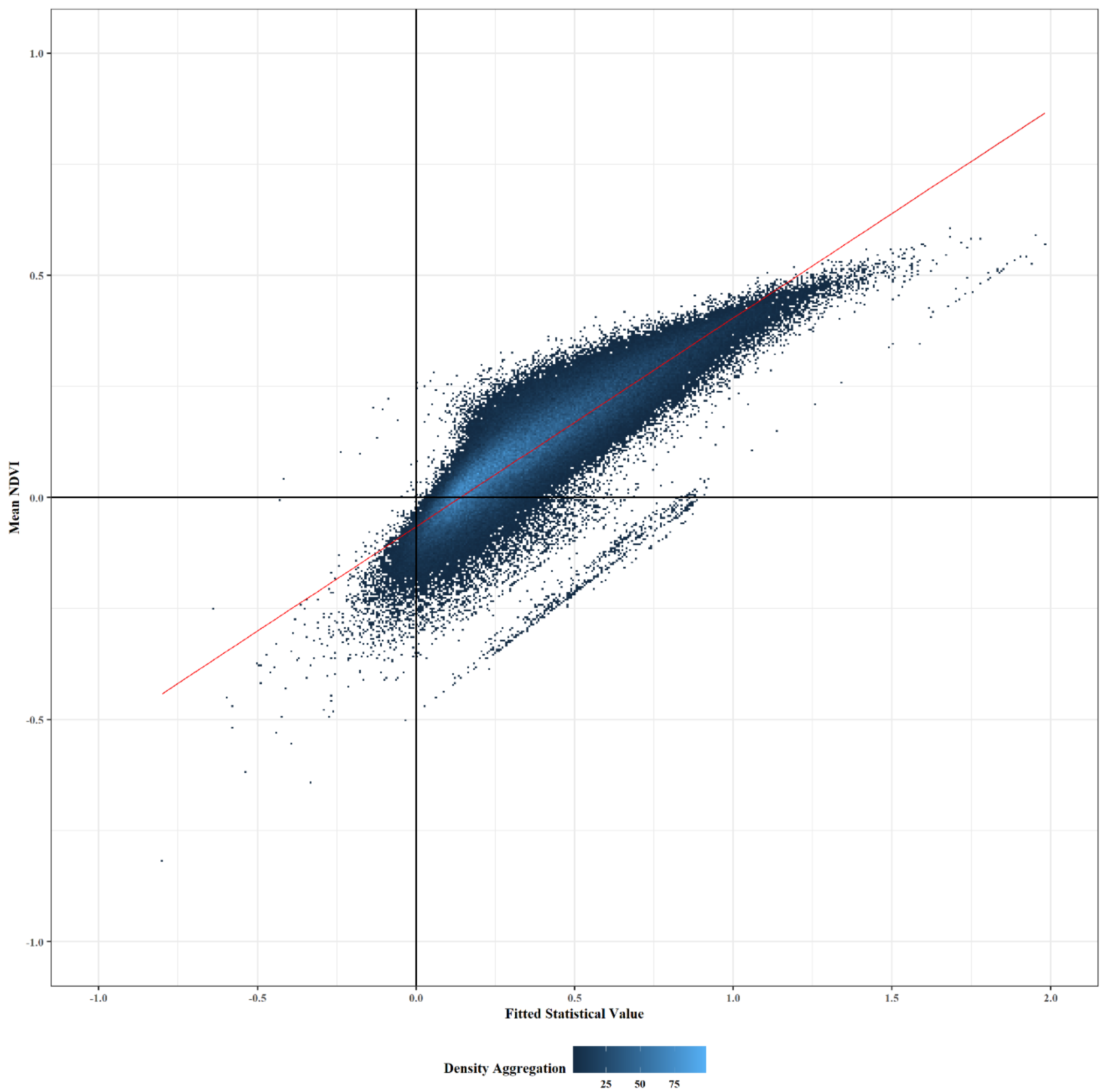


Figure 13: Density scatterplot showing the correlation between fitted statistical values and greenness. The bins were situated at 500.

Table 4: Independent and dependent variable definitions and summary statistics of parcel dataset used in statistical analysis.

VARIABLES	DESCRIPTION	TYPE	RANGE	MEAN	MEDIAN	STDEV	
INDEPENDENT							
medianAge	Median household age	Numeric	21.1 - 57.7	35.5807	34.6	6.1507	***
driveAlone	Ratio driving alone	Numeric	0.0243 - 17.2	0.091	0.0633	0.2581	***
carpool	Ratio driving carpool	Numeric	0 - 3.175	0.0134	0.0076	0.0359	***
workTravel	Average commute time (minutes)	Numeric	12.2 - 36	20.9079	20.9	3.5694	***
ged	Ratio having a GED	Numeric	0.0019 - 5.5285	0.0197	0.0129	0.0688	***
bachelors	Ratio having a bachelor’s degree	Numeric	0 - 7.4219	0.0136	0.0091	0.0541	***
graduate	Ratio having a graduate degree	Numeric	0 - 3.6458	0.0074	0.0041	0.0384	***
owned	Ratio houses that are owned	Numeric	0 - 17.5731	0.0687	0.0496	0.23	***
rented	Ratio houses that are rented	Numeric	0 - 25	0.0442	0.0284	0.2208	***
occupied	Ratio houses that are occupied	Numeric	0.0269 - 21.6398	0.0998	0.0716	0.303	***
houseAge	Age of house (years)	Numeric	1 - 128	44.735	45	24.8482	***
medIncome	Median household income	Numeric	9250 - 137105	56862.23	53007	26164.49	***
redline	Redline neighborhoods	Factor	0, A, B, C, D	NA	NA	NA	***
ecoregion	Ecoregion	Factor	Central Great Plains, Cross Timbers	NA	NA	NA	***
areaFT	Area of parcel (ft^2)	Numeric	0.011 - 27925367.354	31863.68	7928.976	285832.6	***
perGrass	Percentage grass	Numeric	0 - 100	32.009	30.64	14.7383	***
meanNDVI	Mean NDVI	Numeric	-0.8164 - 0.6064	0.1147	0.1108	0.1318	***
DEPENDENT							
perTrees	Percentage Trees	Numeric	0 – 100	18.6015	12.92		***

****** p < 0.001***

Table 5: Table showing the statistical means of independent variables filtered to the redline districts for fitted value comparison. Med is short for median.

REDLINE DISTRICTS	TOTAL POP	MED AGE	OWNED PARCEL	RENTED PARCEL	OCCUPIED PARCEL	VACANT PARCEL	AGE OF HOUSE
0	2.7779	37.2875	0.0734	0.0293	0.0927	0.01	41.3981
A	2.5883	34.3684	0.0716	0.0511	0.1045	0.0182	87.4716
B	3.0763	32.1749	0.0446	0.0534	0.0831	0.0149	85.7289
C	2.6354	34.8503	0.0436	0.0467	0.0769	0.0134	72.4802
D	3.7797	29.4698	0.0555	0.1607	0.169	0.0473	70.6976

REDLINE DISTRICTS	MED INCOME ($)	PARCEL AREA (FT^2)	GRASS (%)	TREES (%)	MEAN NDVI	MORAN'S – I	FITTED VALUE
0	68488.69	80841.84	22.8098	34.5242	0.15	2.9774	0.5172
A	54125.13	9560.173	20.5896	54.109	0.3076	2.8306	0.8646
B	35514.57	7792.797	20.8203	56.2993	0.3307	3.3318	0.8837
C	32933.66	8130.821	22.6895	55.8729	0.3321	3.0439	0.8662
D	27118.08	8820.053	19.5689	59.0348	0.3209	3.704	0.8803

4.3 Spatial Autocorrelation

The neighbor list of each parcel resulted in an average of 3.36 neighbors per parcel. I used a true zero policy for creating a neighbor list and produced 3108 parcels with no queen's case connections to neighboring parcels. The global spatial autocorrelation resulted in a Moran's-I statistic of 0.68 with a statistically significant p-value of less than 0.05. The global Moran's-I result shows spatial clustering with parcels sharing similar characteristics to the neighboring parcels allowing us to reject the null hypothesis. The null hypothesis in the global spatial autocorrelation is that there is no spatial autocorrelation between parcels and every parcel is random dispersed when examining the correlation between socio-economic variables and bio-physical variables to percentage of trees. A Monte-Carlo simulation of Moran's-I reinforces the significance of the global result by running 1000 simulations and producing the same 0.68 Moran's-I and a p-value less than 0.05.

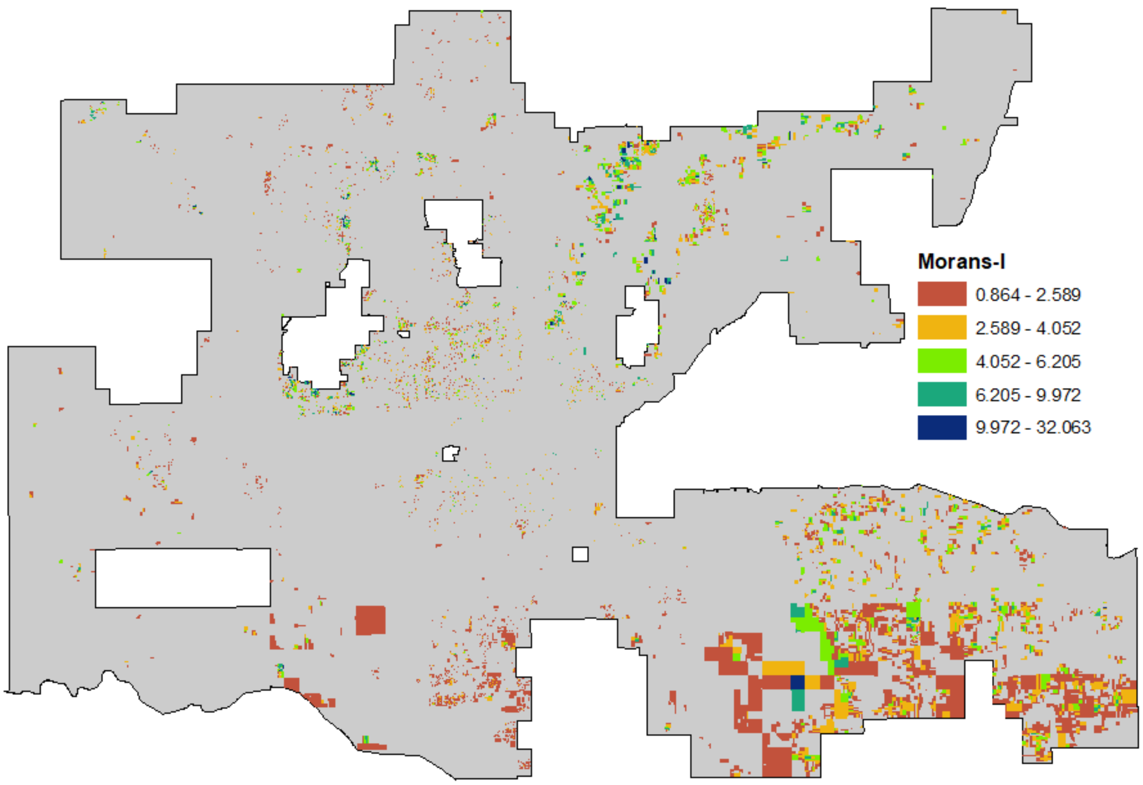


Figure 14: Spatial distribution of local Moran's - I statistics at every statistically significant parcel in Oklahoma City.

Local indicator of spatial autocorrelation resulted in a Moran's-I range of -6.32 to 32.06. There were 11 parcels presenting low-low spatial clustering, meaning significant parcels will exhibit opposite trends compared the neighboring parcels. There were 13,608 parcels presenting high-high spatial clustering, meaning significant parcels will exhibit similar trends compared the neighboring parcels. Insignificant parcels were removed 176,212 parcels in the LISA analysis due to parcels containing a p-value above 0.001. Parcels that contain a p-value above 0.001 are essentially spatially random in comparison to the neighboring parcels.

Table 6: Local indicator spatial autocorrelation classifications and total number of parcels for each classification.

LISA	DESCRIPTION	CLUSTER TYPE	TOTAL
0	Insignificant	None	176212
1	Low – Low (-)	Spatial cluster	11
2	Low – High (-)	Spatial outlier	7439
3	High – Low (+)	Spatial outlier	0
4	High – High (+)	Spatial cluster	13608

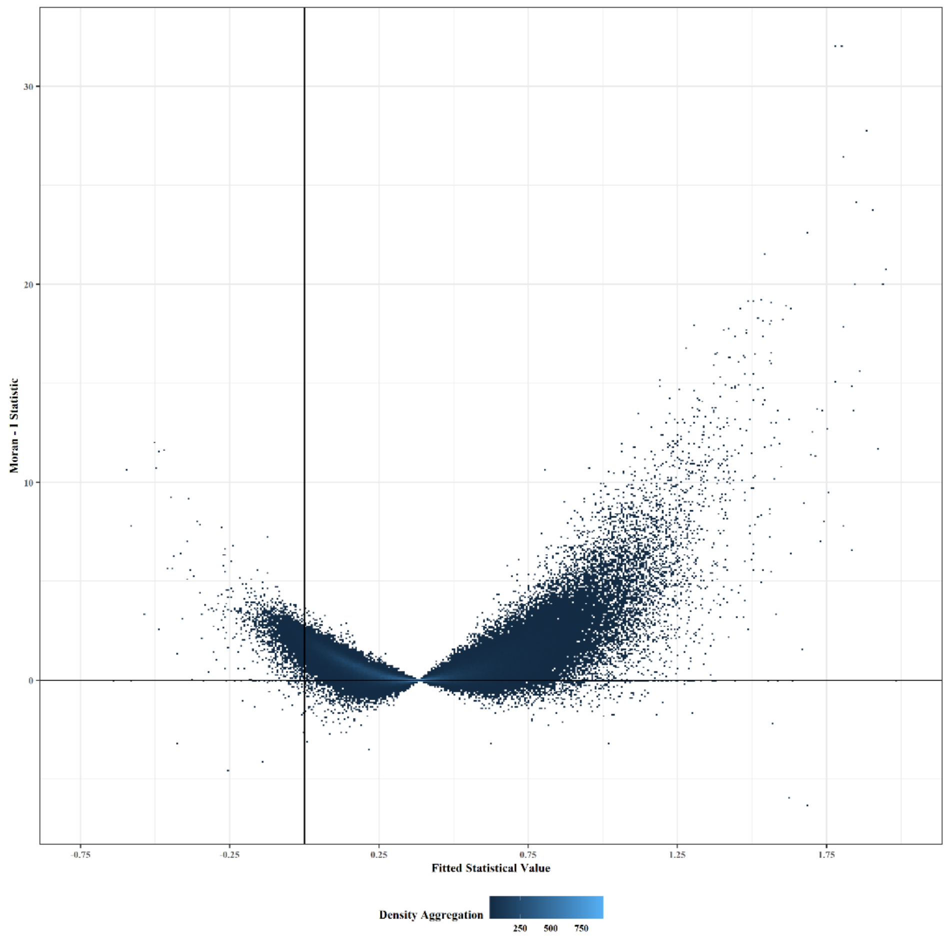


Figure 15: Density scatterplot showing the local Moran's-I statistic compared to the statistical fitted values of each parcel. The bins were situated at 500.

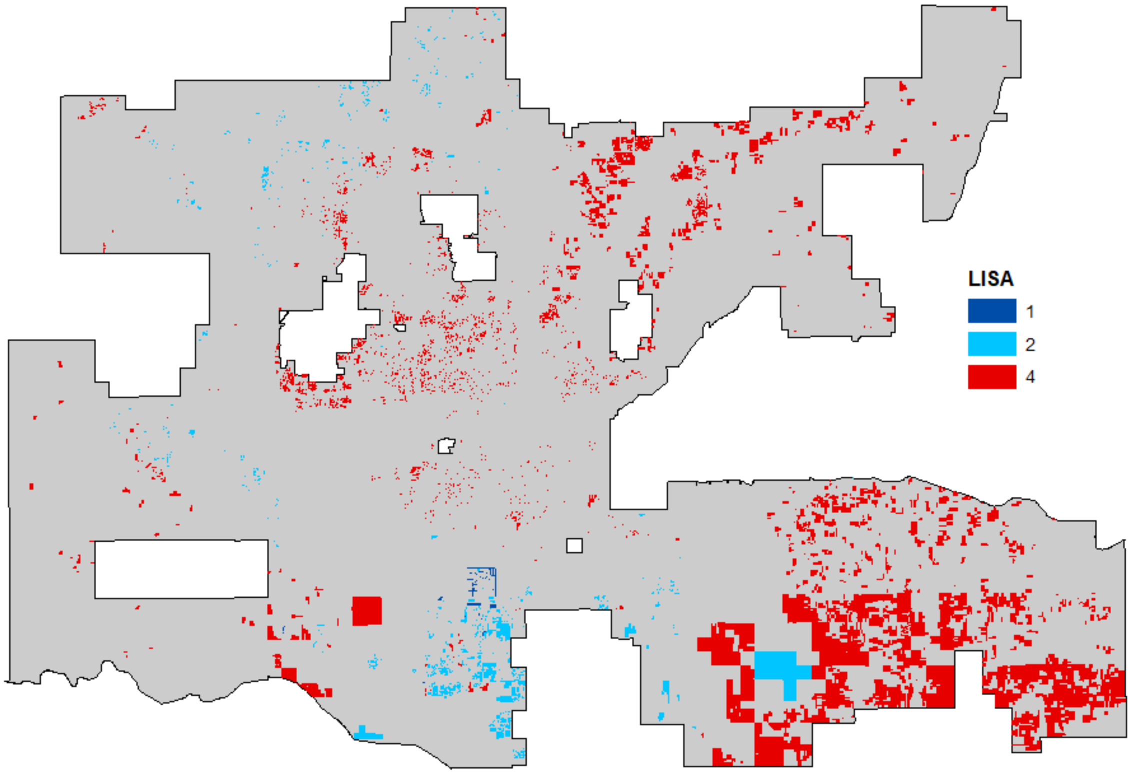


Figure 16: Local indicator spatial autocorrelation cluster analysis showing insignificant parcels with no color, spatial clustering in dark red and blue, and spatial outliers in light blue.

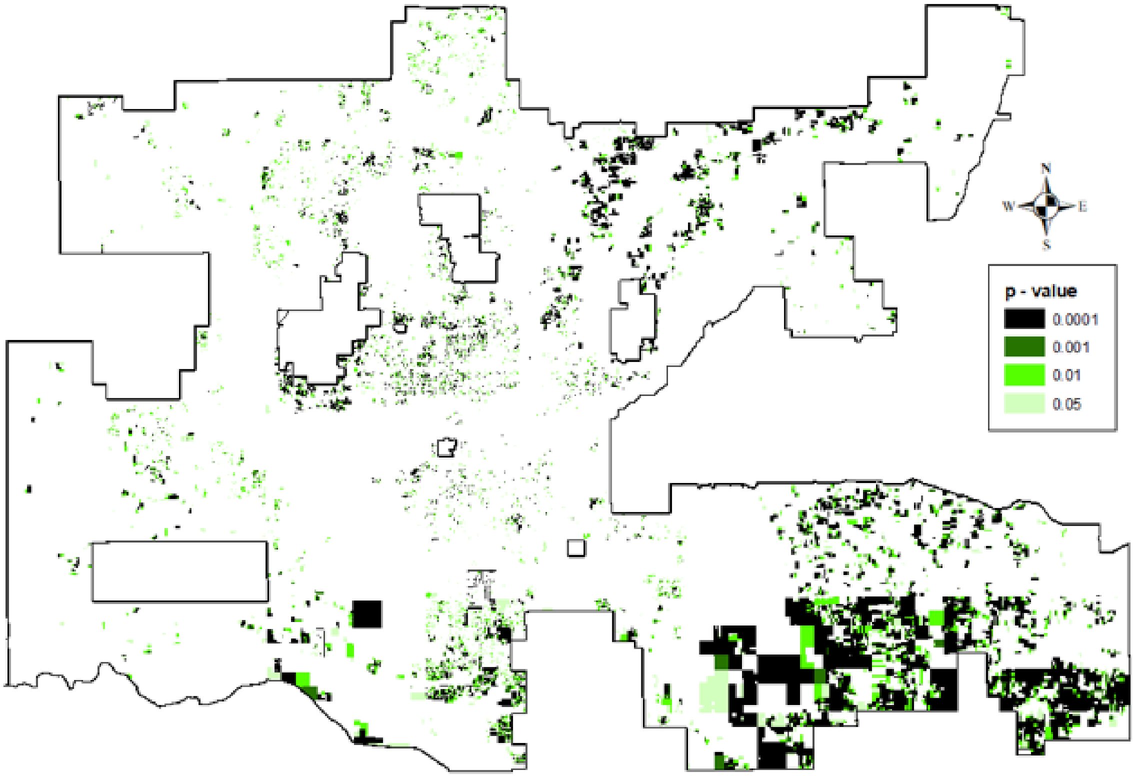


Figure 17: Significance map of Local Indicator Spatial Autocorrelation in Oklahoma City.

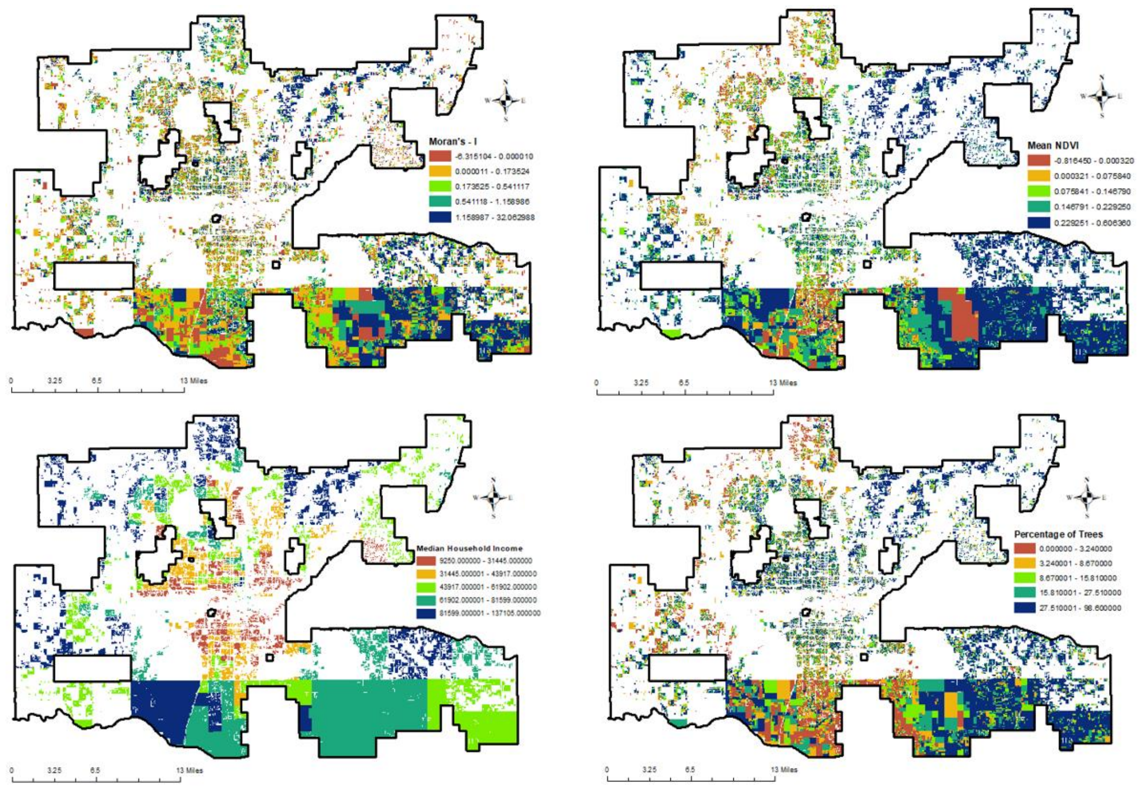


Figure 18: Choropleth maps showing the spatial distribution of a) Moran's – I (top-left), b) mean NDVI (top-right), c) median household income (bottom-left), and d) percentage of trees (bottom-right).

Chapter 5: Discussion

5.1 Spatial Clustering of Trees

Global spatial autocorrelation resulted in a Moran's-I value of 0.68 meaning that Oklahoma City does show spatial clustering of parcels. Neighborhoods and communities tend to have strict rules for the aesthetic curb appeal of parcels. Not following the neighborhood rules for parcel curb appeal will result in fines. Neighborhood associations and HOAs can affect global spatial autocorrelation by creating spatial clustering within the confines of the NA and HOA boundaries.

The local indicator of spatial autocorrelation provides additional insights into the socio-economic trends that are shared by neighboring parcels. Spatial clustering of high-high LISA values is apparent for the areas north and east of downtown Oklahoma City. North and east of downtown also show a relationship with high percentage of trees with high greenness values; the percentage of trees variable has a positive correlation to greenness due to tree canopies typically displaying high LAI (Myneni et al., 2002). Multiple layers of tree canopies reduce the background scatter of sensor sensing heterogeneous pixels. Heterogeneous pixels are caused by lower LAI and gaps in tree canopy causing the sensor to pick up grass or other land cover (Chen and Black, 1992).

The analysis does not show significant local indicator of spatial autocorrelation for the majority of downtown OKC (Figure 16). Figure 16 shows high-high parcels (red) in close proximity of downtown, but the parcels are still north and north-west of downtown. This is in line with findings by Mjaherjani (2016), Obiakor (2012), Onishi

(2010); downtown areas have high population density with a high percentage of impervious surface land cover, i.e., low greenness values. In comparison, suburban areas of cities have lower population densities, and as a result, a lower percentage of impervious surface land cover (Obiakor et al., 2012).

5.2 Socioeconomic Effects on Trees

While socioeconomic variables like median household income can play a big role in the spatial distribution of percentage trees and greenness, this is not always the case. The analysis shows parcels that have a high median household income, higher Moran's-I, and a higher percentage of trees in the statistically significant regions ($p < 0.0001$) of Moran's-I. The high-high LISA analysis of parcels with mean NDVI of the parcel above the average of 0.11467 and parcels having a percentage of trees above the mean value of 12.92%. Rural locations in the southeast section of Oklahoma City show statistically significant parcels with high-high LISA analysis. Rural parcels typically share the same biophysical features (trees and grass). Farmers share the same style of landscape (depending on crops produced) or rural housing has the same biophysical features (overgrown vegetation). Overgrown vegetation on rural parcels will show a higher NDVI due to more vegetation for what the sensor detects. There is a wide range of values for every socioeconomic variable. Moreover, median household income cannot be the only variable used in studies to examine greenness and the percentage of trees. Univariate studies cannot fully understand the systematic patterns that affect greenness.

5.2.1 Redlining Effects on Trees

Redline neighborhoods show the same results which is a wide range of values for every socioeconomic variable. Mean NDVI variable is of some interest as it showed a higher mean NDVI value and percentage of trees in redline neighborhoods classified as hazardous (Grade D). Locke et al (2021) showed that 37 metropolitan areas showed that grade D neighborhoods have on average ~23% tree canopy cover compared to grade A neighborhoods. Oklahoma City seems to show an opposite pattern with grade A neighborhoods having 47.55% and grade D neighborhoods having 52.47%). Hazardous neighborhoods could offer a higher percentage of trees and a higher greenness value since there is a higher percentage of vacant lots in hazardous neighborhoods (Schwarz et al., 2018). Hazardous neighborhoods have a mean vacancy percentage of 0.4178% compared to best neighborhoods having 0.02923%. Vacant parcels will have overgrown vegetation and untrimmed trees. Overgrown parcels and untrimmed trees increase the LAI value which saturates NDVI curves in the higher NDVI values (Chen and Black, 1992).

5.3 Ecological Effects of trees

Higher mean NDVI values of parcels located outside of downtown but are concentrated in and near the Cross Timbers ecoregion. The Cross Timbers ecoregion is ecologically prone to produce more trees in comparison to the Central Great Plains (Olson et al., 2007). Cross Timbers ecoregion is located in the eastern section of Oklahoma City and shows some of the highest Moran’s-I values, mean NDVI, and percentage of trees (Figure 18). Spatial clustering of statistically significant ($p < 0.0001$) parcels are more present in the Cross Timbers ecoregion (Figure 16). Parcels located in the northeast near rivers in the Cross Timbers ecoregion show statistically significant ($p < 0.0001$) parcels with high-high LISA analysis. Trees can be spatially clustered near rivers due to the significance of water for tree sustainable growth (Torquato et al., 2020). Percentage of trees and mean NDVI change drastically on the west side of Oklahoma City located in the Central Great Plains. The Central Great Plains are ecologically different than Cross Timbers ecoregion (Omernik, 2004). The Central Great Plains have more grass, less trees, and less precipitation. Moran's-I values are smaller and less consistent between neighboring parcels. The spatial randomness of Central Great Plains is related to the lack of trees in comparison parcels in the Cross Timbers ecoregion.

5.4 Greenness in Oklahoma City and other cities

Pearsall et al. (2012) examined Philadelphia's UGS and its relationship to socioeconomic variables. The study showed that greenness is not always positively and strongly correlated with household income but does not appear in heterogeneous urban environment. Greenness in heterogeneous urban environments like Oklahoma City show the same results as the Pearsall et al. (2021). Northwest downtown Oklahoma City show drastic changes in urban greenness and Moran's-I values denoting drastic changes in parcels from the parcels neighbor. Oklahoma City UGS has a negative correlation to median household income. Philadelphia and Oklahoma City share the association of high vacancy associated with mean NDVI in lower income neighborhoods.

Environmental injustice is seen throughout cities, but in Oklahoma City higher mean NDVI values are seen in redline districts classified as hazardous. Li et al. (2015) showed that lower income neighborhoods contain less street greenery in Hartford, Connecticut. Higher mean NDVI values can be associated with vacant lots which are more likely to be seen in lower income neighborhoods. Projects to refurbish lower income neighborhoods are less likely to happen due to the financial risk involved in funding reforestation projects on the street view of neighborhoods. Higher income neighborhoods are more likely to appreciate reforestation projects. My study examines the parcel level rather than street greenery, but the parcel dataset used in my study contains streets in some sections.

5.5 Study Limitations

The limitations to this study are strongly influenced by the parcel dataset. The parcel dataset shows parcels located on the streets of neighborhoods or where parcels are split across census tracts. Neighborhoods can own streets located within their borders but the problem with streets labeled as residential and rural residential is that no people live on the street that are recorded in the census tract data. The parcel dataset skews the census tract data by causing an increase in the individual household socio-economic values located in each census tract. The parcel number reported in the disaggregation of census tract socioeconomic data is wrong due to the wrong number of parcels located in each census tract. Disaggregating census tract information down to the parcel scale brings error into the estimate of what is actually going on at the parcel level. The only way to fully understand the socioeconomic variables at the parcel scale is to conduct a survey at every single house in the study area and that is only doable if every single house is willing to provide personal information to a study. This is unfeasible as people are not willing to provide personal information for a study and there is a very large number of parcels in a city.

The redline district dataset is a major limitation as there is lack of spatial distribution throughout Oklahoma City. The redline district dataset is only located in the downtown region of the city. The spatial clustering of redline districts will cause bias in the results for redline spatial autocorrelation as only parcels located downtown will be associated with any type of redline factors. The redline district dataset is not normally distributed spatially throughout Oklahoma City, but the data in some sections did help show bio-physical variables that were present in each HOLC grade.

The land cover classification map presents some limitations to the study as NAIP has a very low temporal resolution of one, maybe two days every 2-3 years (depending on the state). Land cover classification training data should have one- or two-years' worth of data to examine the seasonal changes of the vegetation. Examining seasonal changes of vegetation can help with classifications by locating greening cycles. Greening cycles that show high NDVI throughout the year will show evergreen vegetation while multiple peaks and troughs of NDVI throughout the year will show types of crops. The lack of temporal resolution for NAIP can prevent the study from examining if there is significant land cover changes in pixels from image acquisition to image acquisition.

5.6 Future studies

In the future, I would like to research on urban greenness in Oklahoma City by examining a systematic study on ecological effects on urban green spaces without socioeconomic variables. Socioeconomic variables are important to understanding where UGS are spatially distributed. Ecological studies into what type of grasses and trees produce the best sustainable results may help UGS managers make informed decisions for water management in neighborhoods and cities. C_3 and C_4 grasses make a big difference in water consumption and landscape on parcels. Parcels that make proper use of vegetation on their property can produce a sustainable green environment.

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Chapter 6: Conclusion

This study provides a discussion of UGS parcels and the correlation to the socio-economic variables in the spatial extent of OKC. Oklahoma City has not had extensive research into the topic of UGS and there is a need for creating a sustainable UGS parcel. Bio-physical research is conducted on vegetation in OKC but bio-physical variables cannot encompass the full relationship of humans and UGS. Humans provide a significant impact on the physical environment we share with nature. Socio-economic variables can provide insight into the demographics that use UGS. Urban green spaces are beneficial for our environment, and our physical and mental health. Researching the spatial distribution of healthy UGS and the associated socio-economic variables can provide further insight into UGS.

The limitations of the study are strongly influenced by the parcel dataset. Census Tract data is not meant to be scaled down to the Census Block level as it loses accuracy in the survey data. Census data does a good job representing the community as a whole but to examine the differences of each household provides privacy issues. The bio-physical variables provide a source of error as NAIP imagery for this study is only available every other year during the growing season. Getting a mean value of vegetation with only the growing season of two years is not the best representation of parcel vegetation. Most studies do not examine the redline districts of cities. The dataset for redline districts do not encompass the entire study area extent. Redline districts are not measured out in rural areas causing the redline districts to be skewed to urban landscapes.

This study showed that there are the general same spatial greenness patterns across the OKC metropolitan area. The same spatial greenness patterns are that we notice neighborhoods located further from the central portion of OKC have a higher NDVI value in comparison to downtown neighborhoods. The spatial distribution of greenness across OKC can be positively related to median household income. We also notice that redline neighborhoods classified as hazardous (grade D) do present higher NDVI value compared to desirable neighborhoods (grade A). The redline information could show that grade D regions may have higher vacant lots or overgrown vegetation which could contribute to the higher NDVI values.

Future research into this subject can change the way we perceive UGS. Urban green space does not have to be large park or recreational areas. Urban green space on the parcel level can provide insight into how neighborhoods can create lower budget UGS. Research must look into the bio-physical variables that have an effect on ecological connectivity to enhance the research I have presented in this paper.

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