DEVELOP Technical Report

Harrisonburg Health & Air Quality

Assessing Land Change and Urban Heat Islands for Future Tree Planting in Harrisonburg, Virginia

Spring 2025 | Pop-Up Project – James Madison University
April 4th, 2025

Authors: Emma Holm-Olsen (Analytical Mechanics Associates), Riley Barlett (Analytical Mechanics Associates), Alexander Temoshok (Analytical Mechanics Associates), Benjamin Lengane (Analytical Mechanics Associates)

Abstract: In recent years, Harrisonburg, Virginia has experienced a substantial decrease in urban tree canopy. This is largely due to the arrival of the emerald ash borer, a pest that feeds on species of ash trees, coupled with an increase in urban development. Exposure to excess heat and flooding has become a growing concern for the city's 51,000 residents because these phenomena can diminish the quality of life, limit economic opportunity, and increase costs related to energy and infrastructure. NASA DEVELOP partnered with the City of Harrisonburg Public Works Department to map and quantify changes in land cover and land surface temperature from 2014 – 2024. The team utilized NASA Earth observations from Landsat 8 Thermal Infrared Sensor (TIRS) and Landsat 9 TIRS-2 to analyze land surface temperature. Additionally, the team utilized imagery from the United States Department of Agriculture National Agriculture Imagery Program to quantify tree canopy and impervious surface change. Decreases in tree canopy cover and increases in impervious surfaces correlated with increases in land surface temperature. These results will support the City of Harrisonburg Public Works Department in identifying areas for future tree plantings and focusing resiliency efforts on vulnerable areas within their municipality.

Key Terms: Harrisonburg, satellite, remote sensing, urban heat, LST, LULC

Advisor: Dr. Xiaojing Tang (James Madison University)

Lead: Ella Haugen (Virginia – Langley)

1. Introduction

Urban areas face unique challenges in reducing ambient temperatures and managing stormwater runoff due to their high percentage of heat-absorbing structures and impervious surfaces (Environmental Protection Agency, 2024; Selbig et al., 2022). Planting trees to increase urban tree canopy is widely accepted as an effective solution to lowering land surface temperature (LST) and reducing the effects of urban heat islands (UHIs) as vegetation cools surrounding air via evapotranspiration (Yaşli et al., 2023). Increasing urban tree canopy is also an accepted practice to managing stormwater runoff in cities because tree canopy intercepts and stores rainfall, thereby lessening the volume available for throughfall (Selbig et al., 2022).

The City of Harrisonburg, Virginia (Figure 1) is no exception to facing the challenges that result from tree canopy loss. Harrisonburg sits in the central Shenandoah Valley between the Blue Ridge and Allegheny Mountain ranges. The city has experienced a substantial decrease in tree cover since 2014 (Urban Canopy Works, LLC, 2021). This change was largely driven by the arrival of the emerald ash borer, an insect from northeastern Asia which feeds on species of ash trees. In 2017, the insect ravaged ash trees in the City of Harrisonburg, devastating Harrisonburg's urban tree canopy (Urban Canopy Works, LLC, 2021). Clearing to make way for urban development projects has also significantly reduced the urban tree canopy in Harrisonburg and increased the amount of impervious, heat-absorbing surfaces. This compounded attack on the city's trees, in addition to the increase in impervious, heat-absorbing surfaces from development, has raised ambient temperatures and exacerbated stormwater management challenges.

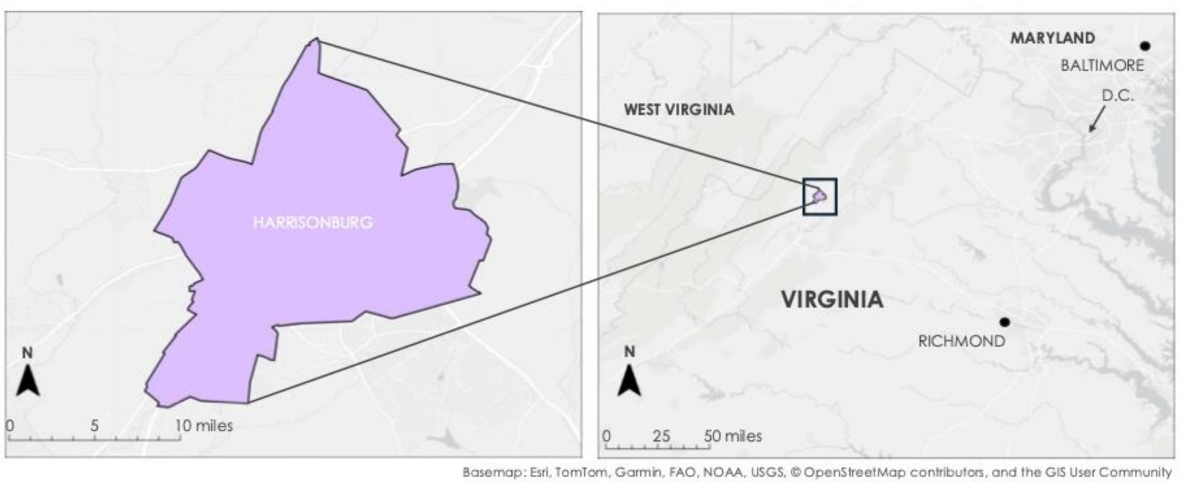

Figure 1. The City of Harrisonburg, Virginia, shown in purple.

The City of Harrisonburg Public Works Department, the end user for this project, previously quantified canopy cover and impervious surface distribution in 2018 and mapped locations of urban hotspots within the city in 2021 (Green Infrastructure Center, 2018; CAPA Strategies, LLC, 2021). These rudimentary studies that were conducted by an external GIS team utilized drone footage, GIS techniques, and infrared thermometers. The City of Harrisonburg has yet to utilize any kind of satellite data to assess land cover and has yet to quantify changes in land cover or LST over time.

Although there are many ways to track changes in urban tree canopy and identify areas with high LST, the use of remote sensing data has become a cornerstone in the characterization of urban climate and land cover changes (Ayala-Silva, 2009; Zhu et al., 2019). For example, Puligadda et al. (2024) used imagery from the National Agricultural Imagery Program (NAIP) to detect and analyze changes in land cover over time through object-based image classification, as data from high resolution satellites minimizes the "mixed pixel effect" and more accurately captures the complexity of urban landscape composition. Additionally, Guha et al. (2018) used data from Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) to determine the relationship between land cover and LST. Remote sensing has also been used to identify UHIs, specifically via the thermal band of satellite sensors (PlanIT Geo, Inc., 2023). In 2023, the City of Fairfax published an urban heat map using this technique, then classified the heat spots to understand where LSTs were the highest (PlanIT Geo, Inc., 2023).

To address the gaps in temporal and spatial data and assist the City of Harrisonburg Public Works Department in their mission to restore the city's urban tree canopy and reduce hot spots, the team assessed the feasibility of using NASA satellite imagery to quantify changes over the past decade. To do so, the team aimed to map Harrisonburg's tree cover change, impervious surface change, and annual LST from 2014 to 2024. The team also sought to analyze how these factors have contributed to UHIs in order to identify potential tree planting sites in the city.

2. Methodology

2.1 Data Acquisition

The team acquired Landsat 8 TIRS and Landsat 9 TIRS-2 imagery through the United States Geological Survey's (USGS) Earth Explorer data portal (Table 1). The collection of Landsat images was filtered by location and date to compile a subset of images covering Harrisonburg taken during summer months (June – September). The team then manually selected images with minimal cloud cover. Finally, the Collection 2 LST data from both sensors were selected and exported as TIFF files for processing in Esri ArcGIS Pro 3.4.0.

Table 1
NASA Earth observations used in this study

Platforms/Sensors	Product Level	Dates
Landsat 8 TIRS	Collection 2, Level 2	2014 to 2024 (May – September)
Landsat 9 TIRS-2	Collection 2, Level 2	June 2023

In addition to Landsat 8 and Landsat 9 imagery, the team acquired high-resolution (1m) NAIP imagery through the USGS Earth Explorer data portal to assist with land use and land cover estimations (Table 2). The collection of NAIP images were filtered by date and location to compile a subset of images covering Harrisonburg during the study period. The team then exported red, blue, green, and near infrared bands as TIFF files and imported them into ArcGIS Pro. The team also obtained a city boundary shapefile from Tiger Census and a census blocks shapefile from the United States Census Bureau.

Table 2
Data used for Land Use Classification

Source	Product Level	Dates
NAIP	Leica ADS40-SH51 (Serial Number 30106) Leica ADS80-SH81 (Serial Number 30101) Leica ASD80-SH81 (Serial Number 1318)	August 2014, August 2016, September 2021, October 2023

2.2 Data Processing

To calculate LST from the thermal band data imported into ArcGIS Pro, the team used the 'Raster Calculator' tool. A formula was applied (Equation 1) to display the thermal band data for each year in Fahrenheit (Earth Resources Observation and Science Center, 2020). This was done to display temperature in the unit used most by the teams and project partners.

$$LST = \left(\left((B10 \times 0.00341802) + 149.0\right) - 273.15\right) \times \frac{9}{5} + 32 \quad (1)$$

After mosaicking NAIP images to cover the entire study area and clipping them to the shapefile of Harrisonburg, the team conducted an object-based supervised classification for each year. A segmentation was created to generate spatial clusters of spectrally similar pixels. The team then collected training samples to classify those clusters as either canopy, grass, or development. The team omitted a water class due to little composition in the city which may result misclassification. The team then classified the mosaics using the 'Classification Wizard' tool in ArcGIS Pro. The team manually reclassified larger errors and added a water class using the 'Pixel Editor' tool. Then, the team selected 100 random samples to assess the accuracy of each classified high resolution raster. The team then conducted an accuracy assessment for each classification, verifying an accuracy of $\geq$ 90% for each of the four images in 2014, 2016, 2021 and 2023.

To determine total canopy loss, it was critical to quantify the change in area of canopy cover and impervious surfaces and to identify when changes in land cover classification occurred during the 10-year period. To do this, the team used the 'Change Detection Wizard' tool in ArcGIS Pro. To execute the change detection for tree canopy, the team identified pixels that changed from canopy to grass or development from 2014 to 2023, as well as pixels that changed from grass or development to canopy. To execute the change detection for impervious surfaces, the team looked at pixels that changed from development to canopy or grass as well as pixels that changed from being classified as canopy or grass to development. The team ran these change detections for the entire study period from 2014 to 2023.

The team exported the four change detections – canopy increase, canopy decrease, impervious surface increase, and impervious surface decrease – as individual feature classes to show instances of change in classification as polygons. The team ran the change detection using the fullest processing extent to detect changes across the entire study area and smoothed the results based on a neighborhood of 7-pixel rows by 7-pixel columns to detect notable changes rather than those caused by shadows or angular differences in image capturing. The team also used the majority statistics fill method, which calculates the pixel value that occurs most frequently within the neighborhood. To further separate significant changes from minor variations or noise resulting from angular differences in imagery or shadows, the team applied a threshold of 50 pixels to the change raster. If the change was smaller than the threshold, then the team considered the change insignificant, and it was not mapped. Smoothing results, using the majority statistics fill method, and applying a minimum pixel threshold to the change raster were essential in minimizing the amount of noise in the change detection analysis to increase the overall accuracy.

2.3 Data Analysis

2.3.1 Tree Canopy and Impervious Surface Data Analysis

To quantify change over the entire study period, the team summed the area of all identified instances of change for each of the four change detections. The study period is further divided into three intervals, 2014-2016, 2016-2021, and 2021-2023, based on the years of available NAIP data. To identify and quantify during which interval each change occurred (i.e., 2014 – 2016, 2016 – 2021, 2021 – 2023), the team overlaid the 2014 – 2023 change detection layer over the classification map for each interval. The team then identified the classification of every instance of land cover change that occurred during each year. From there, the team merged the resulting tables with the 2014 – 2023 change detection layer. Once joined, the team created a new field and input the majority statistics into the attribute table of each change. The team then did a basic query across all four of the year fields to identify the interval during which each change occurred. Finally, the team queried for each year and summed the shape area for all instances of change attributed to that year to quantify the amount of change that happened during each interval.

2.3.2 LST Data Analysis

The team overlaid the LST data for each year with the census block shapefile to determine the mean temperature of individual census blocks, created tables of the means for each year, and joined them to the census blocks attribute table. Then, the team generated the mean LST per census block, classifying each mean LST as "high," "medium," and "low" to identify hot spots. The team then analyzed changes in LST by census block over the entire ten-year study period.

3. Results

3.1 Analysis of Results

3.1.1 Land Cover Change Analysis

From 2014 to 2023, canopy cover in the city decreased by approximately 617 acres, or 5.5% of the city's area whereas imperviousness in the city increased by approximately 224 acres, or 2% of the city's area (Table A1). The team created a change map, identifying where 1) canopy decreased and 2) imperviousness increased in Harrisonburg during the entire study period (Figure 2). Although there are many areas that saw both a decrease in canopy and an increase in impervious surfaces, not all areas of canopy decrease turned into impervious surfaces – some turned into grass. Areas of change are evident throughout Harrisonburg, with the largest areas in the southern and northeastern portions of the city. These larger changes are near Interstate-81, which runs through Harrisonburg and James Madison University. When analyzing change between year intervals, the largest amount of land cover change for both canopy and impervious surface occurred between years 2021 and 2023 (Figure 3). While impervious surfaces increased during the study period, canopy cover decreased by more than twice as much.

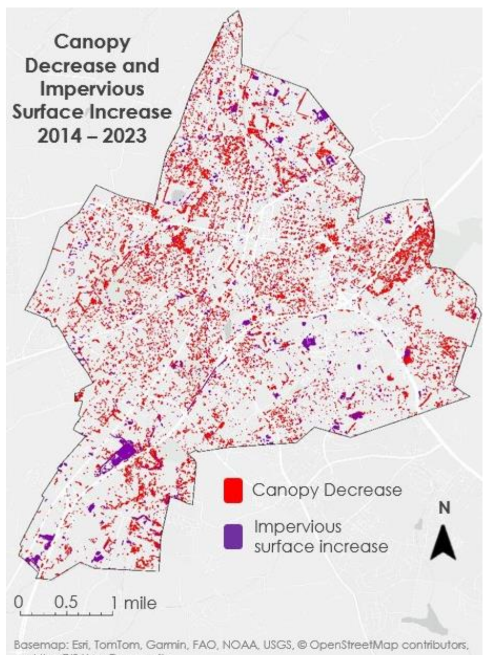

Figure 2. Tree canopy decrease, shown in red, and impervious surface increase, shown in purple, in Harrisonburg from 2014 – 2023.

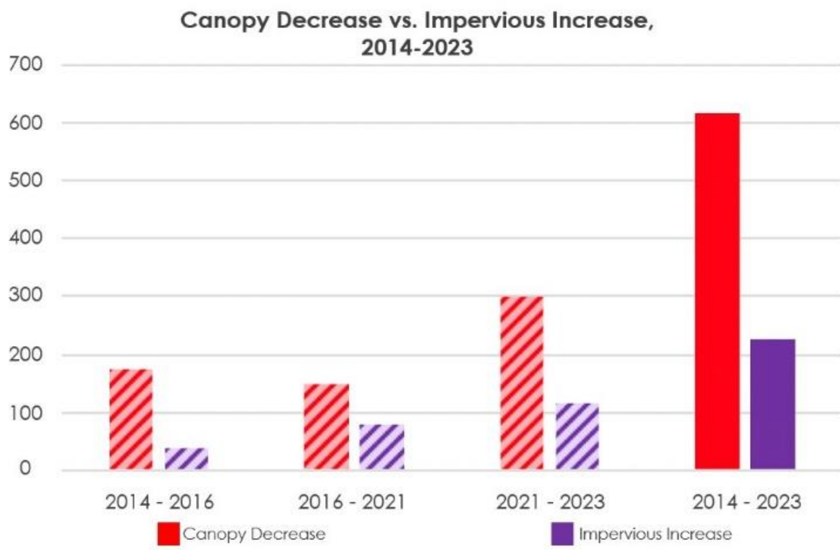

Figure 3. This graph shows the quantified land cover change from 2014 – 2023. The three individual time interval quantifications are dashed while the quantification for the overall study period is solid.

3.1.2 LST Analysis

The team quantified the average LST by census block for 2014 and 2024 (Figure 4). These maps show which census blocks in the study area had "high," "medium," and "low" LST. The blocks were analyzed using a rank-based method where blocks were given individual orders from warmest to coolest and then split into terciles in both 2014 and 2024. Census blocks designated as being "high" in LST were in the top tercile, census blocks designated as being "medium" in LST were in the middle tercile, and census blocks designated as being "low" in LST were in the bottom tercile.

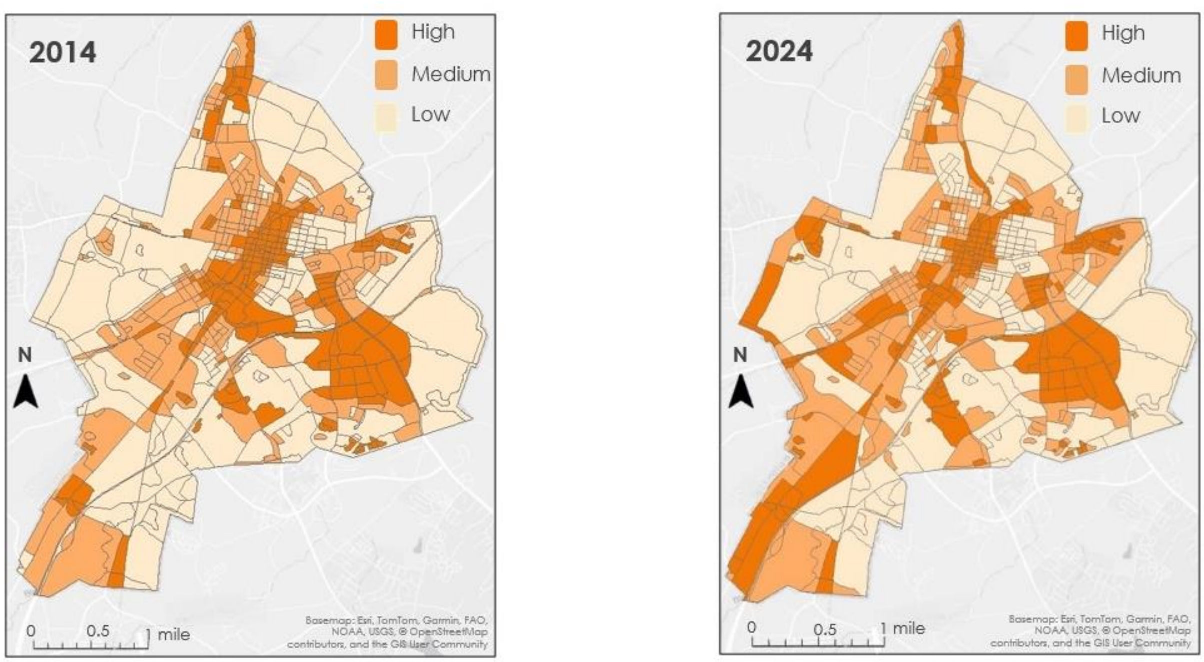

Figure 4. LST in Harrisonburg by census block in 2014 (left) and 2024 (right).

The team also quantified the change in LST by census block. If a census block increased in rank from a lower tercile in 2014 to a higher tercile in 2024, it was denoted as an increase. If a census block decreased in tercile rank from 2014 to 2024, it was denoted as a decrease (Figure 5). Approximately 14% of census blocks (90 out of 646) in Harrisonburg experienced a relative increase in LST during the study period.

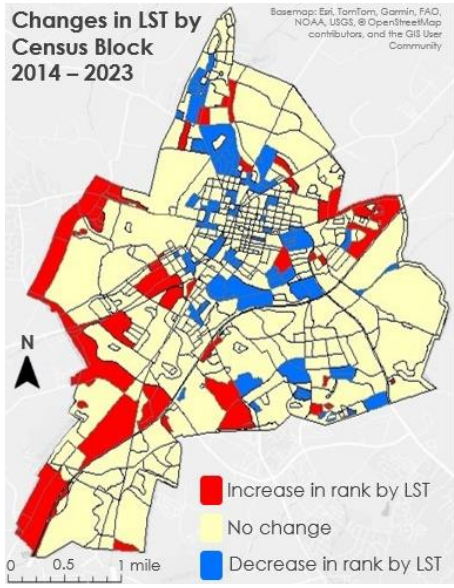

Figure 5. This map shows whether each census block experienced an increase, decrease, or no change in rank by LST from 2014 to 2023.

3.2 Errors & Uncertainties

Inherently, there were errors and uncertainties pertaining to the results of this study. Due to the high resolution of NAIP imagery, shadows were occasionally misclassified as impervious surfaces, which resulted in some errors in the land cover classification. While all four land-use classifications had an accuracy of at least 90% (Table 3), these errors compounded when the team conducted the change detection over time. To best reduce errors, a higher accuracy threshold could be applied. Additionally, because cloud cover can affect the calculation of LST, the team was unable to acquire viable Landsat imagery from the exact same month each year. Instead, the team acquired a viable, low-cloud cover image for each year from sometime during the summer (June – September). As such, it is uncertain whether temperature differences can be entirely attributed to changes in land cover or if these temperature differences were caused in part by seasonal weather patterns. This uncertainty could be reduced by obtaining multiple Landsat images per year and creating a composite that produces a normalized average LST for each year.

Table 3
Accuracy assessment by year for land cover classifications

Year	Accuracy (%)
2014	94
2016	92
2021	93
2023	90

4. Conclusions

4.1 Interpretation of Results

The team successfully quantified changes in tree canopy, impervious surfaces, and LST over the course of the study period using remote sensing observations. There are several census blocks in Harrisonburg that experienced either a decrease in canopy or an increase in impervious surfaces as well as an increase in LST rank over the course of the study period. This suggests a correlation between land cover and LST. Of the blocks that increased in LST rank, most experienced an increase in imperviousness rather than a decrease in canopy. This is likely because most of the canopy loss resulted in conversion to farmland or grassland. This change type does not appear to affect LST in the same way as conversion to impervious surface, as these areas were still comprised of relatively high amounts of vegetation. These data can help to guide the City of Harrisonburg Public Works Department in identifying suitable locations for future tree plantings in the city, allowing them to direct resiliency efforts towards areas of greatest hazard vulnerability.

4.2 Feasibility & Partner Implementation

This study affirmed that remote sensing methods are feasible for quantifying change in land cover and LST over time, as they allow for change detection over large areas. Using NAIP imagery to perform land cover classifications and analyze change can be done with consideration. Errors resulting from the classification process can be alleviated with more time spent on manual corrections. Using Landsat data to quantify change in LST is feasible but with limitations due to cloud cover and seasonal weather patterns which possibly resulting in skewed temperature change data from month to month. Related errors and uncertainties may be alleviated by creating a composite from multiple Landsat images for several years. Partners from the Harrisonburg Public Works Department could employ the methodology discussed herein to update land cover and LST datasets in the future.

The geospatial products created in this study will specifically allow partners to prioritize tree planting based on identified hotspots and areas of impervious surface concentration. Additionally, partners could continue to monitor subsequent changes in land cover and LST following the same methodology developed in this project. Finally, the Harrisonburg Public Works Department could integrate the land cover and LST datasets into their urban forestry planning and decision-making processes to guide canopy restoration efforts.

5. Acknowledgements
The team would like to acknowledge partners at the City of Harrisonburg: Jeremy Harold, Brittany Clem-Hott, Shayna Carter, Tom Hartman, Mike Hott, and Keith Thomas; James Madison University: Dr. Xiaojing Tang, Lead Science Advisor; DEVELOP Virginia – Langley: Ella Haugen, Pop-Up Project Lead; and DEVELOP Maryland – Goddard: Marisa Smedsrud, Geoinformatics & Project Coordination Fellow.

Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Aeronautics and Space Administration.

This material is based upon work supported by NASA through contract 80LARC23FA024.

6. Glossary
Earth observations – Satellites and sensors that collect information about the Earth's physical, chemical, and biological systems over space and time.
Emerald ash borer – An insect from north-eastern Asia which feeds on species of ash trees.
Evapotranspiration – The combined process of water moving from the land surface to the atmosphere via evaporation and transpiration. This process has a cooling effect because it requires heat energy to change liquid water to a gas, thus drawing heat away from the environment.
Impervious surface – Hard, non-porous surfaces that water cannot soak through, such as roads, parking lots, and buildings.
Land surface temperature – The temperature of the Earth's surface. This differs from air temperature which is measured at a certain height above the ground. The two may differ significantly given that land heats and cools more quickly than air.
NAIP – National Agriculture Imagery Program; a program administered through the USDA that makes high-resolution digital ortho photography available to governmental agencies and the public.
Remote sensing – The practice of deriving information about the Earth's surface using images taken from satellites or aircraft.
Urban heat island – An urban area that experiences significantly warmer temperatures than its rural counterparts due to the concentration of buildings, roads, and other infrastructure that absorb and retain heat.
Urban tree canopy – A measurement of the total leaf, branch, and stem coverage within a defined area when viewed from above. Urban tree canopy is typically expressed as a percentage of the ground covered.

7. References

Ayala-Silva, T., Gordon, G., & Heath, R. (2009). Use of satellite data to study the impact of land-cover/land use change in Madison County Alabama. *American Journal of Applied Sciences*, *656*-660. http://dx.doi.org/10.3844/ajas.2009.656.660

CAPA Strategies, LLC. (2021). *Virginia Foundation for Independent Colleges (VFIC) Heat Watch Report.* https://www.harrisonburgva.gov/sites/default/files/publicworks/files/SWM/heat_watch_vfic_report_110321.pdf

Earth Resources Observation and Science (EROS) Center. (2023). Aerial Photography - National Agriculture Imagery Program (NAIP) [Data set]. United States Geological Survey. https://doi.org/10.5066/F7QN651G

Earth Resources Observation and Science (EROS) Center. (2020). Landsat 8-9 Operational Land Imager / Thermal Infrared Sensor Level-1, Collection 2 [Data set]. United States Geological Survey. https://doi.org/10.5066/P975CC9B

Environmental Protection Agency (2024, December 10). *What Are Heat Islands?* https://www.epa.gov/heatislands/what-are-heat-islands

Guha, S., Govil, H., Dey, A., & Gill, N. (2018). Analytical study of land surface temperature with NDVI and NDBI using Landsat 8 OLI and TIRS data in Florence and Naples city, Italy. *European Journal of Remote Sensing, 51*(1), 667 – 678. https://doi.org/10.1080/22797254.2018.1474494

The Green Infrastructure Center Inc. (2018). *Trees to Offset Stormwater: Case Study 08: City of Harrisonburg, Virginia.* https://gicinc.org/books/harrisonburg-trees-to-offset-stormwater/

PlanIT Geo, Inc. (2023). *An Assessment of Urban Tree Canopy in Fairfax, Virginia.* https://engage.fairfaxva.gov/24801/widgets/84713/documents/56638

Puligadda, P., Manne, S., & Raja, D. R. (2024). Land Cover Changes Detection Based on Object-Based Image Classification Using the Google Earth Engine. In V. Shrivastava, J. C. Bansal, & B. K. Panigrahi. (Eds) *Power Engineering and Intelligent Systems*, *1098*. Springer, Singapore. https://doi.org/10.1007/978-981-99-7383-5_22

Selbig, W. R., Loheide II, S. P., Shuster, W., Scharenbroch, B. C., Coville, R. C., Kruegler, J., Avery, W., Haefner, R., & Nowak, D. (2022). Quantifying the stormwater runoff volume reduction benefits urban street tree canopy. *Science of The Total Environment, 806*(3). https://doi.org/10.1016/j.scitotenv.2021.151296

Urban Canopy Works, LLC. (2021, September). *Urban Forest Management Master Plan, City of Harrisonburg, Virginia.* https://www.harrisonburgva.gov/sites/default/files/public-works/files/UFMP%20Final.pdf

Yaşli, R., Yücedag, C., Ayan, S., & Simovski, B. (2023). The role of urban trees in reducing land surface temperature. *SilvaWorld*, *2*(1), 36 – 49. https://doi.org/10.29329/silva.2023.518.05

Zhu, Z., Zhou, Y., Seto, K. C., Stokes, E. C., Deng, C., Pickett, S. T. A., & Taubenböck, H. (2019). Understanding an urbanizing planet: Strategic directions for remote sensing. *Remote Sensing of Environment, 228,* 164 – 182. https://doi.org/10.1016/j.rse.2019.04.020

8. Appendices

Appendix A: *Land Cover Change Statistics*

Table A1
Canopy and impervious surface change in intervals from 2014 to 2023 in Harrisonburg, VA.

Interval	Canopy Increase (acres)	Canopy Decrease (acres)	Impervious Surface Increase (acres)
2014 – 2023	**33**	**617**	**224**
2021 – 2023	14	297	113
2016 – 2021	10	148	75
2014 – 2016	9	172	36