Urban vegetation and demographics in Denver: A story of equitable distribution of green space

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Introduction

Urban greenness can be associated with better hydrological processes, such as infiltration and water recharge, as well as better human health and wellbeing (Keeler et al., 2019). We consider urban greenness to include parks, urban forests, and privately owned green spaces like lawns, etc. In urban environments, remote sensing technology has become an increasingly useful as a way to monitor urban vegetation (Jensen et al., 2007). Greenness indices like Normalized Difference Vegetation Index (NDVI) can be calculated using Landsat satellite imagery and used to asses greenness trends over time.

Decreasing greenness can be an indicator of increased impervious surfaces. Over the past two decades, Denver has experienced significant infill redevelopment, which creates increased impervious surfaces despite being a more efficient use of land in urban environments. As reported by the Fourth National Climate Assessment, the southwest United States is expected to experience increasing downpours, which when compounded with more impervious surfaces will put pressure on deteriorating storm water infrastructure (Maxwell et al., 2018).

This research identifies the relationships between urban vegetation and demographic data to understand how these factors are interrelated. We examine demographic factors that may influence change in urban greenness such as median income, percent poverty, and education attainment levels. Understanding the relationships between these factors may shed light on the inequalities associated with distribution of green spaces. Nature or urban greenness based solutions can mitigate issues like air quality and urban heat mitigation which can affect human health and wellbeing (Keeler et al., 2019). It is important to recognize these inequalities in order to promote favorable living conditions for all demographics residing in urban areas.

Methods

Demographic data were gathered from the American Community Survey (ACS) via American FactFinder for 2012 and 2017 for zip code tabulation areas in Denver (U.S. Census Bureau, 2012 & 2017). We selected median household income, percent below poverty, and percent with a Bachelor's degree or higher. Using percent below poverty and percent with a Bachelor's or higher, we used linear regression to identify the relationship between these two demographics. From this regression, three zip codes were selected for a more detailed analysis. Each zip code represents different socio-demographic samples: high poverty and low education, low poverty and high education, and an intermediate between the two demographic extremes.

To investigate urban greenness, we analyzed NDVI, percent tree canopy, and percent park area by zip code. The mean of the maximum composite NDVI was calculated using Landsat 5, 7, and 8 imagery as the normalized difference between the near infrared and red bands. The values for Landsat 5 and 8 were converted to the Landsat 7 equivalent using a linear transformation (Su et al., 2017). These values were then evaluated for anthropogenic or climatic influence using precipitation data gathered from the Parameter-Elevation Regression on Independent Slopes Model (PRISM) and using Residual Trend analysis (RESTREND) (PRISM Climate Group, 2019). In RESTREND, observed NDVI values and annual precipitation are regressed to calculate predicted NDVI and corresponding residuals (Neel, 2017). By removing climatic influence from our NDVI results, we can assess whether changes in NDVI over time are due to climatic or anthropogenic influences. A negative trend suggests that change in NDVI is due to human degradation, a positive trend suggests positive anthropogenic influence, and no trend suggests that any changes in NDVI are due to inter-annual variations in precipitation. RESTREND was applied from 2001 to 2015 to identify anthropologically-induced significant trends in greenness in the three zip codes representing variations in socio-demographics.

Percent tree canopy was calculated using shapefiles generated by NCDC Imaging of Colorado Springs and maintained by the City and County of Denver Technology Services (NCDC Imaging, 2018). Percent tree canopy was found for each of the zip codes in Denver using QGIS. This same process was also applied to find the percent park area by zip code using Denver parks shapefiles generated by Denver Parks and Recreation (Denver Parks and Recreation, 2019). We then used linear regression to determine the relationship between our urban greenness characteristics (NDVI, percent tree canopy, and percent park area) and the three demographics. Zip codes which did not fully fall within the Denver city limits were excluded from the percent park and tree canopy analysis because the data were incomplete in these areas.

Results

All of the zip codes picked for further greenness analysis had significant results for change in NDVI over the time sample (not shown). Only one of the representative zip codes had a significant relationship for residuals over time, with a p-value less than 0.05. In the intermediate zip code, residual analysis showed an increasing trend from 2001 to 2015 (Figure 1b). This suggests that a change in NDVI can be attributed to non-climatic enhancement. In this case, historical Landsat images identified a golf course present in the zip code that may be experiencing increases in irrigation. The low poverty, high education zip code results suggest that any change in NDVI is due to climatic influence (Figure 1a; p=0.01). The results for the high poverty, low education zip code are also not significant (Figure 1c; p=1.00).

Figure 1a.

80209, Low Poverty, High Education

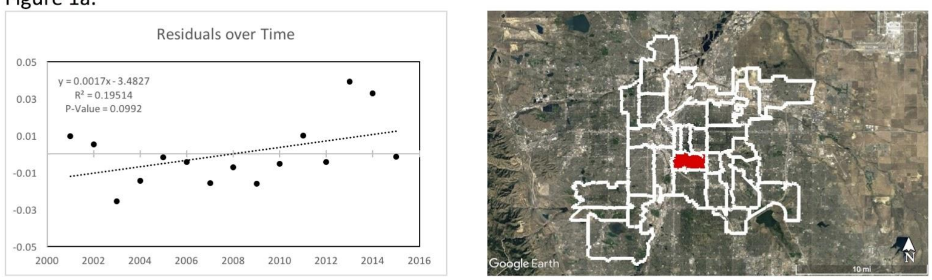

Figure 1b.

80231, Intermediate

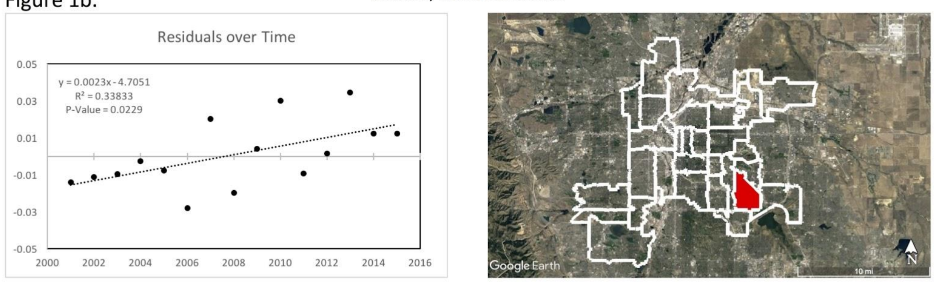

Figure 1c.

80239, High Poverty, Low Education

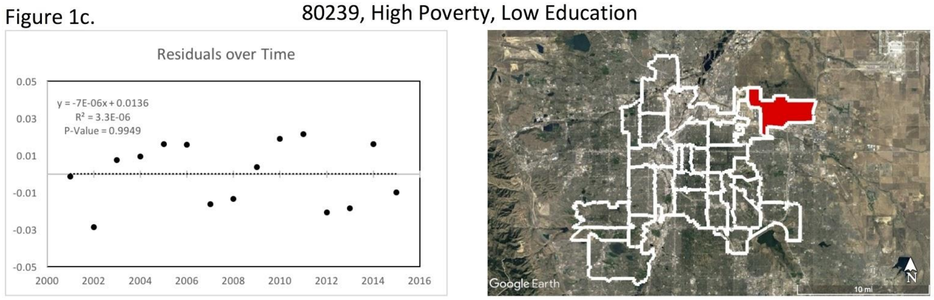

Figure 1a-c. Residuals over time and spatial plot showing location of zip codes

The relationships between (a) percent tree canopy cover and median income and (b) percent tree canopy cover and percent below poverty were not significant (p>0.05; not shown). The relationship between percent tree canopy cover and NDVI was significant (p=.01 not shown). The NDVI calculations include the influences of the tree canopy. The relationship between the percent tree canopy and NDVI serves to validate the percent tree canopy layer. NDVI also had a significant inverse relationship with the percent below poverty demographic (Figure 2). Percent park area only displayed a significant relationship with the median income demographic (Figure 3). This suggests that zip codes with higher median income have greater park areas.

Conclusion

The results show a distinct relationship between demographic data and the distribution of green spaces in Denver. Greenness, measured by NDVI and percent park area, is found more often in Denver zip codes whose residents are more economically secure. These results are indicative of inequalities in the distribution of urban vegetation. As cities continue to grow, it is important to identify these inequalities in order to better plan for the future and ensure all communities are able to have access to green spaces. Incorporating urban green space is important to ensure urban development promotes healthy, sustainable cities.

Further research will look into other demographic factors or metrics that could be influencing urban greenness, such as age and change in median income over time. Looking at census blocks rather than zip code tabulation areas could decrease some of the heterogeneity we could be seeing in our demographic data and clarify relationships not identified as significant in these analyses. More work should be done to identify the factors that are influencing the decreased amount of greenness we see in less economically secure areas. Finally, future work should utilize thermal remote sensing to examine the effect of trees and greenness on urban heat island, which bears importance for human health, especially in less affluent communities.

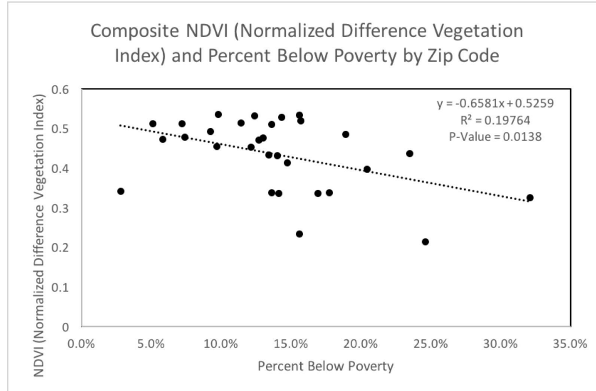

Figure 2. Composite NDVI and Percent Below Poverty by Zip Code.

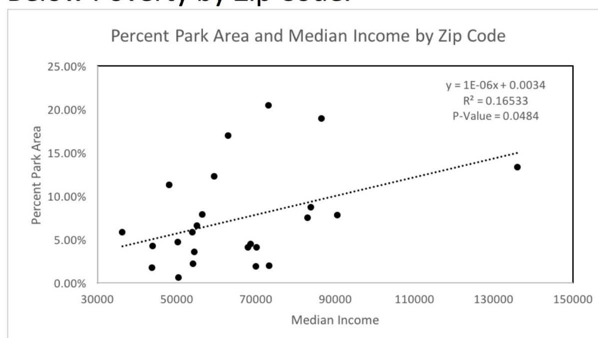

Figure 3. Percent Park Area and Median Income by Zip Code.

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