Quantifying Urban Greenness in Madison, Wisconsin

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Abstract

Urban green space has numerous health-promoting benefits for city residents. Parks and other large open green spaces encourage recreation and physical activity, which has been shown to improve both physical and mental health. Other types of vegetation, such as trees planted throughout a city, contribute significantly to reducing the urban heat island effect and cooling urban areas during hot periods. There is an existing body of work dedicated to assessing the number and distribution of parks throughout cities across the United States, but less work has been done to quantify the overall greenness of cities. The present analysis quantifies the amount of green space – parks, trees, shrubs, and other green vegetation – in the city of Madison, Wisconsin.

Keywords: parks, vegetation, urban green space, quantifying greenness

Introduction

Access to outdoor green spaces has myriad benefits, including improving individuals' physical, mental, and social health. Simply spending time in nature has been shown to reduce stress and improve measures such as blood pressure and cholesterol. Outdoor recreation typically involves some type of physical activity, commonly walking. Walking has many health benefits, particularly for older adults, such as decreasing weight, lowering the risk of stroke, and improving sleep, among many others. Spending time in nature has also been shown to provide many benefits to children, including encouraging physical activity, which helps reduce rates of childhood obesity (Godbey 2009). Nature can also improve psychological health and lead to an increase in positive emotions. Some researchers have even suggested that viewing outdoor scenes can restore diminished attentional capacity (Hartig et al. 2011). Finally, time spent in nature has been shown to lead to more prosocial behaviors and a higher sense of connectedness (Passmore & Holder 2017).

Aside from the benefits of green spaces on individual health and wellbeing, the presence of vegetation in urban areas also has an effect on the physical landscape. Cities without much green vegetation are prone to a phenomenon called the urban heat island (UHI) effect. The UHI effect is well-documented in major urban areas. Heat is released from sources such as vehicles, power plants, and air conditioners; that heat is then stored and re-radiated by urban structures made from concrete or asphalt (Memon et al. 2008). The presence of vegetation has been shown to have a cooling effect in urban areas. Susca et al. (2011) found that highly vegetated areas in New York City were an average of 2°C cooler than areas with little green vegetation.

Despite the many benefits of green space and public lands for individual and community health, access to these spaces is highly variable across the United States. Multiple studies have demonstrated that youth from low-income and minority demographic groups have limited access to green areas and trails (Frumkin 2005, Hood 2005). Neighborhoods that serve predominantly lower income or minority demographic groups also have reduced access to parks than white neighborhoods (Wolch et al. 2002). Because access to urban green space is widely recognized as an important component of health, multiple resources exist to rank cities based on the amount and distribution of urban green areas. One such website is ParkScore, which ranks cities based on the number of parks, where parks are located with respect to different community groups, and the amenities present in parks (Trust for Public Land n.d.).

The existence of parks is an important component of how "green" a particular city is, but sites like ParkScore typically do not account for the presence of trees and other vegetation throughout urban areas outside of parks. Green vegetation outside of parks plays a different but equally important role in creating a healthy environment for a city's residents. The present analysis aims to quantify the total amount of greenness in Madison, WI – this measure includes parks, trees, lawns, shrubbery, and other vegetation. Additionally, a regression model was created to allow urban green space to be estimated for years without NAIP imagery available over Madison. NAIP imagery is generally collected once every three years for a given location; the regression model created by this work allows for a more thorough and consistent understanding of the distribution of urban green space across a city.

Study Area

The city of Madison is located in south-central Wisconsin in the Midwestern United States at latitude 43° 4' 22.9836" N and longitude 89° 24' 4.4280" W. The city covers approximately 54,273.7 acres.

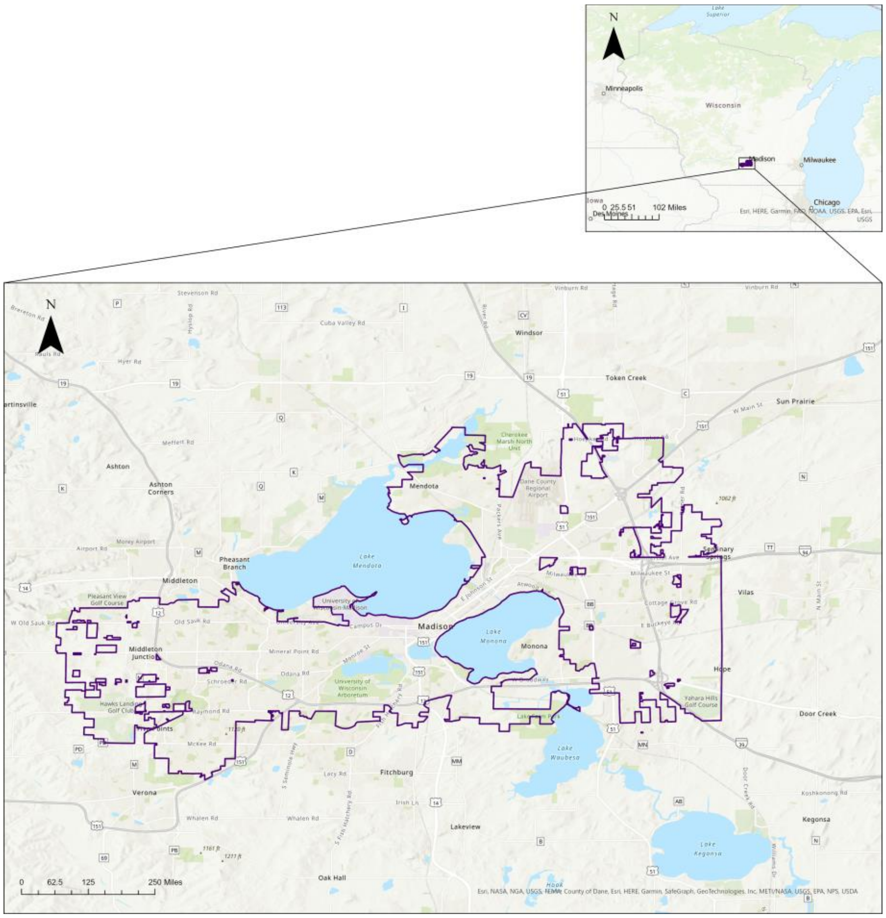

Figure 1. Madison city limits.

Methods

Data

The remotely sensed images used in this analysis were collected from several sources. Aerial imagery of Madison from the summer of 2020 was acquired by the National Agriculture Imagery Program (NAIP), while data on land cover was obtained through the Multi-Resolution

Land Characteristics Consortium's (MRLC) National Land Cover Database (NLCD) collection. Images from Landsat 8 (Operational Land Imager) were also used. All images used in this analysis were obtained through the Google Earth Engine Data Catalog (Gorelick et al. 2017). The shapefile containing the boundary lines for the city of Madison was obtained from the city's open data hub (City of Madison n.d.).

Software

This analysis was primarily conducted in Python, predominantly utilizing the gdal and rasterio packages. All Python code used in the analysis can be accessed from the following Google Colaboratory workbook: https://colab.research.google.com/drive/1vwH-e4TrqCtyxjH9wqseoIMtbEbF6u5E?usp=sharing. Image collection, filtering, and export was done using Google Earth Engine's JavaScript code editor (Gorelick et al. 2017). The Google Earth Engine code can be accessed with the following link: https://code.earthengine.google.com/26cbb32615ef3b756683ab4cbcfa3225. Additional processing of the boundary area shapefiles and supplementary maps were completed using ArcGIS Pro 3.0.0.

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Image pre-processing

Pre-processing was conducted only for the Landsat images. After the Landsat images were retrieved for the date range of interest, a cloud mask was applied to remove pixels identified as containing clouds and cloud shadows by the QA_PIXEL band of the image. A scaling factor was then applied to extract the actual surface reflectance values from the image. After this processing, a cloud-free composite for the period of interest (summer 2020) was created for the study area using a median reducer.

Classification

The NAIP mosaic was classified using supervised classification methods to identify the land cover classes present in the study area. Training data was obtained from the National Land Cover Database's 2019 release. The original NLCD dataset was cropped to the study area and reclassified to simplify the land cover types. Land cover was divided into two classes: green and not-green. The green class was comprised of forest, shrubland/herbaceous cover, agriculture, and wetlands. The not-green class contained developed land, open water, and barren land.The random forest algorithm is an ensemble classifier that produces multiple decision trees using a subset of the training data. This classifier is popular within the remote sensing community due to its high level of accuracy (Belgui et al. 2016).

A stratified random sample of the reclassified data was used as the input to an initial random forest classifier with 150 trees. The rest of the parameters were set to their default value: max_depth = None and min_samples_split = 2. After fitting the initial model, a GridSearch was then performed to optimize the model's hyperparameters and improve accuracy. The model chosen by the GridSearch had 250 trees, max_depth = 5, and min_samples_split = 100. The model constructed through the GridSearch was then used to classify the land cover types present in the 2020 summer mosaic of NAIP imagery.

Regression

The classified map of green space in Madison was then resampled from its original resolution of 5-meter pixels to match the Landsat resolution of 30-meter pixels using the mean as the resampling method. The value for a single 30-m pixel was computed as the average of all the smaller NAIP pixels that make up the larger pixel, resulting in a measure of fractional greenness for each 30-m pixel. Landsat bands 2-7 (blue, green, red, near infrared, and shortwave infrared 1 and 2) were used as the inputs to a random forest regression model to predict fractional greenness based on Landsat characteristics.

Results

Classification

The initial random forest classifier, constructed without GridSearch, achieved 65.6% overall accuracy for the NAIP summer image mosaic. The error matrix for the classifier is shown in Table 1. Employing the GridSearch method to tune the model's hyperparameters resulted in an accuracy of 72.8%. The error matrix for the updated model is shown in Table 2.

Ground Truth			
		Not Green	Green
Classified Results	Not Green	49	17
	Green	26	33

Table 1. Error matrix for the untuned classifier.

Ground Truth			
		Not Green	Green
Classified Results	Not Green	57	17
	Green	17	34

Table 2. Error matrix for the model after tuning hyperparameters.

Based on this classification, 31,740.90 acres of Madison, WI are green space. The classified map of green and not-green areas of Madison is shown in Figures 2 and 3.

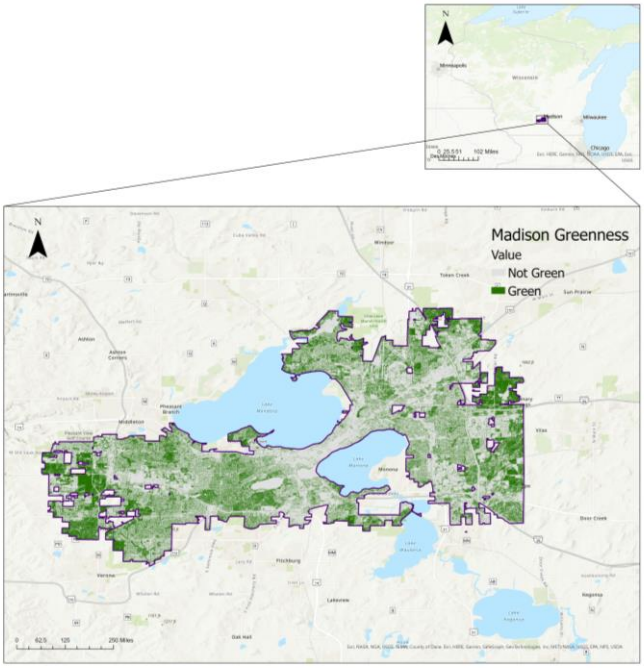

Figure 2. Madison, WI with green areas shown in green and non-green areas shown in gray.

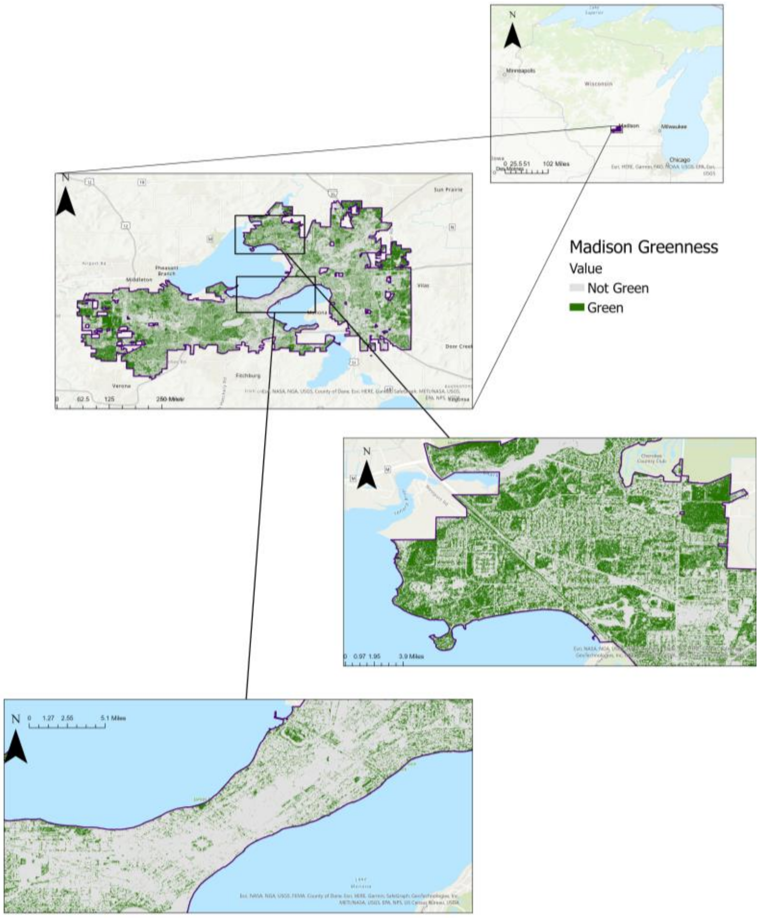

Figure 3. Map of Madison zoomed to show detail in several areas.

Regression

The final model predicting fractional greenness based on Landsat characteristics had an $R^2 = 0.29$.

Discussion

The results showed that approximately 58% of land in the city of Madison was green space. This acreage is a significant portion of the city, and the results align well with Madison's high ranking from ParkScore. In 2022, Madison was ranked 13th in the country for the number, quality, and distribution of its parks (Trust for Public Lands n.d.). Future work could extend this analysis to other comparable cities in the United States. Such cities could include Rochester NY, Fort Collins CO, and Fort Wayne IN, which all have a similar size as Madison.

The accuracy of the green space classification could be improved. Future work could explore additional features to use as inputs to the random forest classifier. These features could be calculated based on existing data (such as NDVI) or additional data could be found for the study area (such as aerial photos taken at different times of year or in different years). The regression model could also benefit from additional feature engineering, as the R^2 value is quite low.

Future work could also incorporate the thermal information collected by Landsat 8's Thermal Infrared Sensor (TIRS) or the thermal-infrared channel of Sentinel 3-A. Urban green space is known to reduce the urban heat island effect and noticeable lower temperatures in cities. The addition of the thermal information could improve both the classification and regression steps of the project.

Conclusion

In summary, urban green space has been shown to have significant physical and mental health benefits for city residents. This study utilizes high resolution aerial imagery combined with traditional satellite remote sensing imagery to quantify the acres of green space in Madison, WI in 2020. A regression model was also developed to extend this quantification to years without high resolution aerial imagery available. We found that a high percentage of the city is covered by green areas such as parks, forests, lawns, trees, and other green spaces. The city of Madison appears to have prioritized including green spaces in both urban and more suburban areas of the city, which is ultimately beneficial for its residents.

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