DEVELOP Technical Report

Treasure Valley Health & Air Quality

Analyzing Urban Heat Trends in the Context of Rapid Urban Expansion in Treasure Valley, Idaho

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Abstract: Treasure Valley, Idaho is experiencing increasing temperatures caused by urbanization and a lack of urban tree canopy. This phenomenon is the urban heat island (UHI) effect, where cities are generally hotter compared to surrounding rural areas. Municipalities within Treasure Valley are concerned about urban heat in areas without robust tree canopies. The team used the land surface temperature data from Landsat 8 Thermal Infrared Sensor (TIRS), Landsat 9 TIRS-2, and Ecosystem Spaceborne Thermal Radiometer Experiment on Space Station (ECOSTRESS) to analyze urban heat and how it has changed from 2019 to 2024. The team also used National Agriculture Imagery Program (NAIP) aerial imagery to examine land cover and create a paired sample analysis of tree canopy with impervious surfaces in each municipality. The project found that while 2019 and 2024 had similar heat distribution, municipalities were hotter overall, with an expansion and increase in temperatures. The team also found that while tree canopy cover has increased, impervious surface growth outpaced it by about double. Lastly, a qualitative analysis at the neighborhood scale showed sites with (1) less tree canopy coverage and (2) more impervious surfaces were hotter than sites with the inverse. These findings will help the Treasure Valley Canopy Network (TVCN) non-profit continue to focus its tree-planting efforts on areas without robust tree canopy and/or that cannot cool down effectively. The findings will also help TVCN communicate the benefits of its programs and the importance of urban trees to the public. Lastly, the findings will help the City of Boise's Climate Action Division understand the urban heat trend and the efficiency of tree planting plans as a mitigation solution.

Key Terms: Landsat, ECOSTRESS, remote sensing, urban heat islands, urban tree canopy, urbanization

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1. Introduction

Urban areas are currently facing rapid population growth, resulting in an increase in paved impervious surfaces like concrete and asphalt. Impervious surfaces change water flow, restrict infiltration, and retain more heat than vegetated areas (Singh & Kapoor, 2025), driving the urban heat island (UHI) effect, where urban areas are warmer than surrounding rural areas. The UHI effect poses risks to urban populations since it compounds heatwaves and creates considerable public health concerns (Shandas et al., 2019; Xia et al., 2022). This is problematic for individuals with underlying health conditions, who may be more susceptible to heat-related illnesses, like heat stroke (Hsu et al., 2021). Vegetation, including trees, is known to mitigate the UHI effect through evapotranspiration, or the combined release of water vapor from soil and vegetation into the atmosphere (Cheela et al., 2021). Thus, increasing urban tree canopy coverage is a strong avenue for local municipalities aiming to reduce heat exposure during summertime.

One urban area affected by the UHI effect is the Treasure Valley region, a semiarid landscape with a land area of 216.9 square miles in southwestern Idaho (Figure 1). Treasure Valley covers multiple municipalities, including Boise, Nampa, Caldwell, Eagle, and Meridian, making up about 40% of Idaho's population (City of Boise, 2015; COMPASS, 2024). The valley has seen a rise in temperatures and a tripling of the average number of days a year above 100°F since the 1940s (City of Boise GIS, 2024; Davisson et al., 2017). Treasure Valley experienced rapid urbanization and population growth - the area's population grew from 543,120 in 2019 to an estimated 623,080 in 2024 (COMPASS, 2024). The rapid urbanization and population growth both contribute to the UHI phenomenon in Treasure Valley (CAPA, 2024).

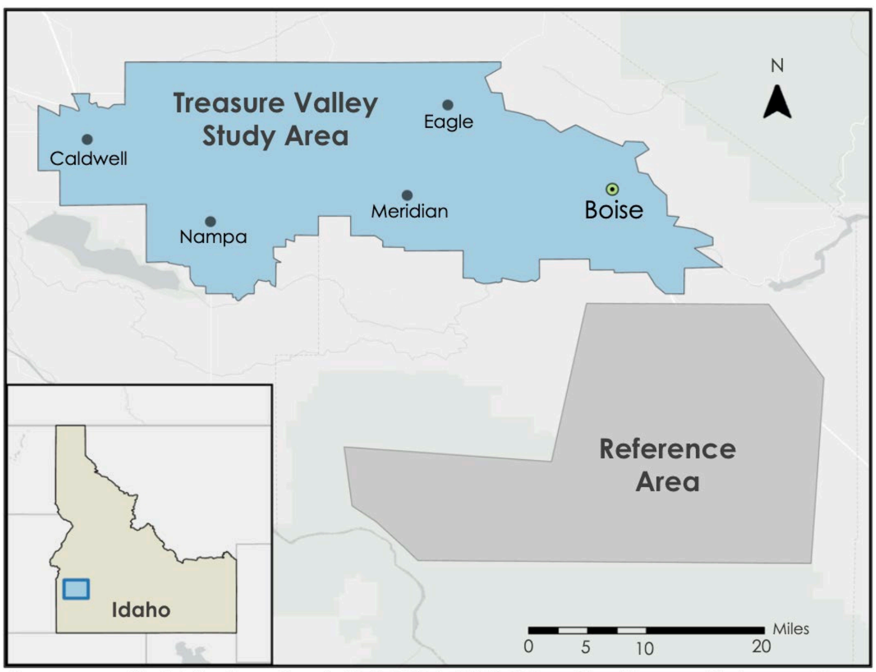

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Figure 1. Study area (blue) and reference area (gray)

The team partnered with the Treasure Valley Canopy Network (TVCN), a local non-profit, and the Climate Action Division of the City of Boise. TVCN works to plant trees throughout Treasure Valley and expand the region's urban tree canopy. In addition, the City of Boise has numerous climate goals, culminating in being carbon-neutral by 2050. Both entities have complementary goals, such as informing the planning, development, and maintenance of the region's urban tree canopy; fostering community resilience; and engaging the public in solutions and increasing understanding about the importance of trees (TVCN, 2025a; City of Boise, 2025a).

An estimated 16% of Boise was covered by tree canopy in 2020, and the municipality has set a goal to raise its tree canopy coverage by 30% over the next decade (City of Boise, 2021; City of Boise, 2025b). The partners are facilitating the City of Trees Challenge, with the goal of planting 100,000 trees in Boise by 2030 (City of Boise, 2021; CAPA 2024). As of 2024, they have already planted 19,166 trees since starting the program TVCN, 2024). The partners' work to date has shown that neighborhoods in Boise with less shade and fewer green spaces are hotter than nearby areas with more trees (City of Boise GIS, 2024; TVCN, 2025b; CAPA, 2024). While other municipalities in the region are not direct partners, they also have goals to grow urban tree canopy (City of Eagle, City of Meridian, City of Nampa, and City of Caldwell). TCVN and the Climate Action Division of the City of Boise have assessed urban heat and tree canopy coverage in Boise, but previous work with remote sensing methods has been limited. This project used remote sensing imagery to explore UHI and inform effective tree planting throughout Treasure Valley.

In recent years, researchers have increasingly utilized remote sensing techniques to study urban heat and land cover dynamics, including tree canopy change and urbanization (Zhu et al., 2019). Various approaches have been developed to derive land surface temperature (LST) from data captured by spaceborne sensors, such as ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station (ECOSTRESS), Moderate Resolution Imaging Spectroradiometer (MODIS), and Landsat Thermal Infrared Sensor (TIRS) (Hook & Hulley, 2018; U.S. Geological Survey, 2024; Wei & Sobrino, 2024). The temporal capture frequency, global coverage, and spatial resolution at which satellite data are available make it useful for assessing change over time. Wei & Sobrino (2024) showed a case study of Valencia, Spain, leveraging Earth observation data from Landsat and ECOSTRESS with GIS data to investigate the spatiotemporal dynamics of LST and surface UHI intensity during heat waves based on land cover type. Their findings emphasized the moderating effects of urban greening and water bodies on LST. In another case study of central Massachusetts from 2008-2010, Rogan et al. (2013) assessed the impacts of tree canopy loss and urbanization on LST using data from Landsat and the National Agriculture Imagery Program (NAIP). Their findings indicated that tree canopy loss in areas with high impervious surface cover yielded the greatest LST increase, highlighting the relationship between land cover and LST in the context of urban development.

Like other rapidly urbanizing regions, the partners in Treasure Valley have expressed concerns about heat-related impacts on quality of life. The aims of the study were threefold: (1) assess and map changes in LST, urban heat islands, and tree canopy from June through September 2019-2024; (2) quantify the impacts of urbanization and tree canopy on urban heat patterns over time; and (3) visualize spatial distribution of heat patterns at the city and neighborhood scale. The team used satellite imagery from Landsat 8 TIRS, Landsat 9 TIRS-2, and ECOSTRESS with NAIP data to analyze the spatiotemporal patterns of LST in the context of urban growth and tree canopy change. These will contribute to regional urban heat island data, help the partners prioritize high-impact tree planting locations and engage the public, and inform future climate resilience strategies.

2. Methodology

2.1 Data Acquisition

This project involved a variety of remote sensing data sources to analyze daytime and nighttime LST and UHI effects in Treasure Valley (Table 1). The team used Landsat 8 TIRS and Landsat 9 TIRS-2 for daytime imagery, acquired from the United States Geological Survey (USGS) EarthExplorer database. This imagery is collected at 100-meter spatial resolution, gridded to 30-meter spatial resolution, and has a combined temporal resolution of 8 days. The team acquired nighttime imagery from ECOSTRESS, a sensor aboard the International Space Station (ISS), obtained from the NASA Earthdata Search database. This imagery is gridded to 70-meter spatial resolution and has an irregular temporal resolution, returning every 3-5 days. The team obtained land cover imagery through the National Agriculture Imagery Program (NAIP) at a 0.6-meter resolution. The 2019 NAIP imagery is from mid-June to mid-July, while the 2023 NAIP imagery is only from mid-July. The team also used estimated daily surface temperature data, at a 1-kilometer spatial resolution and obtained from the Daymet model, to understand the historical weather trends in Treasure Valley (Weber, 2025).

Table 1
Satellite Imagery & Weather Observations

Platforms/Products	Product Level and Version	Dates
Landsat 8 TIRS & Landsat 9 TIRS-2	Collection 2, Level 2, Version 6.0	June – September, 2019 – 2024
ISS ECOSTRESS	Level 2, Version 2	June – September, 2019 – 2024
NAIP Land Cover	N/A	June – July 2019, July 2023
Daymet Surface Weather	Version 4.1	April – September, 1980 – 2022

In USGS Earth Explorer, the team selected images with less than 25% cloud cover and filtered for tiles within path 42 and row 30 using the Landsat tiling scheme. This produced images that completely covered the Treasure Valley study and reference areas. In NASA Earthdata Search, the team filtered for nighttime ECOSTRESS imagery with identification number 11TNJ, which also covered the study and reference areas. While USGS Earth Explorer provides an option for cloud coverage filtering, Earthdata Search does not. Thus, the team manually selected images with minimal cloud cover (less than 25% of both study and reference area covered) in ArcGIS Pro 3.5.2 after exporting. In total, this produced 50 Landsat daytime images and 48 ECOSTRESS nighttime images across 5 years. The team aggregated a total of 76 NAIP images in 2019 and 76 in 2023 for analysis. Historical temperature trends via Daymet included the yearly maximum temperature of the study and reference area during the growing season (April – September) from 1980-2022, totaling 43 datapoints.

Another important dataset was the municipal borders of Treasure Valley (Table 2). The Community Planning Association of Southwest Idaho (COMPASS) provided municipal boundaries, which the team used to verify the location of UHI effects throughout Treasure Valley cities. Lastly, the team used the Deep Learning tool provided by Eagle Technology from the Deep Learning Essentials library within the ArcGIS Pro to classify NAIP imagery into land cover classifications, including tree canopy.

Table 2
Tree Canopy Observations

Data Source	Product	Most Recent Update
COMPASS	City Boundaries	October 2024
Esri Deep Learning Tool - Eagle Technology	New Zealand Land Cover Classification (Aerial Imagery)	September 2024

2.2 Data Processing

2.2.1 Landsat 8/9 and ECOSTRESS Cloud Masking

To ensure accurate LST calculation for Landsat, the team removed pixels with cloud cover from the Landsat 8 and Landsat 9 images. The team brought the Quality Assessment band and Surface Temperature files for each Landsat image into ArcGIS Pro and used the Remap and Clip Raster tools to identify and remove data with cloud cover, keeping only "clear" pixels (USGS, 2024). ECOSTRESS imagery was already cloud-masked, so this step was not necessary for nighttime imagery.

2.2.2 Finding Median Temperatures and Unit Conversions

The team used the Cell Statistics Spatial Analyst tool in ArcGIS Pro to create a new median temperature layer for the aggregated Landsat 8/9 images and another layer for ECOSTRESS images. Landsat raster data are in digital number (DN) format when exported. The team converted DNs to new temperature formats, using a temperature conversion. The team scaled the Landsat 8 and Landsat 9 DN to temperature in Kelvin (T_K) and then Fahrenheit (T_F) using the Raster Calculator tool as shown in equation 1 and 2 (NIST, 2025; USGS 2024):

$$T_K = (DN \times 0.00341802) + 149 \tag{1}$$

Where DN is a number from the initial image

$$T_F = 1.8 \times (T_K - 273.15) + 32 \tag{2}$$

Where T_K is temperature in Kelvin from the image

The ECOSTRESS LST data were already in Kelvin, so the team used the Raster Calculator tool to convert to Fahrenheit using Equation 2 above. After conversion, the team used Zonal Statistics as Table tool to extract summary statistics for both the study and reference areas.

2.2.3 NAIP and Land Cover Classification

The team used high-resolution (0.6 meter) NAIP imagery as the input for the land cover classification. In preparation for the classification, the team mosaicked the NAIP imagery tiles using the Mosaic to New Raster tool for both 2019 and 2023, creating a high-resolution image for each year for the entire region. Then, the team created a land cover classification for each year using ArcGIS Pro's "Classify Pixels Using Deep Learning" tool and the "New Zealand Land Cover Classification (Aerial Imagery)" deep learning model (Eagle Technology, 2024). This process resulted in a land cover classification image for each year with seven classes: Tree Canopy, Grass/Shrubs, Bare Soil, Water, Building, Roads/Railroads, and Other Paved.

Next, the team created Boolean raster layers to investigate changes in tree canopy and impervious surface cover. To identify tree canopy, the team used the Con tool in ArcGIS Pro to create a new raster layer, where all pixels classified as "Tree Canopy" were set equal to one and all other pixels were set equal to zero. Similarly, the team used the Con tool to create a new impervious surface raster, where all pixels classified as "Building," "Roads/Railroads," and "Other Paved" were set equal to one and all other pixels were set equal to zero. This resulted in two Boolean True/False (T/F) raster layers for each year, one showing tree canopy cover and another showing impervious surfaces.

2.3 Data Analysis

2.3.1 UHI

The team calculated daytime and nighttime UHI for 2019 and 2024 to identify locations that experienced the most extreme UHI intensity. To do this, the team used the Raster Calculator tool in ArcGIS Pro to subtract the median reference area temperature from the study area LST. Large positive values indicated locations experiencing extreme UHI, while locations with large negative values indicated cool spots. Values close to zero indicated that a given location was experiencing a temperature similar to the reference area.

2.3.2 Day-Night LST Difference

The reference area consists primarily of rangelands, characterized as a sagebrush-steppe ecosystem, so it tends to experience similar or higher average daytime temperatures than the study area. Thus, daytime LST and UHI alone are not enough to establish UHI presence in Treasure Valley. Since grasses and bare ground do not retain heat like impervious surfaces do, the team hypothesized that as the study area continued to undergo development and urbanization, it would experience a greater magnitude of change in day-night temperature difference over the study period than the reference area. To account for resolution differences, the team resampled the Landsat median LST composites from 100 meters to 70 meters to match the ECOSTRESS median LST composites, using the ECOSTRESS 2024 composite as the snap raster. Then, the team used the Raster Calculator tool in ArcGIS Pro to subtract the nighttime median LST composite from the daytime median LST composite for 2019 and 2024. Finally, the team used the "Change Detection

Wizard" tool in ArcGIS Pro on the study area and reference area independently to assess how the day-night difference has changed over time.

2.3.3 Daymet Trend Analysis

To understand the full picture of UHI change in Treasure Valley, it was necessary to assess the temperature trends during and beyond the study period. The team used the Temporal Profile capability in ArcGIS Pro to create a chart showing the trend line of the maximum growing season temperatures for the study and reference areas from 1980-2022. To determine if the trend shown was significant, the team visualized the scores and p-values of a Mann-Kendall trend analysis and extracted zonal statistics for the combined study area and reference area.

2.3.4 Tree Canopy Analysis

One of the primary interests of the partners was to understand if and how tree canopy change and tree planting efforts have helped to mitigate urban heat over the study period. To understand the impacts of Treasure Valley's tree canopy on its UHI, the team quantified the changes in canopy cover area during the study period. They ran a change detection analysis to identify areas where tree canopy changes occurred. NAIP data were only available up to 2023, so the change detection covered the years 2019–2023, rather than the entire study period.

To supplement the change detection, the team extracted zonal statistics to calculate the approximate tree canopy cover in Treasure Valley. Using the T/F canopy layers, the team calculated the zonal statistics for the study area, reference area, and for each of the five cities in the study area. The team used the resulting statistics to calculate the percentage and total area of tree canopy cover for each of the previously specified zones for the years 2019 and 2023. The team repeated this process using the T/F impervious surface layers to calculate the percentage and total area of impervious surface cover for each zone.

2.3.5 Paired Samples Comparison

The team selected two pairs of sample locations per city to qualitatively compare the influence of land cover type and tree canopy coverage on LST. The team selected pairs of points in proximity, one point in an area with dense tree canopy, and the other with no tree canopy. The team selected appropriate sample locations using the 2023 T/F canopy raster to determine canopy presence, then confirmed by visually comparing the site to the 2023 high-resolution NAIP imagery. The team created 100-meter buffers around each point to calculate the land cover and temperature statistics for each location.

3. Results and Discussion

3.1 Analysis of Results

3.1.1 Urban Heat

Before beginning the spatial analysis of urban heat using Earth observations, the team used daily temperature maximums, aggregated to the growing season (April-September), to establish the temperature trends in the Treasure Valley region. The plot shows an increasing trend of about 0.06°F/year using the mean maximum temperature during the growing season from 1980-2022 (Figure 2). The results of the Mann-Kendall test (Figure 2) indicate this positive trend is significant for both the study and reference areas at the 95% confidence level.

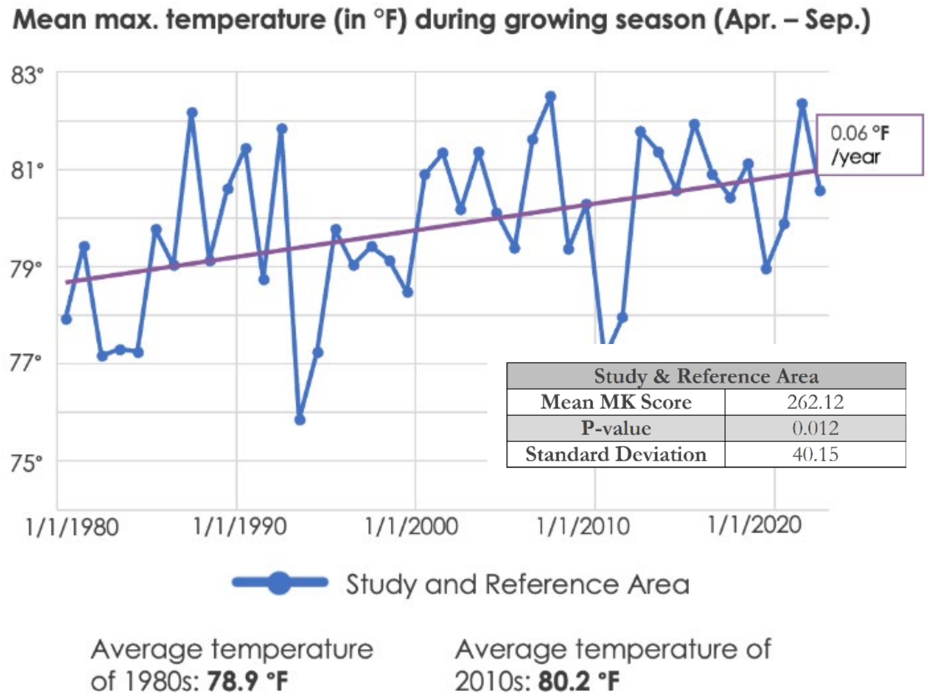


Figure 2. Mean maximum temperature trend during the growing season (April – September) from1980 to 2022. The inset table shows the Mann-Kendall test results.

The team created three sets of maps to help visualize the distribution of heat across the Treasure Valley region. The first set depicts the day and night LST for 2019 and 2024 (Figure 3). The distribution of heat across the study area is similar across years and between day and night, with a few notable exceptions. The warmest pixels tend to correspond with the locations of dense urban development, while the cooler pixels tend to occur in locations further away from city centers, where there are fewer impervious surfaces and more vegetation. While the Boise River appears cool relative to the study area during the daytime, it appears moderately warm relative to the study area at night, highlighting the ability of water to store and retain heat. It is worth noting that these maps show land surface temperature rather than ambient air temperature. While ambient air temperature measures the temperature at a standard height above the ground (typically 2-meters), LST includes surfaces like roads and building roofs, which tend to get much hotter than surrounding air temperatures.

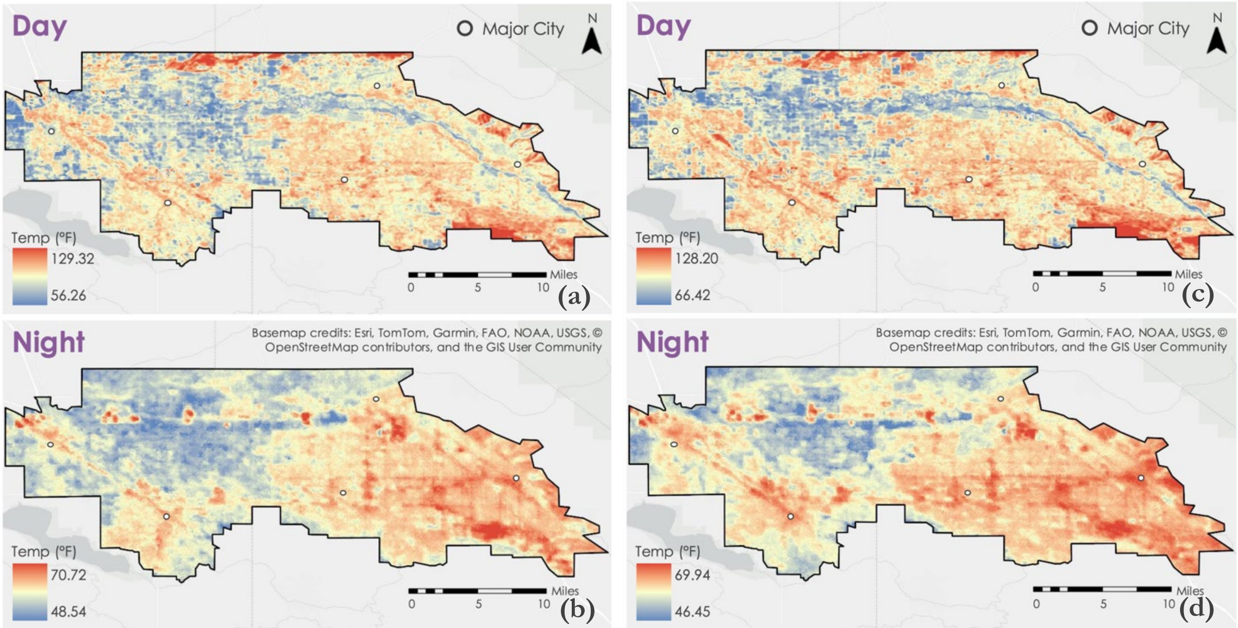


Figure 3. Median LST during daytime in 2019 (a), nighttime in 2019 (b), daytime in 2024 (c), and nighttime in 2024 (d).

The second set of maps depicts daytime and nighttime UHIs for 2019 and 2024 in Figure 4. The nature of the reference area is rangelands, which are generally more barren than the study area. This causes the reference area to get very hot during the daytime, making it seem like parts of the study area may not experience an intense UHI effect. Thus, the team considered both daytime and nighttime UHI. Though the distributions of UHIs throughout the study area are similar across day and night, more intense UHI patterns emerge at night, when the reference area can cool more drastically than the more developed locations present in the study area. The nighttime UHI intensified and became visibly more widespread across the entire study area between 2019 and 2024. These effects tended to spread outward from urban cores, most noticeably in Caldwell, Nampa, and Meridian. This spread makes hotspots experiencing reduced nighttime cooling apparent on the maps.

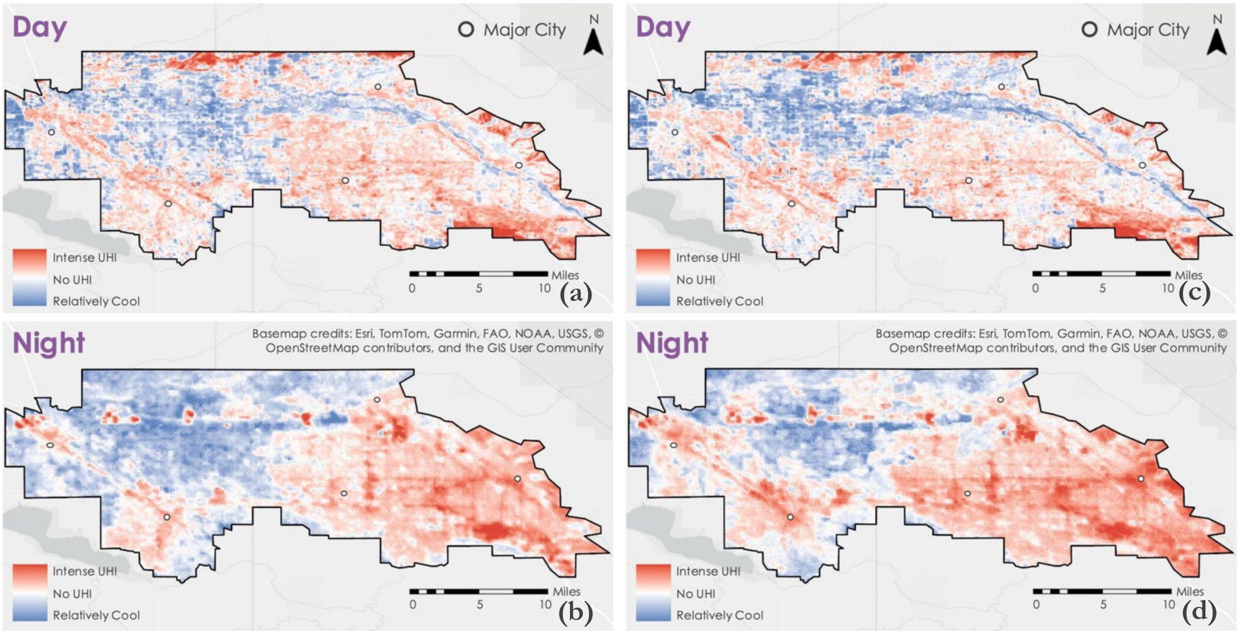


Figure 4. UHI in daytime 2019 (a), nighttime 2019 (b), daytime 2024 (c), and nighttime 2024 (d).

The third set of maps depicts the difference in daytime and nighttime LST for 2019 and 2024 (Figure 5). These expand upon the previous results and are indicative of how a given location retains heat and cools overnight. Most of the change between 2019 and 2024 saw shifts from a greater difference to a smaller difference, indicating a narrowing in the difference between daytime and nighttime temperatures. A few of these locations are noted by the pink circles on the maps. The patterns signify an overall strengthening of Treasure Valley's UHI, which became apparent when the team compared the magnitude of change in day-night difference between the study area and the reference area (Figure 6). Change detections of day-night LST difference for the study and reference areas separately yielded ranges showing that the study area underwent a greater magnitude of land use land cover change than the reference area. This aligns with the context of the study area as a developing, urbanizing region vs. the reference area, which is not undergoing the same processes.

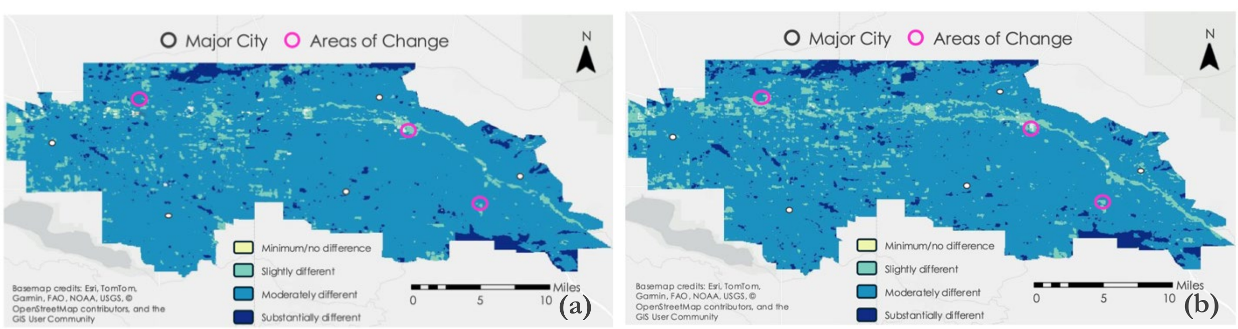


Figure 5. Difference between daytime and nighttime LST for 2019 (a) and 2024 (b).

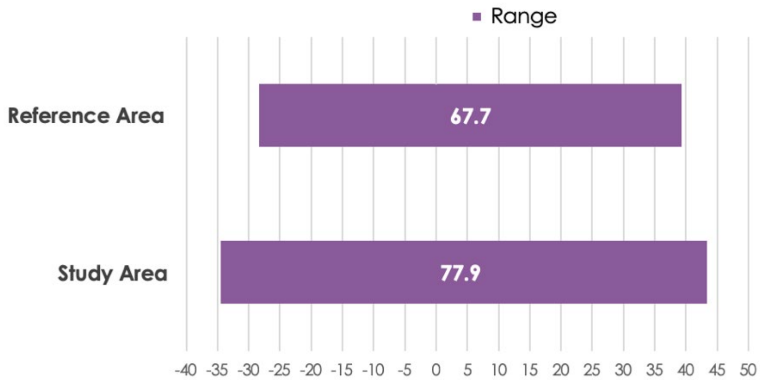


Figure 6. Ranges of change of daytime and nighttime LST difference.

3.1.2 Land Cover Change

The maps below (Figure 7) depict the changes in the study area's tree canopy (TC) and impervious surface cover (IS) between 2019 and 2023, while the table (Table 3) breaks those changes down by percent and square mileage for the study area, reference area, and each of the five cities of interest. Tree canopy gain and loss tend to exhibit specific patterns throughout the study area. Canopy loss tended to occur in clusters, while canopy increase was more evenly distributed across the study area. Increases that occurred near rivers were an exception to this pattern, as trees tend to naturally grow and cluster around rivers in this region. Overall, each zone saw an increase in the percent tree canopy. Notably, the entire study area went from 4.6% tree canopy to 7.5%, an increase of about 9.5 square miles. Eagle saw the greatest increase in percent canopy, from 5.4% to almost 12%. Boise saw the greatest square mile increase, gaining about 4 square miles of tree canopy. However, in most of the study area, tree canopy growth did not outpace urbanization. The entire study area saw an increase from 31.5% impervious surface cover to 37.4%, an increase of 18.7 square miles. All zones, except Eagle, experienced an increase in impervious surface cover, and Boise was the only area where the tree canopy growth in square miles was greater than the impervious surface increase. It is worth noting that the reference area did not see a 10 square mile impervious surface increase – this was largely a result of the deep learning model misclassifying bare ground as roads in the reference area. Generally, the study area underwent greater change than the reference area over the study period.

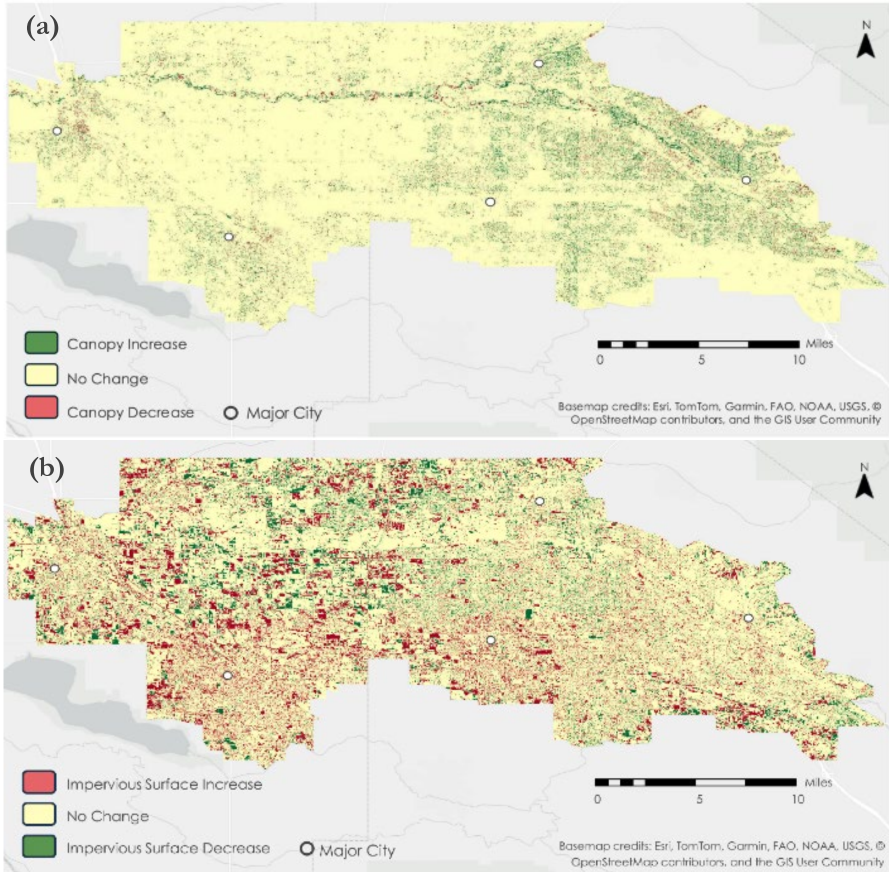


Figure 7. Tree canopy change (a) and impervious surface cover change (b) between 2019 and 2023.

Table 3. Tree canopy and impervious surface change for the study and reference areas, as well as for cities.

	Type	2019 (%)	2023 (%)	Change (Sq mi)
Study Area	TC	4.6	7.5	+9.5
	IS	31.6	37.4	+18.7
Reference Area	TC	0.02	0.1	+0.2
	IS	22.4	26.4	+10.2
	Type	**2019 (%)**	**2023 (%)**	**Change (Sq mi)**
Boise	TC	7.8	13.2	+4.1
	IS	35.0	39.0	+3.0
Caldwell	TC	4.4	5.0	+0.1
	IS	38.2	48.9	+2.5
Eagle	TC	5.4	11.9	+1.3
	IS	28.1	26.8	-0.3
Meridian	TC	2.1	5.2	+1.1
	IS	44.8	55.2	+3.5
Nampa	TC	3.0	4.3	+0.4
	IS	33.0	52.5	+6.8

3.1.3 Paired Samples Comparison

The paired samples comparison visualizes differences in land cover for proximal locations with different percentages of tree canopy cover to help contextualize how and why LST differs across space. The paired samples for Boise (Figure 8) and Eagle (Figure 9) are shown below. Meridian, Caldwell, and Eagle showed similar patterns (Figures A1-3). Overall, locations with higher proportions of tree canopy compared to impervious surfaces tended to display cooler temperatures (lower LST) than those with high proportions of impervious surface and low tree canopy. For instance, the Boise paired sample showed an almost 20°F temperature swing between the tree sample with 38.66% tree canopy coverage and 0.03% impervious surfaces, and its impervious pair which is 99.93% impervious surface.

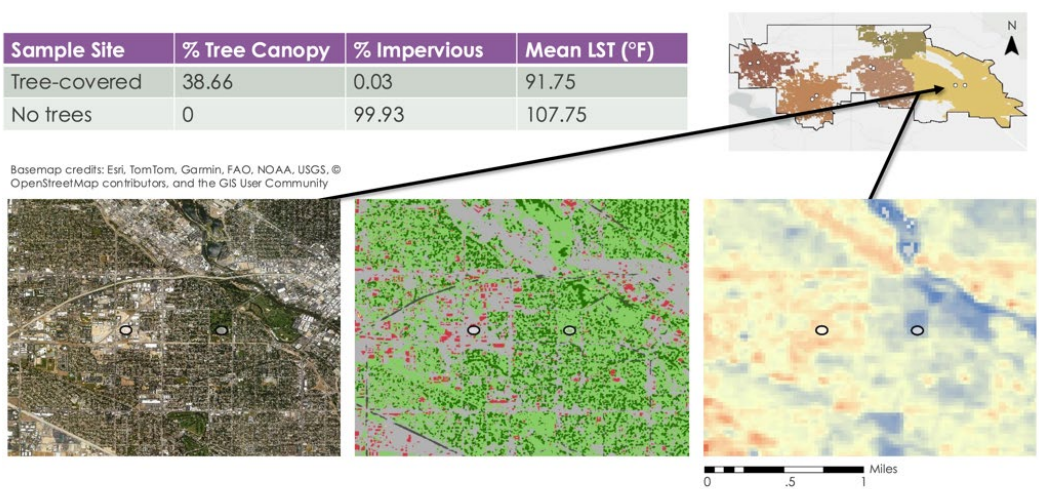
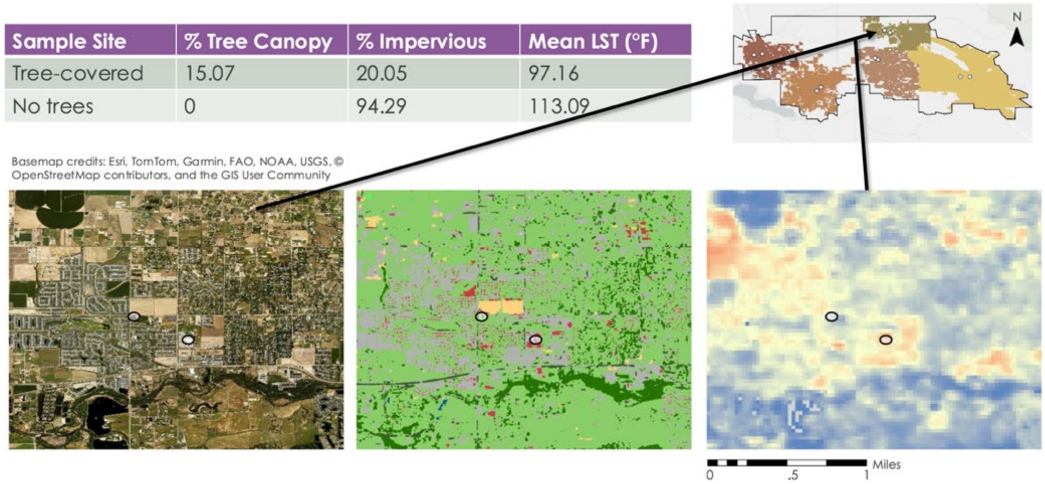


Figure 8. Paired samples comparison in Boise.



Sample Site	% Tree Canopy	% Impervious	Mean LST (°F)
Tree-covered	15.07	20.05	97.16
No trees	0	94.29	113.09

Figure 9. Paired samples comparison in Eagle

The paired sample in Eagle followed the same pattern, showing cooler temperatures in an area with more tree coverage. The Eagle impervious sample with 0% tree canopy coverage was about 16°F hotter than its paired proximal tree sample, which has 15.07% tree canopy coverage. Interestingly, the tree canopy sample also has about 5% more impervious surface coverage than tree canopy coverage. The other paired samples (Appendix A) further exemplify these patterns.

3.2 Errors & Uncertainties

3.2.1 Data Acquisition

The native LST product from Landsat TIRS/TIRS-2 has an original resolution of 100 meters but is processed and resampled to 30 meters to match the spatial resolution of Landsat OLI/OLI-2. This means there may be less detail in the resampled version the team used than if the data were originally collected at a 30-meter resolution. Landsat and ECOSTRESS have different temporal resolutions. This creates variation in the dates when data are available between sensors, meaning Landsat and ECOSTRESS rarely have usable images from the same date. This was not a substantial issue, however, as the team aggregated and created one median layer for all images captured during the summer of each year. In terms of availability, NAIP imagery is not collected annually but rather on a 2-3-year cycle, resulting in no available data for 2024. Using 2023 was a good substitute, but the team may have missed certain land cover changes that occurred from the end of 2023 to the end of 2024 in the paired samples analysis. Lastly, setting the filter for lower cloud cover (less than 25%) in USGS Earth Explorer may have impacted the number of available Landsat tiles.

3.2.2 Data Processing

The team manually selected ECOSTRESS images where less than 25% of the combined reference and study areas were covered by clouds. This approach leaves more room for error than using a programmatic approach to filter cloud-covered images. In terms of processing, to compare day-to-night land surface temperature trends, the team resampled the Landsat daytime imagery from its native 100-meter resolution to 70-meter resolution to match ECOSTRESS. This technique may have resulted in data loss when the larger pixel size converted to the smaller size.

3.2.3 Data Analysis

The variation in spatial resolution between the data sources likely caused uncertainties when comparing the land cover data to the temperature-related results. The team accounted for this by choosing a buffer size (100 meters) for the paired samples analysis to match the Landsat LST resolution and summarizing the land cover breakdown within, but it is not a perfect solution. The LST results may not accurately visualize the spatial patterns associated with fine-scale land cover differences.

While the qualitative comparison is intuitive and helpful for communicating the results to a variety of audiences, they do not quantify the impact of land cover on urban thermal conditions. Further analysis would be required to quantify these impacts, especially at finer scales. This is also true of the mitigating effect of tree canopy, which was shown in each paired sample but not directly compared to the region's total UHI effect.

The Esri deep learning tool was a more effective approach to classify land cover compared to a manual classification of impervious tree cover derived from NAIP imagery. However, it did not classify all land cover types correctly and did not identify all trees or forested areas within the study area. In addition, it was more accurate in the study area than the reference area, as it tended to classify bare ground as impervious surfaces or roads. The confusion matrices (Tables B1-B4) further summarize the performance of the model.

4. Conclusions

4.1 Interpretation of Results

The team found that Treasure Valley experienced a consistent rise in mean maximum temperatures from 1980-2022, about 0.06°F/year ($p=0.012$). Establishing this trend was an important first step to ground LST, UHI, and land cover change findings and interpretations. For LST and UHI, the team found that while the beginning and end years of the study had similar heat distributions, the warmest areas were in built-up areas near city centers. Locations farther from the cities of interest and areas surrounding natural features (e.g., rivers) tended to be cooler. Overall, the LST maps show an expansion of high-temperature areas, and the UHI maps show an expansion and intensification of UHI across the study area. These increasing effects appear to spread outward from city centers. These patterns are most apparent in Caldwell, Nampa, Meridian, and the outskirts of Boise, highlighting the impact of land cover change on urban heat since these cities all experienced urbanization during the study period. The effects of urbanization, namely the increase in impervious surfaces and decrease in tree canopy associated with development, are clearly seen in the outward expansion of heat and UHI effects. Furthermore, the changes in day-night difference in the study area indicate that specific locations in the region are heating up more during the day and cooling down less at night, an effect that worsened during the study period due to changes in land use and land cover. These changes could indicate that there are several places in Treasure Valley where (1) more heat is being absorbed throughout the day and slowly released over the course of the night, and (2) these areas may have undergone changes, such as development, that inhibit the normal overnight cooling process. While the area is experiencing a rise in temperatures, the overall trend (0.06 °F/year) is small, and its impact on UHI and changes in day-night difference is negligible.

The land cover analyses added another dimension to urban heat patterns through the quantification of tree canopy and impervious surface change throughout the study area. The results show that canopy loss tended to occur in clusters, where land was clear-cut for development. On the other hand, canopy increase was more evenly distributed across the study area from a mix of tree planting efforts and natural canopy growth. Overall, Treasure Valley experienced an almost 3% growth in tree canopy coverage across the entire study area – equivalent to about 9.5 square miles. Eagle, a primarily residential municipality located on the Boise River, saw the greatest percent increase, from 5.4% to 12%; however, some of that could be due to natural growth along the river. Despite this, urbanization outpaced tree canopy growth as impervious surface cover increased twice as much as tree canopy. All zones except Eagle saw an increase in impervious surface cover, and Boise was the only area where the tree canopy growth in square miles was greater than the impervious surface increase. These findings support the notion that impervious surface increase (i.e., development and urbanization) and tree canopy loss correspond with UHI expansion and intensification.

The team undertook a qualitative analysis of paired locations to contextualize the effects of tree canopy on LST. The team found that at a neighborhood scale, locations with tree canopy cover were cooler than their uncovered counterparts. For each pair, the sample with a higher tree canopy percentage had a cooler LST in every instance. The paired samples in Nampa and Caldwell showed a 20°F and 10°F temperature swing, respectively, in proximal locations – one forested, and the other with minimal tree cover. Interestingly, while Meridian, Caldwell, and Eagle follow the same pattern, their tree sample also had some, about 20%, impervious surface coverage – showing that even in locations with concrete, trees can help drastically reduce temperatures. Furthermore, there appears to be a diminishing returns effect, where continuing to increase tree canopy past a certain threshold may not significantly influence temperature. For example, this can be seen between the Boise and Eagle pairs. Although Boise's tree-covered site has more than double the canopy coverage of Eagle's, the temperature difference between the covered and uncovered locations is virtually the same. These findings offer important and actionable insights into how development and tree presence influence thermal conditions at the neighborhood level.

4.2 Feasibility and Partner Implementation

It is feasible and useful to use Earth observations to look at urban heat and land cover. There are several challenges, such as observation frequency and resolution, but the benefits outweigh the challenges as Earth observations provide key results and insights. The project partners, TVCN and the City of Boise, will benefit from these findings in three ways. First, the results update and extend previous findings across the entire region – showing regional LST and UHI distribution and intensification patterns. This will allow the partners to communicate these patterns with community members and municipalities – bringing attention to the circumstances and importance of addressing LST and UHIs. Secondly, the results also highlight the impact of tree canopy coverage on LST and UHIs throughout the region, helping the partners underscore the importance of expanding the regional urban tree canopy. Moreover, these findings will allow the partners to support engagement, fundraising, and project proposal efforts with relevant heat and land cover statistics for the region and inlying municipalities. Third, while additional quantification and comparison of LST, UHI, and land cover over the study period were beyond the scope of this feasibility study, the partners can undertake a more in-depth analysis of the materials provided to identify areas of interest, such as locations with no tree canopy coverage. Overall, these results contribute to regional urban heat island data, help the partners prioritize high-impact tree planting locations, engage the public, and inform future climate resilience strategies in the Treasure Valley region.

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6. Glossary

Cloud masking – the process of removing cloud-covered pixels in satellite images
Community Planning Association of Southwest Idaho (COMPASS) – an association of local governments within Treasure Valley, Idaho providing data on city boundaries and census tracts
Daymet – a data product using daily meteorological information from weather stations to provide temperature at a 1-kilometer scale
Deep learning – a type of artificial intelligence that uses information to train and create modeled outputs, such as land cover types
ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station (ECOSTRESS) – a sensor aboard the International Space Station (ISS) that measures land surface temperature
Esri – the company that operates mapping software including ArcGIS Pro
Evapotranspiration – the combined release of water vapor from soil and water bodies (evaporation) and vegetation (transpiration) that cools surrounding areas
Impervious surface – non-porous surfaces including cement, asphalt, and concrete that are high in solar heat absorption and low in water absorption
Land cover – the types of structures or natural elements that cover a given area, including soil, water, roads, buildings, and more
Landsat – a series of satellite missions including Landsat 8 & 9 dedicated to Earth observations
Land surface temperature (LST) – the observed temperature of Earth's surface; different from air temperature as it includes elements like buildings and roads and heats more intensely
National Agriculture Imagery Program (NAIP) – a program under the USDA that provides high-resolution aerial imagery for the contiguous United States
Remote sensing – the practice of obtaining information about an object from a distance, especially Earth observations from satellites and aircraft
Thermal Infrared Sensor (TIRS/TIRS-2) – a sensor aboard the Landsat 8 and 9 satellites that measures land surface temperature
Urban heat island (UHI) – the phenomenon of built-up areas retaining more heat compared to surrounding rural areas with more vegetation
Zonal statistics – the statistics obtained from raster data including mean and median

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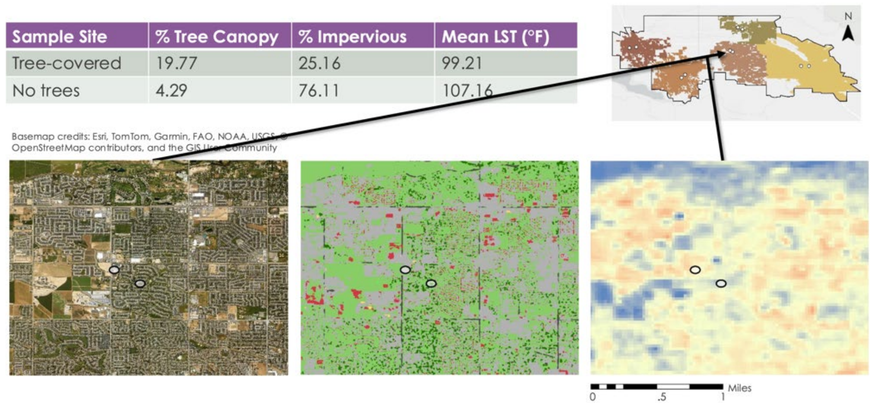
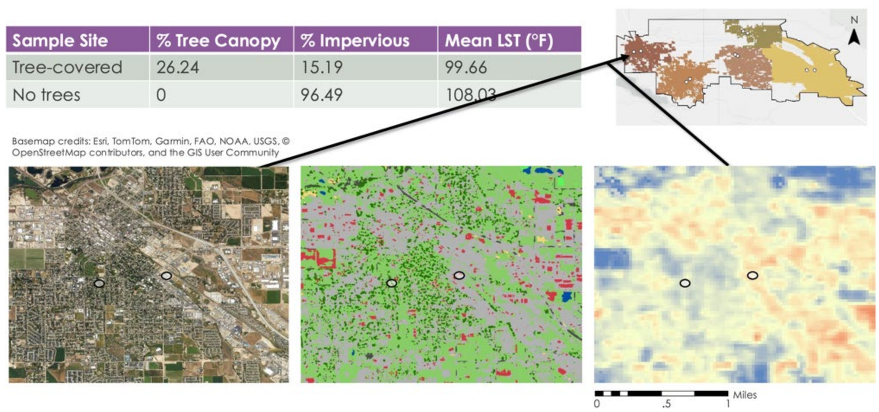
Appendix A: Paired Samples



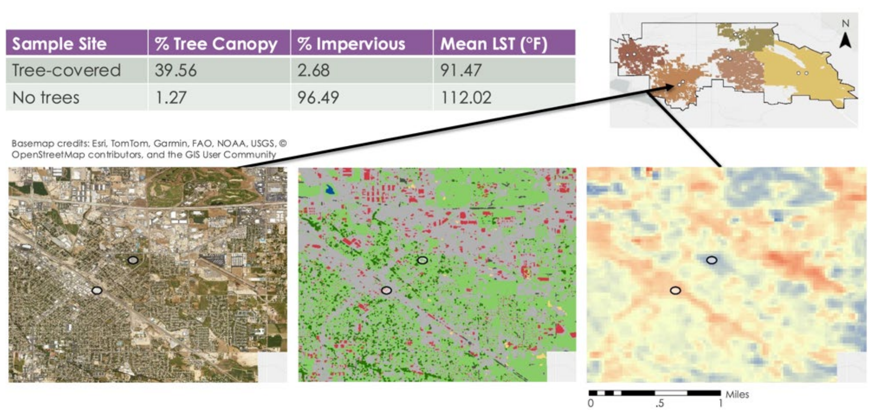
Sample Site	% Tree Canopy	% Impervious	Mean LST (°F)
Tree-covered	19.77	25.16	99.21
No trees	4.29	76.11	107.16

Figure A1. Paired samples comparison in Meridian.



Sample Site	% Tree Canopy	% Impervious	Mean LST (°F)
Tree-covered	26.24	15.19	99.66
No trees	0	96.49	108.03

Figure A2. Paired samples comparison in Caldwell.



Sample Site	% Tree Canopy	% Impervious	Mean LST (°F)
Tree-covered	39.56	2.68	91.47
No trees	1.27	96.49	112.02

Figure A3. Paired samples comparison in Nampa.

Appendix B: Confusion Matrices

Table B1

Confusion Matrix for Boolean Tree Canopy Classification (2019)

Class Value	Not Canopy	Canopy	Total	U Accuracy	Kappa
Not Canopy	93	7	100	0.93	N/A
Canopy	29	71	100	0.71	N/A
Total	122	78	200	N/A	N/A
P Accuracy	0.76	0.91	N/A	0.82	N/A
Kappa	N/A	N/A	N/A	N/A	0.64

Table B2

Confusion Matrix for Boolean Tree Canopy Classification (2023)

Class Value	Not Canopy	Canopy	Total	U Accuracy	Kappa
Not Canopy	95	5	100	0.95	N/A
Canopy	39	61	100	0.61	N/A
Total	134	66	200	N/A	N/A
P Accuracy	0.71	0.92	N/A	0.78	N/A
Kappa	N/A	N/A	N/A	N/A	0.56

Table B3

Confusion Matrix for Boolean Impervious Surface Classification (2019)

Class Value	Not Impervious	Impervious	Total	U Accuracy	Kappa
Not Impervious	92	8	100	0.92	N/A
Impervious	52	48	100	0.48	N/A
Total	144	56	200	N/A	N/A
P Accuracy	0.64	0.86	N/A	0.7	N/A
Kappa	N/A	N/A	N/A	N/A	0.4

Table B4

Confusion Matrix for Boolean Impervious Surface Classification (2023)

Class Value	Not Impervious	Impervious	Total	U Accuracy	Kappa
Not Impervious	93	7	100	0.93	N/A
Impervious	60	40	100	0.4	N/A
Total	153	47	200	N/A	N/A
P Accuracy	0.61	0.85	N/A	0.665	N/A
Kappa	N/A	N/A	N/A	N/A	0.33