Estimating the Impacts of Changes in Wealth on the Physical Characteristics of Neighborhood Environments

**Abstract**

While remotely sensed data has been shown to be an effective tool in modeling housing prices where up-to-date and detailed administrative records are unavailable, little work has examined the change in regional wealth over time and its impacts on the physical environment. This study uses publicly available remotely sensed datasets measuring vegetation coverage and nighttime light, in conjunction with U.S. Census Bureau data, to examine the impacts of areal changes in wealth on the physical environment of urban landscapes. The analysis is intended to investigate changes in neighborhood wealth, and accordingly employs smaller geographic units (census tracts and county subdivisions) than previously used by similar research, while covering the entire United States. The results indicate no clear relationship between increases in wealth and changes in the physical environment measured by vegetation cover and nighttime light, both immediately and when incorporating temporal lags. The findings suggest an alternative causal mechanism for differences in the physical environments of neighborhoods. The methods developed here, employing time-series data to study changes in areal wealth and housing costs, demonstrate a promising new direction of research, which should expand the temporal and spatial scope of the analysis offered here.

**Introduction**

The spatial distribution of poverty in the United States, analyzed with GIS methods, has provided insight in relation to topics ranging from healthcare access and quality, to voter behavior, to food access (Hawthorne & Kwan, 2012; Knotts & Haspel, 2006;Naylor et. al., 2019). These geographic approaches to understanding inequality are critical to both understand spatial disparities and to begin addressing them: geographic analysis of inequality allows federal and state governments as well as charities and non-governmental organizations to specifically direct funding and aid (Hotchkiss & Phelan, 2017, p. 3, 8, 24).

However, in taking an extremely macro view of the impacts of wealth and spatial distributions, research in these areas often neglects perhaps the most critical impact of wealth and location: what the day-to-day life of the people being studied actually looks like. Research into poverty and home value generally provides little insight into the actual three-dimensional environments in which the research subjects exist. These physical characteristics of space in American urban environments are poorly understood in relation to the spatial distribution of wealth and income.

The clustering and isolation of wealth in upper-class neighborhoods is produced by the segregation of affluence and the clustering of low families in high density housing accommodations. Research shows that income inequality encourages high-income families to move far away from their lower-income counterparts, which, combined with historical practices of white flight and redlining, generates the extreme income segregation that we see today (Reardon & Bischoff, 2011; Mallach, 2024; Connolly et al., 2018).

The affluence of neighborhoods is not, however, inflexible. Processes of urban revitalization and business investment can improve the conditions and wealth of low-income neighborhoods. On the other hand, low-income residents can be harmed by gentrification and rising property values, rents, and taxes (Lees et al., 2008, p. 196). These changes in wealth also produce changes in the urban environment of neighborhoods – as they increase of decrease in wealth. Gentrification often involves the process of rebuilding or restoring old homes and buildings, updating and sometimes creating a distinct visual appearance of the area (Lees et. al., 2008, pp. 16-17).

Studies of gentrification typically focus on theoretically abstract or invisible factors, such as wealth, income, home value, race, and occupation. However, little existing reach focuses on the changing physical characteristics of neighborhoods in a systematic way. This gap in the literature opens questions about how changing wealth in an area, through processes like gentrification or desertion, impacts the physical environment that people live in.

The physical environment is an extremely important topic of research: while measures of income, wealth, and race supply important information about some aspects of inequality, they provide little information about the spatial realities of the subjects being studied. While some generalization can be made, knowing the changes in income of a specific census tract doesn’t provide any solid information about *what it’s like to live there*. This kind of contextual information and real-life relevance is the goal of my analysis here. Additionally, because case studies emphasize the relationship of phenomena like gentrification with changes to the physical environment, measures of those physical aspects may be able to assist in identifying areas undergoing changes in wealth and home value (Lees et. al., 2008, pp. 10-30).

These questions of experience of physical environments invites the use of remotely sensed data (i.e. data products of satellite sensors). Remote sensing directly offers data about physical environments of neighborhoods at a wide scale, without losing detail. Alternative methods of collecting information about physical environments, such as qualitative analysis or survey methods are restricted in their scope by expense, access, and time. While the “birds-eye-view” offered by remote sensing is hardly an accurate depiction of an individual’s perception of their urban environment, the data may offer important clues to patterns in changes of neighborhood environments.

**Literature Review**

Remote sensing and computer vision literature provide substantial evidence for relationships between spatial distributions of wealth and physical characteristics of the areas. A study in Lisbon, Portugal using remotely sensed data to produce vegetation indices found that proximity to urban forests and other green spaces corresponded to statistically significant increases in dwelling cost (Franco & Macdonald, 2018, pp. 164-169). The increase in dwelling cost was more pronounced for larger areas of vegetation, and for more densely green (as opposed to sparser) spaces (Franco & Macdonald, 2018, pp. 156, 168). This evidence suggests that access and exposure to green space is a desirable factor in individuals’ decisions about where to live.

Additional research examining Wuhan, China, finds that physical characteristics, like vegetation coverage and thermal heat islands, produce significant impacts on the housing prices. The research uses remotely sensed Landsat data to quantify negative physical environmental factors (high heat and low vegetation coverage). This data, compared with housing price data, provides strong evidence for the spatial impacts of physical “urban disservices” on wealth distribution, but does not examine changes to housing costs over time (Jiao et al., 2017, pp. 28-31). Similar analysis from Shanghai modeling housing prices with urban environmental characteristics support these findings, demonstrating regional positive impacts on home price from vegetation cover and proximity to bodies of water (Chen et al., 2020, pp. 17-23).

Non-remote sensing approaches likewise provide evidence for the impacts of local environmental factors. Analysis of Google Street View images with neural networks to extract visual features incorporates human-level perception of physical characteristics at an extremely local level. This analysis draws in remotely sensed data to produce more accurate housing price models in the London area. The authors find that Google Street View images provide significant predictive ability in estimating housing prices, suggesting that approaches to wealth assessment using physical characteristics of neighborhood environments may be a fruitful approach (Law et. al., 2019, pp. 2-5, 7-8).

Nighttime lights has also been used as an indicator of areal wealth. Using capital cities of Chinese provinces, Li et al. predict housing prices at the city-scale using existing remotely sensed time-series nighttime light (NTL) data to estimate NTL values for more recent years. These estimated NTL values are found to be predictive of housing prices, aggregated by city (Li et al., 2020, pp. 8, 10-18). This study employs an extremely large scale: the smallest city examined covers 6988 square kilometers, but provides support for the use of NTL as an indicator of physical environments with a connection to housing and wealth (Li et al., 2020, p. 8).

Other remote sensing measures, including Normalized Difference Built-up Index and the Built-Up Index are used in research employing Landsat data to estimate urbanization and its impact on housing prices. Urbanization is demonstrated to have a positive effect on housing prices at the district level (Long & Trung-Kien, 2024, p. 1). In general, existing remote sensing research employing physical environmental characteristics perform analysis on a large scale, providing no insights into neighborhood-level patterns. Additionally, the limited use of temporal data across the literature prevents causal analysis of changes to housing prices, a major gap in the literature, and an opportunity for further research.

**Methods**

In order to identify any relationships between neighborhood changes in wealth and subsequent changes to the physical environment, I required satellite and demographic/income data over a large period of time. While simply isolating relationships between physical characteristics and areal wealth can be done with a single time slice, measuring changes over time requires a greater temporal scope, and much more involved analysis.

In the sections that follow, I first discuss the operationalization of the variables used in this study, then explain the process of scope and case selection, before turning to the sources of data that I used. Finally, I provide a narrative of the analysis operations that I performed and provide replication code.

*Operationalization*

The independent variable is the level of wealth in a given neighborhood. The best source of current and historical data demographic and housing information comes from the U.S. Census Bureau, which offers Decennial Census data and American Community Survey Data aggregated for areas ranging in size from the block-group level to the entire nation.

Research suggests that gentrification is more accurately measured by changing home values than changing income (Bunten et al., 2024, pp. 20, 34-36). This paper assumes that other types of neighborhood change can also be measured by changing home values with some level of accuracy, in addition to measures of income change.

The dependent variable is specified as the change in physical environments. I chose two measures of physical environments: greenness/vegetation and nighttime lights. These two measures were chosen due to the accessibility of data and the correspondence to real-world experiences of urban environments.

Specifically, vegetation was measured using the Normalized Difference Vegetation Index (NDVI), a calculated index that quantifies the presence of healthy vegetation. The NDVI measures the “red edge,” or the strong increase in reflectance of healthy, photosynthesizing vegetation in the near-infrared portion of the electromagnetic spectrum between 700 and 800 nm. Values of NDVI range from -1 to 1, where 1 is the maximum, 0 represents a pixel without vegetation, and a negative value represents no dry land. Values for NDVI are calculated as follows:

(Huang et al., 2021, pp. 1-3)

Nighttime Lights (NTL) data measures the amount of light visible in each pixel, often algorithmically altered to remove unneeded and unwanted contamination by solar and lunar reflectance. As such, NTL data is intended to show the amount of light produced by humans. Nighttime Light is not a measure of reflectance or emissivity (Elvidge et al., 2021, pp. 1-2, 4).

*Demographic Data*

Demographic variables representing Median Gross Rent, Average Home Value, and Median Household Income were extracted to determine change in neighborhoods. The American Community Survey (ACS) began data collection in 2007, and aggregate data products at the Census Tract level are only available beginning in 2010, so Decennial Census data was used for income and wealth data prior to 2010.

American Community Survey data was extracted from the U.S. Census Bureaus (USCB) ACS Application Programming Interface (API), using the R package “tidycensus” to query estimate values and geography information. Decennial data the 2000 Census was also drawn from the UCSB API with “tidycensus,” but the Census Bureau does not currently support API requests prior to 2000. Census data for 1990 was downloaded from the National Historical Geographic Information System, created by the Institute for Social Research and Data Innovation at the University of Minnesota.

The values were extracted at both the census tract and county subdivision level of geographies. The lower spatial resolution of the available NTL data (~500m) required a larger geography than census tracts to successfully find an average value within the geography’s boundaries. County subdivisions were sufficiently large to perform the averaging reducing function on the NTL data, so the corresponding level of demographic data was needed to perform the analysis.

Demographic data was drawn for the following years: 1990, 2000, 2010, 2012, 2017, and 2022. The 2012 through 2022 data allowed for 5-year gaps of comparison, mirroring the 5-year aggregation of ACS data, and providing a time span roughly equivalent to the operating history of the sensor supplying nighttime light data. No demographic data was extracted prior to 1990, due to diminishing quality of remotely sensed data, and 2000 and 2010 were selected as additional years to provide even spacing of observations leading up to the first available ACS 5-year dataset in 2010.

See Appendix A for a table of the exact variable names and their sources.

*Remotely Sensed Data Sources*

All remotely sensed data employed in this project was extracted and aggregated with Google Earth Engine (GEE), using publicly available datasets. Data was drawn for all geographies of the United States, excluding territories.

Vegetation data was extracted from 32-Day NDVI composites of Landsat data produced by the United States Geological Survey and provided by Google (United States Geological Survey, 2024). The composites are each constructed from orthorectified, reflectance-calibrated Tier 1 Level 2 scenes. For the time period selected, NDVI composites included data from Landsat 7’s Enhanced Thematic Mapper Plus (Bands 3 and 4 at 630-690 and 770-900 nm respectively), and Landsat 8’s Operational Land Imager (Bands 4 and 5 at 640-670 and 850-880 nm respectively). The relevant Landsat 7 and 8 bands operate at a spatial resolution of 30 meters, and a temporal resolution of 16 days, theoretically providing two images covering each pixel for each composite image (*Landsat Band Designations*, n.d.). The spatial resolution was sufficiently high to allow aggregation of NDVI within census tracts.

Images for NDVI were only collected during the growing season for all years to maximize consistency between observations. The growing season was roughly defined as May through August, which allowed three NDVI composites to be aggregated for each growing season. The first 32-Day composite of each year began on May 8, and the last of each year ended on August 11.

To minimize the impacts of yearly variation irrelevant to the relationship of study, NDVI composites of the growing season were also collected from the year before and after each year of study, providing a collection of 9 images for each target year, with 3 composites per year over the 3 year span. Reduced images calculated by the median value of each pixel from these selections. This process served to reduce the number of masked pixels due to cloud cover, minimize the impacts of yearly growth variation, and provide data across the entire growing season.

The collection of images for 1990 was broadened to use data from 2 years before and after the target year, due to large numbers of missing pixels. Accordingly, the corresponding calculated 1990 image includes data from 15 images across 5 years.

Nighttime Light composite images were drawn from data products of the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB). The DNB provides high sensitivity in low-light situations, and allows for the production of science-quality data products of the earth at night (NASA VIIRS Land Science Investigator-Led Processing System, 2019). The DNB images light from 500-900 nm at a spatial resolution of roughly 500 meters at the equator, providing daily imagery of the entire earth (NASA VIIRS Land Science Investigator-Led Processing System, 2019. The lower spatial resolution of VIIRS DNB data required larger geographies to allow meaningful aggregation: county subdivision were used rather than census tracts.

Yearly NTL average cloud free composites with algorithmic filtering of sunlight and moonlight were selected to measure nighttime light. The composite images were provided by the Earth Observation Group, the Payne Institute for Public Policy, and the Colorado School of Mines (Elvidge et al., 2021). Annual composites were chosen to minimize the impact of cloud cover and potential seasonal variation in nighttime lighting.

Although the DNB sensor launched in 2012, annual composites from the selected dataset are only available beginning in 2013. As such, the 2013 NTL composite is used for all analyses of 2012 in this paper.

*Geographic Data*

Simplified shapefiles for all relevant geographies (entire U.S., census tracts, and county subdivisions) were downloaded from the USCB’s Tiger/Line dataset using the “tidycensus” package. These shapefiles were both for the visualization of data, and for the geographic aggregation of remotely sensed data. All shapefiles and geographies were extracted from 2022 data only.

*Analysis Operations*

Shapefiles for the entire U.S., all U.S. census tracts, and all U.S. county subdivisions were uploaded to GEE. Remotely sensed data was imported and composite images of NDVI data were produced as previously described. The images were clipped to the U.S. boundary shapefile to avoid including unnecessary data and lengthening processing times. A reducer function was used for each NTL and NDVI image to find the median value for each selected year within each geography (census tracts for NDVI and county subdivisions for NTL). The median was selected to limit the impact of outliers on the values assigned to each census geography. The aggregated data was then exported as a CSV for each image.

The downloaded data was then imported into R, and rejoined to the demographic and geographic datasets by the census geography identifier (FIPS code). Demographic data for Income, Home Value, and Rent were adjusted for inflation to 2022 dollars. The change in NDVI, NTL, Median Household Income, Average Home Value, and Median Gross Rent in each geography for each observation year to the closest previous observation was then calculated, and normalized by the time gap between observations. The percent change between observation normalized by length of time gap was also calculated for each variable in each geography.

The analysis largely consisted of a visual analysis of scatter plots comparing variables and the use of correlation matrices. Primarily, the percent change in Average Home Value, Median Gross Rent, and Household Income was plotted against the percent change in NDVI and NTL for each year-geography combination. Scatter plots were also constructed for percent change in NDVI and NTL against the percent change in wealth measures from first the previous observation and subsequently the observation preceding the previous. This analysis roughly produced a temporal lag, to allow for impacts taking place over a longer period of time.

Linear models were also constructed for each variable in each geography across the entire time period, in order to determine whether overall trends of change aligned between the economic and physical variables. The slopes of the variables were analyzed with a correlation matrix.

To further isolate possible areas of correlation, similar analyses were performed after filtering for combinations of degree of economic change and urbanity. Finally, maps of selected cities were produced for change in economic variables compared to physical variables, employing visual analysis to potentially detect similar spatial patterns between variables.

**Results**

Primary analysis involved constructing correlation matrices for the relationships between economic variables and NDVI and NTL. These correlations were produced for both percent change and raw change. Each value indicates the Pearson Correlation Coefficient between two variables on a scale from -1 to 1, where the sign indicates the direction of the relationship, and the value describes the strength of correlation. No number indicates a p-value of greater than 0.05.

The relevant values (i.e. comparisons between the measure of physical change and the economic variables) fall within the black rectangle. Correlations between physical and economic changes in the same year ranges are in blue squares, while red squares contain correlations between physical change and economic change from the previous observation. This provides a rough temporally lagged analysis: although the time between observations is inconsistent, the offset comparisons allow for an estimate of the influence of time. The yellow squares similarly provide correlations using economic change from observations two prior to the physical change observations. Figures 1 and 2 show the correlation matrices for NDVI and NTL using percent change for all variables.

*Figure 1: Correlation Matrix for NDVI versus Economic Data, using Percent Change*

A diagram of a grid with squares and letters

Description automatically generated with medium confidence

*Figure 2: Correlation matrix for NTL versus Economic Data, using Percent Change*

A screenshot of a game

Description automatically generated

No highly correlated variable relationships were found in among the studied variable interaction in any of the percent change or raw change correlation matrices. There was likewise no apparent difference between the temporally lagged comparisons and the unlagged correlations. To better interpret the correlation coefficients produced, the most correlated relevant variable combination for NDVI and NTL, and for both percent change and raw change, were plotted. Figures 3 and 4 show distributions of data between those relevant data pairs, modelling the change in physical attribute by the economic change.

*Figure 3: Scatter Plot for NDVI Changes most Correlated with an Economic Variable, using Percent Change*

A black and white image of a cloud

Description automatically generated with medium confidence

*Figure 4: Scatter Plot for NTL Changes most Correlated with an Economic Variable, using Percent Change*

A black circle with a white background

Description automatically generated with medium confidence

The scatter plots largely produce a star-pattern, with tract extremes extending out nearer to the x- and y-intercepts. These patternings reflect randomly correlated normal distributions.

Similar correlations were run on limited subsets of the data. This analysis subset the data in multiple ways: by only including inter-observation changes over 10%, and only including urban geographies (defined as tracts within a Core Based Statistical Area). No significantly different results were identified.

Maps of select urban areas were also produced, comparing change in NDVI between 2012 and 2017 to Average Home Value Change between 2000 and 2010. This case was chosen due to the relatively high correlation coefficient among the relevant variable relationships, in order to isolate any potential spatial similarities in economic and physical changes. Figures 5 and 6 show two comparison maps, one of Richmond, Virginia, and one of Chicago, Illinois.

*Figure 5: Map of Richmond, Virginia, Comparing Change in NDVI 2012-2017 to Change in Average Home Value 2000-2010*

A map of a city

Description automatically generated

*Figure 6: Map of Chicago, Illinois, Comparing Change in NDVI 2012-2017 to Change in Average Home Value 2000-2010*

A map of different colored squares

Description automatically generated

While some clustering is evident in both Chicago and Richmond across changes in home value and changes in NDVI, there appears to be no similarities to the patterns between variables. The maps provide little evidence to suggest that the lack of correlation established in previous analyses neglects a spatial component, or that a relationship between NDVI and home values exists but only within certain types of geographies.

**Discussion**

The analysis finds no apparent connection between changes in wealth in an area and subsequent changes to the physical environment, as measured with satellite data of nighttime lights and vegetation. While existing research finds significant evidence that areas with higher housing costs tend to be greener and produce more light at night, this research provides new insight into how those relationships change over time in sub-city areas such as neighborhoods. The lack of relationship between changes in the physical environment and changes in wealth have a few possible explanations.

1. Changes in wealth in an area do not cause measurable (with remote sensing techniques) changes to the physical environment.

It is possible that static (i.e. time-slice) relationships between vegetation and wealth in an area are not the result of any particular action on the part of wealthy individuals, but rather that wealthy areas are greener because they historically have been greener. If this is the case, we would expect to find that the relationship between greenness and wealth slowly becomes weaker over time, as wealth becomes more spatially distributed through processes like gentrification. Another possibility is that any changes to the physical environment are not measurable by remote sensing: gentrification typically occurs in already built-up areas, and usually involves renovation and restoration rather than rebuilding, processes which are largely invisible to remote sensing. Repainting the exterior of a house, for example, is a physical change that would be invisible to satellite sensors. Alternative physical impacts to those hypothesized and studied here may occur, and would likely require alternative methods to quantify.

1. Suburban development offsets any greening effect.

The methodology failed to account for different types or circumstances of changes in wealth. Suburban development in previously forested areas would likely result in a decrease of NDVI in affected tracts, while urban wealth increases may have no impact or cause the opposite. One type of wealth increase may offset the impacts of the other. While the visual analysis of maps of urban areas did not support this conclusion, a more systematic analysis, using Census Bureau data for housing type and quantity could explore different types of development.

1. Changes to the physical environment may exceed the temporal scope of this research.

The time scope of this research was dictated by the availability of high-quality demographic information and satellite imagery. Remotely Sensed data is limited by the lifespan and historical launch date of sensors, and so longer-reaching studies may only be possible in the future.

Additionally, comparing demographic data at a large scale (e.g. the census tract level), is challenging over larger stretches of time due to the continual addition of census geographies and shifting borders. Unfortunately, no level of aggregation with consistent boundaries appears to exist for which the U.S. Census Bureau reliably publishes demographic data.

1. Changes to the physical environment may exceed the spatial scope of this research.

A final explanation is that the hypothesized changes in the physical environment following changes in wealth only happen at a smaller geographic scale. Existing research finds patterns of physical characteristics generally at the city or district level. Census tracts as a proxy for neighborhoods may simply be too granular, and too subject to other unknown variables impacting greenness and nighttime light to demonstrate any pattern.

It is also possible that the research design simply failed to capture any relationship between changes in wealth and changes in physical characteristics of neighborhoods and other sub-city areas. Census Bureau boundaries likely change in response to changes in population. Because comparisons in this research could only be done for each year of observation within the common set of existing tracts, tracts that experienced demographic shifts could have been systematically excluded from the analysis. It is possible that because of this, any existing pattern is simply invisible to highly localized and evolving Census Bureau geographies. Additionally, all satellite data were aggregated using the 2022 census tract and county subdivision geographies, which don’t represent the exact same geographies in previous years. Further research should use year-specific geographies aligned with the remotely sensed data to calculate more representative values for the physical environment.

In all, this research indicates that changes to wealth in an area do not consistently or significantly cause changes in measurable physical characteristics at the neighborhood level, as measured with a vegetation index and by light emission at night. The lack of relationship makes those physical characteristics a poor candidate for modelling or predicting patterns in housing costs or identifying gentrification at the very localized levels studied here. Further research should expand the methods employed here to wider geographic areas in order to determine if a more general pattern exists. Additionally, other methods to measure wealth in an area should be explored, including classification of Google Street View image pixels to provide a more “human,” ground-level approach. While providing no evidence for concrete relationships, the methods employed here suggest that the relationships between wealth and physical environments in urban landscapes are more complex than suggested by the existing literature.

**References**

Bunten, D. M., Preis, B., & Aron-Dine, S. (2024). Re-measuring gentrification. *Urban Studies*, *61*(1), 20–39. <https://doi.org/10.1177/00420980231173846>

Chen, L., Yao, X., Liu, Y., Zhu, Y., Chen, W., Zhao, X., & Chi, T. (2020). Measuring Impacts of Urban Environmental Elements on Housing Prices Based on Multisource Data—A Case Study of Shanghai, China. *ISPRS International Journal of Geo-Information*, *9*(2), Article 2. <https://doi.org/10.3390/ijgi9020106>

Connolly, N. D. B., Winling, L., Nelson, R. K., & Marciano, R. (2018). Mapping inequality: ‘Big data’ meets social history in the story of redlining. In *The Routledge Companion to Spatial History*. Routledge.

Elvidge, C. D., Zhizhin, M., Ghosh, T., Hsu, F.-C., & Taneja, J. (2021). Annual Time Series of Global VIIRS Nighttime Lights Derived from Monthly Averages: 2012 to 2019. *Remote Sensing*, *13*(5), 922. <https://doi.org/10.3390/rs13050922>

Franco, S. F., & Macdonald, J. L. (2018). Measurement and valuation of urban greenness: Remote sensing and hedonic applications to Lisbon, Portugal. *Regional Science and Urban Economics*, *72*, 156–180. <https://doi.org/10.1016/j.regsciurbeco.2017.03.002>

Hawthorne, T. L., & Kwan, M.-P. (2012). Using GIS and perceived distance to understand the unequal geographies of healthcare in lower-income urban neighbourhoods. *The Geographical Journal*, *178*(1), 18–30.

Hotchkiss, M., & Phelan, J. (2017). *Uses of Census Bureau Data in Federal Funds Distribution: A New Design for the 21st Century* [Working Paper]. U.S. Census Bureau. <https://www2.census.gov/programs-surveys/decennial/2020/program-management/working-papers/Uses-of-Census-Bureau-Data-in-Federal-Funds-Distribution.pdf>

Huang, S., Tang, L., Hupy, J. P., Wang, Y., & Shao, G. (2021). A commentary review on the use of normalized difference vegetation index (NDVI) in the era of popular remote sensing. *Journal of Forestry Research*, *32*(1), 1–6. <https://doi.org/10.1007/s11676-020-01155-1>

Jiao, L., Xu, G., Jin, J., Dong, T., Liu, J., Wu, Y., & Zhang, B. (2017). Remotely sensed urban environmental indices and their economic implications. *Habitat International*, *67*, 22–32. <https://doi.org/10.1016/j.habitatint.2017.06.012>

Knotts, H. G., & Haspel, M. (2006). The Impact of Gentrification on Voter Turnout. *Social Science Quarterly*, *87*(1), 110–121.

Law, S., Paige, B., & Russell, C. (2019). Take a Look Around: Using Street View and Satellite Images to Estimate House Prices. *ACM Transactions on Intelligent Systems and Technology*, *10*(5), 1–19. <https://doi.org/10.1145/3342240>

Lees, L., Slater, T., & Wyly, E. (2008). *Gentrification* (1st ed.). Routledge. <https://doi.org/10.4324/9780203940877>

Li, C., Zhu, H., Ye, X., Jiang, C., Dong, J., Wang, D., & Wu, Y. (2020). Study on Average Housing Prices in the Inland Capital Cities of China by Night-time Light Remote Sensing and Official Statistics Data. *Scientific Reports*, *10*(1), 7732. <https://doi.org/10.1038/s41598-020-64506-2>

Long, H., & Trung-Kien, P. (2024). Does urbanization drive up housing prices? Novel evidence from remote sensing and dynamic panel quantile regression. *International Journal of Housing Markets and Analysis*. <https://doi.org/10.1108/IJHMA-06-2024-0081>

Mallach, A. (2024). Shifting the Redlining Paradigm: The Home Owners’ Loan Corporation Maps and the Construction of Urban Racial Inequality. *Housing Policy Debate*, *34*(6), 891–917. <https://doi.org/10.1080/10511482.2024.2321226>

NASA VIIRS Land Science Investigator-Led Processing System. (2019). *VIIRS/NPP Daily Gridded Day Night Band 500m Linear Lat Lon Grid Night* [Dataset]. NASA Level 1 and Atmosphere Archive and Distribution System Distributed Active Archive Center. <https://doi.org/10.5067/VIIRS/VNP46A1.001>

Naylor, K. B., Tootoo, J., Yakusheva, O., Shipman, S. A., Bynum, J. P. W., & Davis, M. A. (2019). Geographic variation in spatial accessibility of U.S. healthcare providers. *PLoS One*, *14*(4), e0215016. <https://doi.org/10.1371/journal.pone.0215016>

Reardon, S. F., & Bischoff, K. (2011). Income Inequality and Income Segregation. *American Journal of Sociology*, *116*(4), 1092–1153. <https://doi.org/10.1086/657114>

United States Geological Survey. (2024). *Landsat Collection 2 Tier 1 Level 2 Annual NDVI Composite* (ImageCollection LANDSAT/COMPOSITES/C02/T1\_L2\_ANNUAL\_NDVI). Google Earth Engine. <https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_COMPOSITES_C02_T1_L2_ANNUAL_NDVI>

*What are the band designations for the Landsat satellites? U.S. Geological Survey*. (n.d.). Retrieved December 10, 2024, from <https://www.usgs.gov/faqs/what-are-band-designations-landsat-satellites>.

**Appendix**

*Appendix A: Variable Names and Sources of Demographic/Economic Data*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Data Type** | Decennial Census | | 5-Year American Community Survey | | | |
| **Source** | IPUMS | “tidycensus” R package | | | | |
| **Year** | 1990 | 2000 | 2010 | 2012 | 2017 | 2022 |
| **Median Gross Rent** | *EYU001* | *H063001* | *B25064\_001* | | | |
| **Average Home Value** | *EST001* | *H085001* | *B25077\_001* | | | |
| **Median Household Income** | *E4U001* | *P053001* | *B19013\_001* | | | |