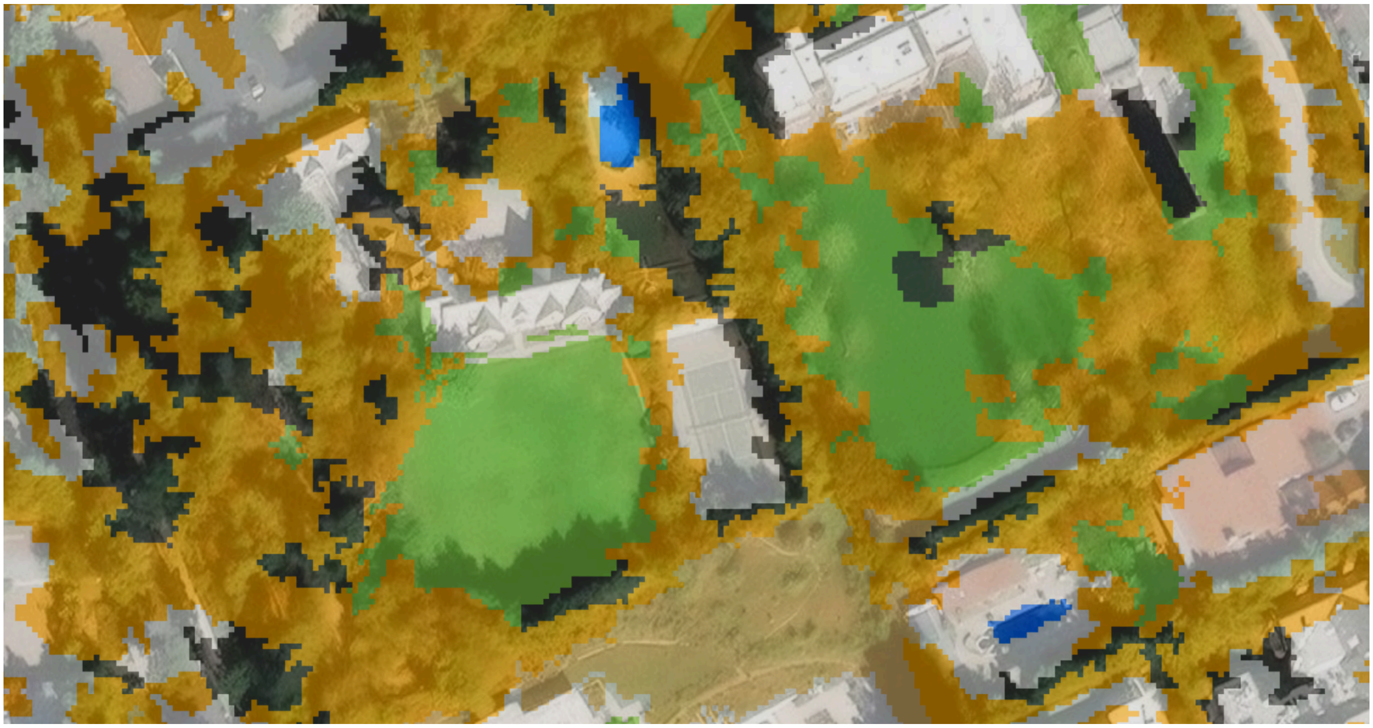
Mapping Landscape Change to Quantify Water Savings in Beverly Hills: A NAIP-Based Vegetation Analysis (2009–2022)



Liam Galleher | December, 2025

Table of Contents

Executive Summary

Since 2009, both regulatory initiatives and evolving public values have moved Southern California toward a culture which champions environmental sustainability. This shift has contributed to a visible reduction in irrigated, turfgrass lawns, and a corresponding rise in native, water-efficient landscaping. To quantify the tangible impacts of this change, this report estimates how much water and money has been saved by reducing turfgrass across the city of Beverly Hills. Using NAIP imagery, object-based classification, and vegetation indices, we quantify the spatial extent of turfgrass in both 2009 and 2022. After assessing classification accuracy, we converted the reduction in grass area to water volume saved by referencing peer-reviewed water usage/value literature. Our analysis shows that over 13 years, Beverly Hills reduced its grass-covered area by 33%. This reduction corresponds to roughly 290 acre-feet of annual water savings (and the annual indoor water usage of nearly 890 residents), saving the City of Beverly Hills up to $580,000 per year. Image classification in such a heterogeneous landscape requires precision and comes with challenges, but accuracy assessments for both 2009 and 2022 resulted in an overall accuracy of 90%. This Analysis demonstrates that ecological initiatives can include measurable, long term, and monetary benefits to communities.

Problem Statement

The city of Beverly Hills aims to understand how much water has been saved by converting turfgrass to xeriscaped or low-water landscapes between 2009 and 2022. This report uses remote sensing to translate grass-cover change to volumetric water savings. There is a challenge in accurately mapping grass across a dense, heterogeneous urban environment using multispectral imagery. To do so, Galleher Geospatial will employ a workflow capable of distinguishing turfgrass from not only urban, impervious surfaces, but also other vegetation, fake grass, and soil.

Introduction

The demand for easily accessible water in urban environments has become increasingly strained by climate change, recurring drought, and the rising costs of imported water (*Addink et al. 2023)*. By replacing irrigated turfgrass on residential lawns and in city greenspaces, this water-demanding landscaping can be replaced with drought-tolerant xeriscaping, contributing to the conservation of natural and monetary resources (*St. Hilaire et al. 2008*). Many Southern California cities, including Beverly Hills, have instated incentive programs and public outreach campaigns to encourage this shift.

By using remote sensing, we can build a reproducible workflow to quantify changes in grass cover over time. This project harnesses object based image analysis, supervised classification, and multispectral vegetation-index techniques over NAIP imagery from 2009 and 2022 to infer an estimate of turfgrass loss, which then informs annual water savings based on evapotranspiration benchmarks. Synthesizing fundamental remote sensing methods, this report produces defensible conservation data for Beverly Hills city planners.

Background

Turfgrass Versus Xeriscaping

Turfgrass is noted as the most water intensive facet of most residential landscapes. In mediterranean climates, turfgrass requires 50 to 60 inches of irrigated water every year (St.

Hilaire et al., 2008). Conversely, Xeriscaped landscapes, which often consist of drought-resistant shrubs, native vegetation, gravel, mulch, or artificial turf, can require 70-90% less water (*UC Davis Center for Landscape & Urban Horticulture, 2010; UC Davis Water Management Program, 2012*). Remote sensing offers the perfect opportunity to record shifts from turfgrass to xeriscape with high-resolution aerial imagery. NAIP enables us to standardize monitoring across entire cities, and the 2009 and 2022 data have comparable spectral bands and seasonality for adequate change detection.

Potential Challenges

- Mixed pixels
- Shadows
- Vegetation heterogeneity
- Distinguishing grass from shrubs
- Distinguishing grass from artificial grass
- High reflectance from impervious surfaces

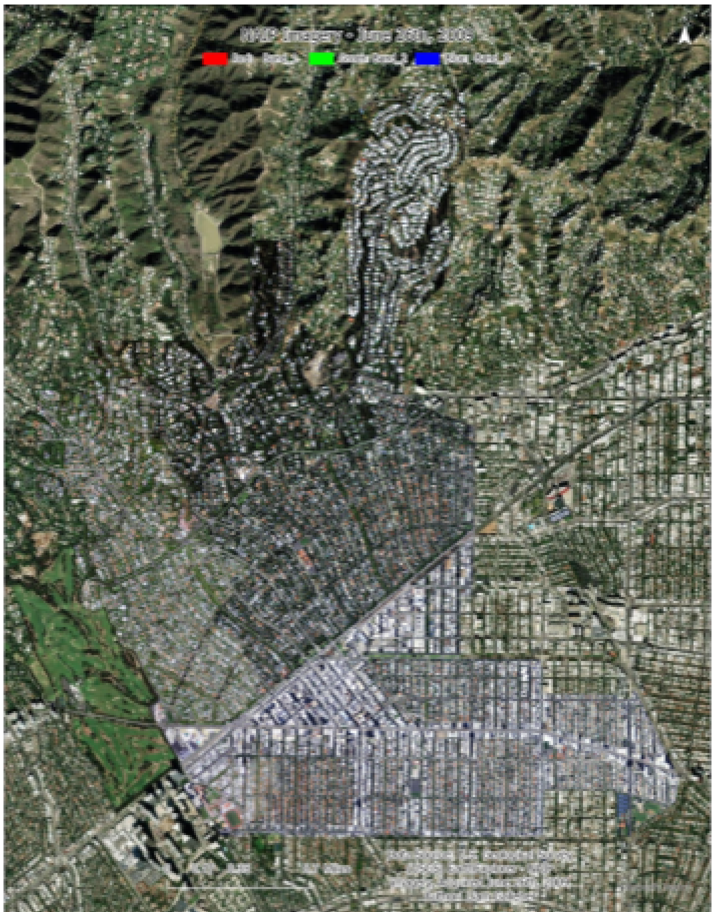
Object-based segmentation helps us address these challenges by reducing pixel noise, and supervised classification ensures that grass is distinguished from trees, shrubs, and impervious surfaces.

Methods and Data

1. NAIP 2009 (1 m, 4-band RGB + NIR)
2. NAIP 2022 (1 m, 4-band RGB + NIR)
3. City of Beverly Hills municipal boundary shapefile

4. Research on water-use requirements of turfgrass

Both NAIP datasets were downloaded from the USGS Earth Explorer portal. Both datasets are close in seasonality, spatial resolution, and band structure, ensuring their suitability for temporal comparison. Both mosaics were clipped to the Beverly Hills municipal boundary shapefile, and both were sampled at exactly 1 x 1 meter to ensure consistent pixel-area calculations.

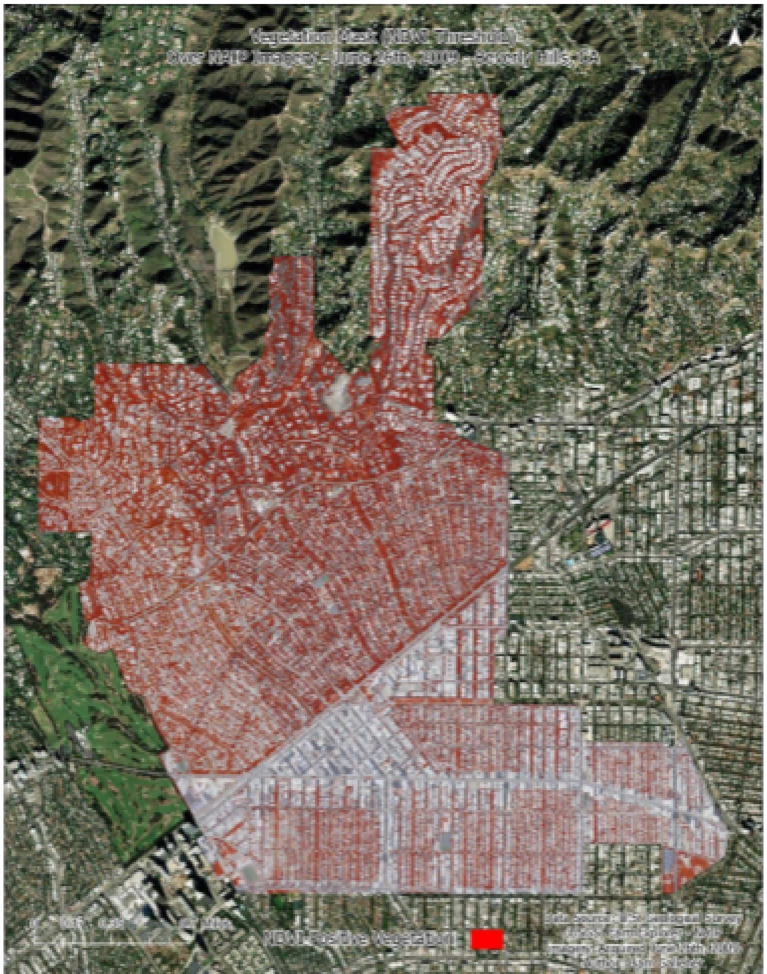


NAIP Imagery, 2009

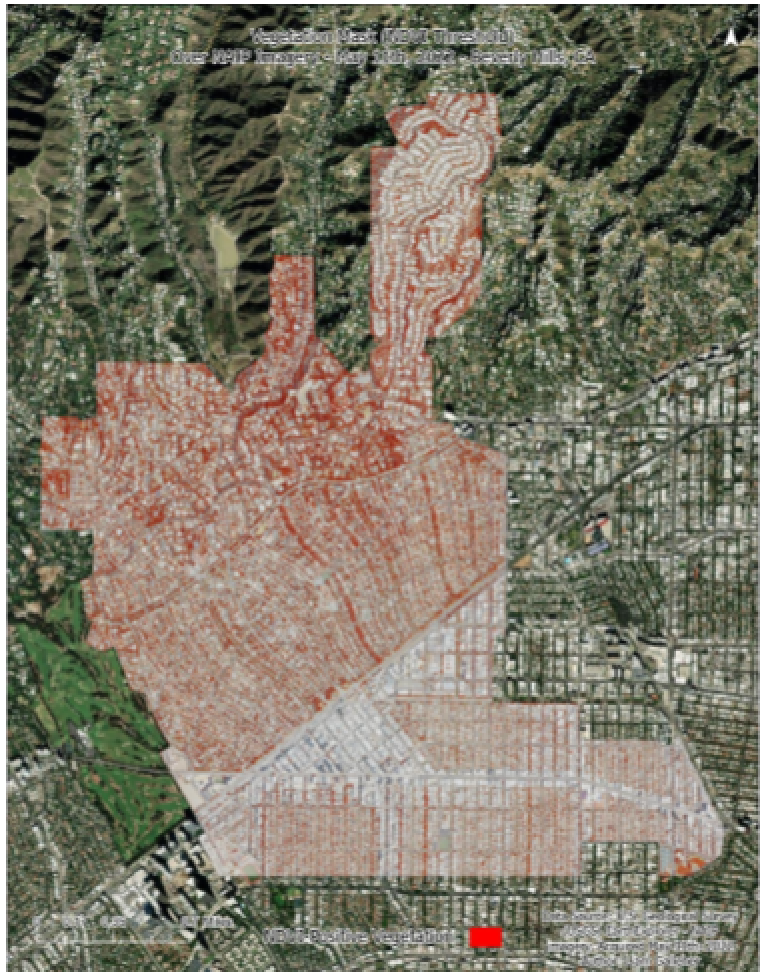
NAIP Imagery, 2022

NDVI Computation

Computing the Normalized Difference Vegetation Index was a pivotal step to distinguish real and fake grass. Using the NDVI Raster function in ArcGIS Pro, one binary dataset (vegetation mask) was produced for each year, where 0 = nonvegetation and 1 = vegetation. If NDVI was greater than 0.3 (a staple metric for NDVI), then it was classified as vegetation. This was helpful while attempting to classify something that *could* be grass visually, like a soccer field. If the soccer field was red, displaying a value of 1, then it was real grass, otherwise it was synthetic. It is important to note that to standardize NDVI across all datasets, each NDVI raster was normalized to the -1 to 1 range using the raster calculator.



Vegetation Mask - 2009



Vegetation Mask - 2022

Object-Based Image Classification

Image classification is a core remote sensing technique used to assign each pixel (or in our case, groups of pixels) to a meaningful category/land cover. Our project uses object-based image analysis to segment the NAIP imagery into "objects" before classifying them. Object classification considers object shape, texture, and surrounding pixel groups instead of isolated pixels, which make it excellent for identifying urban imagery. To complete this step, we used the ArcGIS Pro Image Classification Wizard with the following parameters:

1. Spectral Detail: 15
2. Spatial Detail: 10
3. Minimum Segment Size: 20 pixels
    a. These combined settings proved to best balance homogeneity and pixel sensitivity, ultimately still preserving object shape and color.
4. Classifier: Support Vector Machine (SVM)

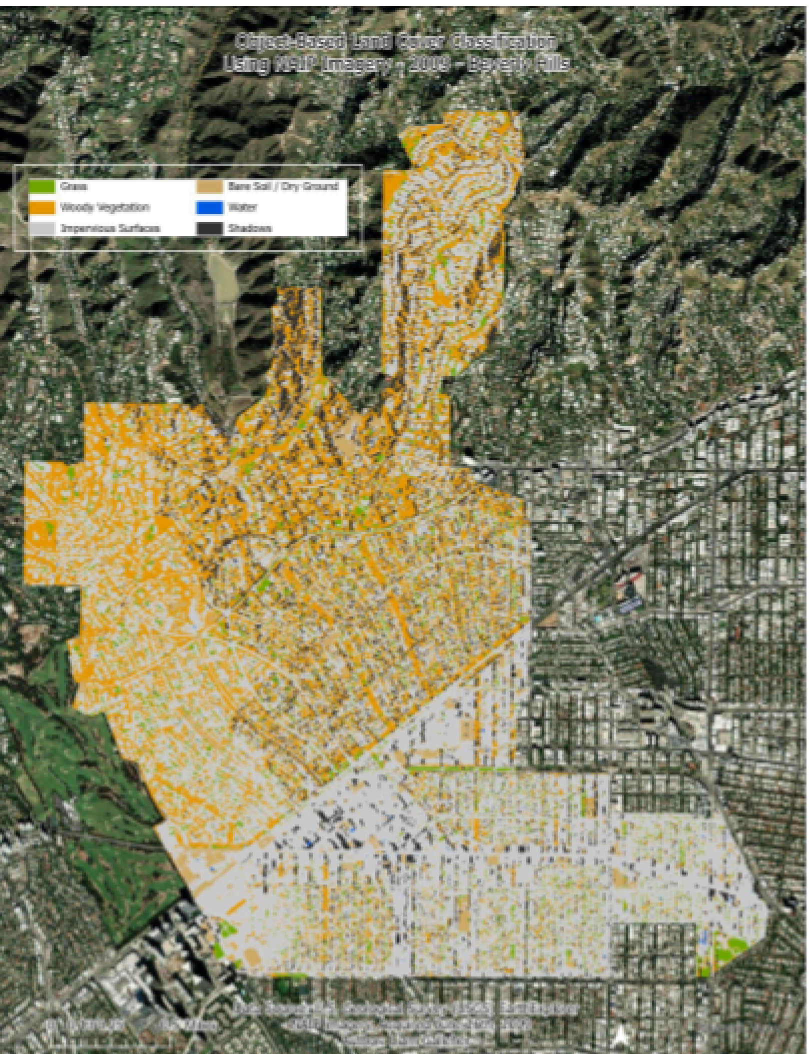
Training samples were manually digitized across diverse sample areas (NSEW, shaded/nonshaded, wealthy neighbourhoods with large and spread out homes, densely packed urban neighbourhoods, etc.). The Classification Wizard produces a segmented image, which identifies different "objects" throughout the NAIP imagery. Over this segmented image, we identified 30-60 training samples for each class in the schema depending on their complexity. For example, 'water' needed fewer samples because the shapes and colors are consistent over the entire image. On the other hand, 'grass' had more diversity, so we needed to make sure we identified all kinds of grass before completing the analysis. After training the classification wizard, we corrected any major mistakes, then trained it again.

The following training samples were selected to ensure that grass would not be mistaken for another land cover type:

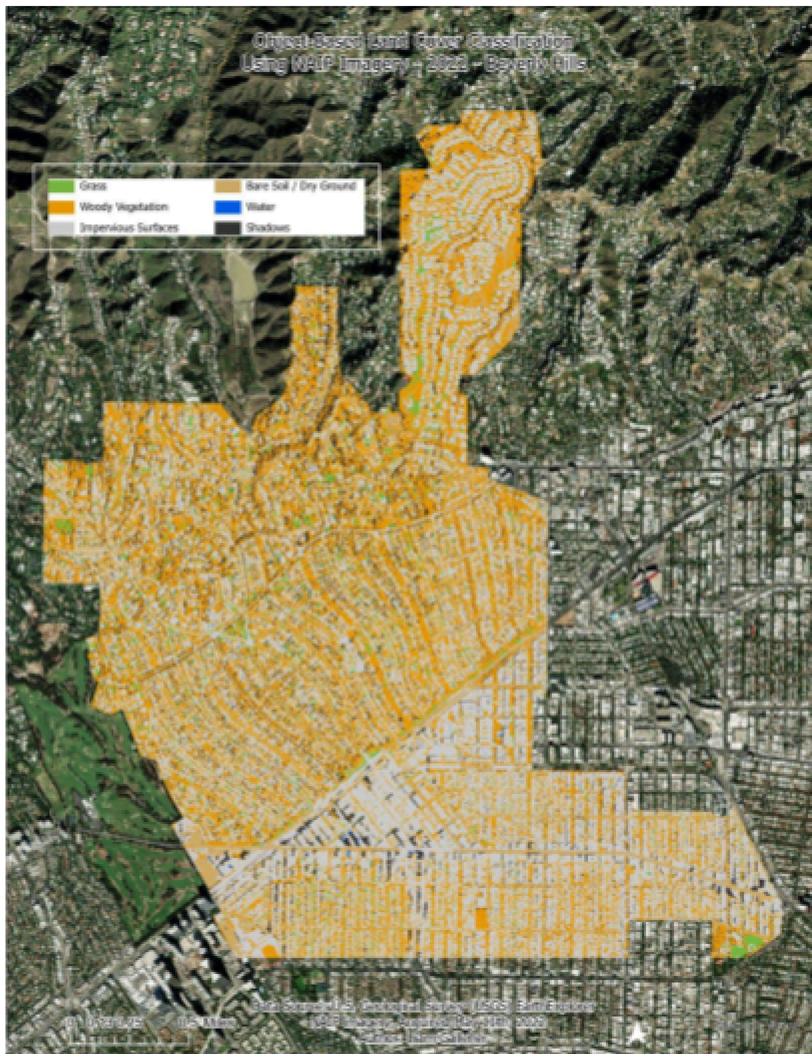
1. Grass

2. Woody Vegetation (trees, shrubs, above-ground biomass)
3. Impervious Surfaces (roads, buildings, tennis courts, roofs, fake grass)
4. Bare Soil / Dry Ground
5. Water
6. Shadows

The following maps depict the final classified images:



Object-based Classification, 2009



Object-based Classification, 2022

Accuracy Assessment

100 stratified random points were generated over each classified image. By using the 'Extract Values to Points' tool in ArcPro, each point was assigned to whichever raster value it landed on. We then manually interpreted the NAIP imagery to provide the GroundTruth classifications.

The overall accuracy for both 2009 and 2022 was **90%**. The 2009 classification produced a kappa coefficient of **0.84**, while the 2022 classification produced a kappa coefficient of 0.85. The corresponding PA and UA values demonstrate a variation in each class' accuracy. The following charts depict this variation:

Confusion Matrix (Object-Based) - 2009

GroundTruth	0 (Grass)	1 (Woody Vegetation)	2 (Impervious Surfaces)	3 (Bare Soil / Dirt)	4 (Water)	5 (Shadows)	Row Total
0	6	1	0	0	0	0	7
1	0	20	2	0	0	0	22
2	0	0	49	3	0	1	52
3	0	0	2	2	0	0	4
4	0	0	1	0	0	0	1
5	0	0	0	0	0	13	13
Total	6	21	54	5	0	14	100

Total Correct
90

Kappa Calculations

Class 0	36
Class 1	441
Class 2	2916
Class 3	25
Class 5	196
Sum	3614

po	0.9
pe	0.3614
Kappa	0.843407454

Accuracy Assessment

	GroundTruth	Recorded	Accuracy
Grass	6	6	100.00%
Woody Vegetation	20	21	95.24%
Impervious	49	54	90.74%
Bare Soil / Dirt	2	5	40.00%
Shadows	13	14	92.86%

Class	PA	UA
Grass	86%	100%
Woody Veg	90.91%	95.24%
Impervious	92%	91%
Bare Dirt	50%	40%
Shadows	100.00%	92.86%
Overall Accuracy	90.00%	
Kappa	0.84340745	

Confusion Matrix (Object-Based) - 2022

GroundTruth	0 (Grass)	1 (Woody Vegetation)	2 (Impervious Surfaces)	3 (Bare Soil / Dirt)	4 (Water)	5 (Shadows)	Row Total
0	2	1	0	0	0	0	3
1	0	41	0	0	0	0	41
2	1	3	32	5	0	0	41
3	0	0	0	6	0	0	6
4	0	0	0	0	2	0	2
5	0	0	0	0	0	7	7
Total	3	45	32	11	2	7	100

Total Correct
90

Kappa Calculations

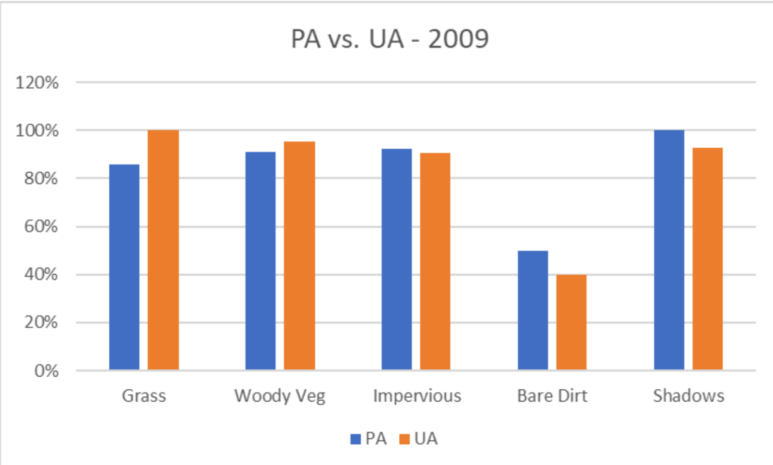
Class 0	9
Class 1	2025
Class 2	1024
Class 3	121
Class 4	4
Class 5	49
Sum	3232

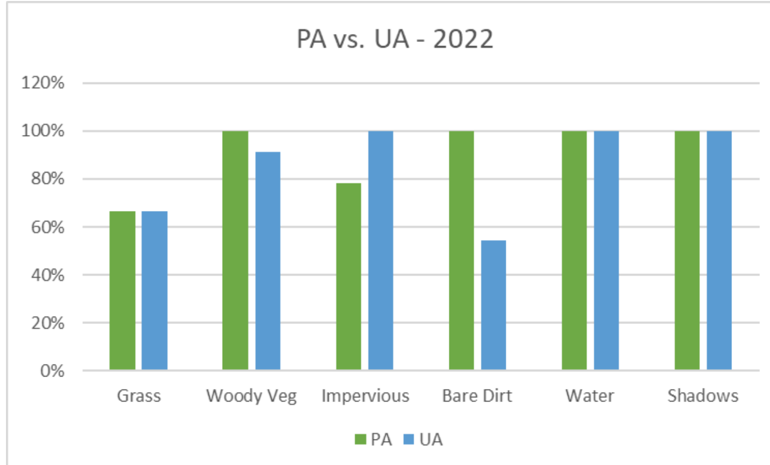
po	0.9
pe	0.3232
Kappa	0.852245863

Accuracy Assessment

	GroundTruth	Recorded	Accuracy
Grass	6	6	100.00%
Woody Vegetation	20	21	95.24%
Impervious	49	54	90.74%
Bare Soil / Dirt	2	5	40.00%
Shadows	13	14	92.86%

Class	PA	UA
Grass	67%	67%
Woody Veg	100.00%	91.11%
Impervious	78%	100%
Bare Dirt	100%	55%
Water	100%	100%
Shadows	100.00%	100.00%
Overall Accuracy	90.00%	
Kappa	0.85224586	

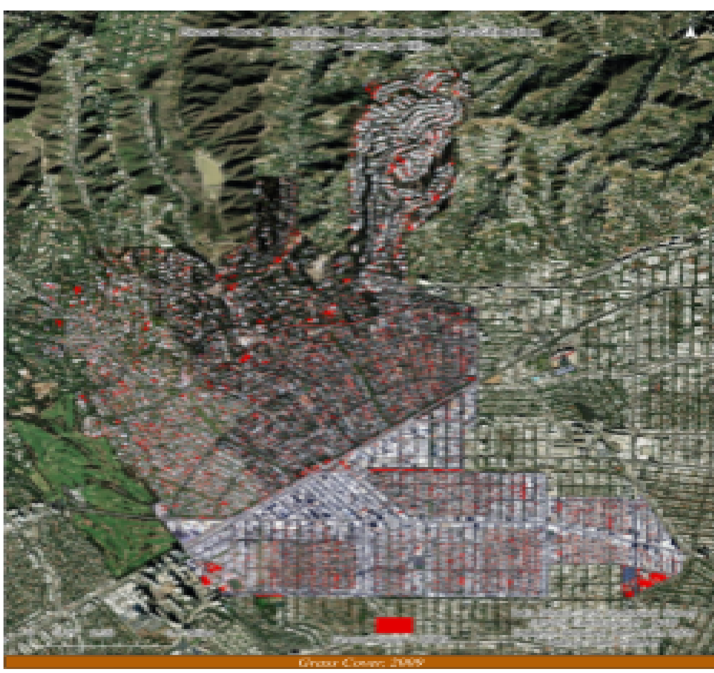


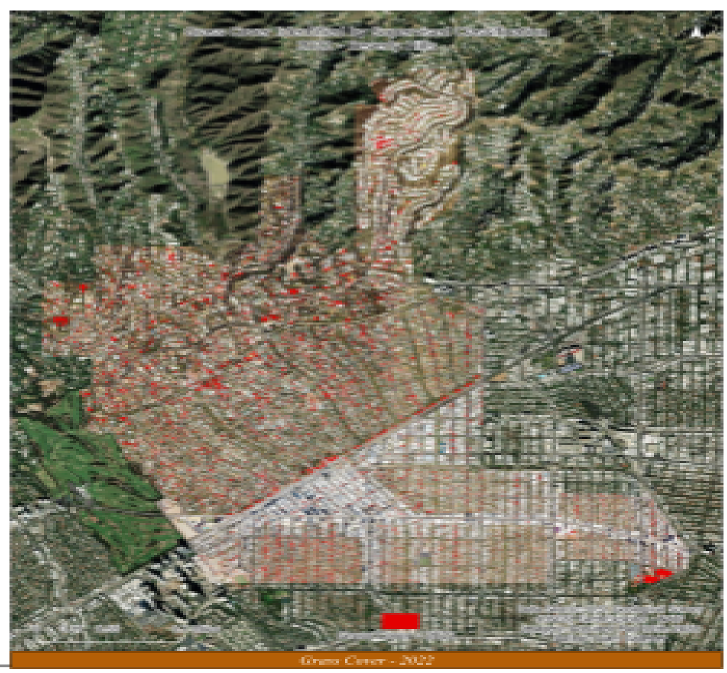


Grass Area Classification

Each classified raster was filtered to extract only pixels assigned to 'Grass.' Pixel counts were converted to acreage by using the following formula: **Acres = pixel count / 4046.8564224**. The results were as follows:

- 2009: 178 acres
- 2022: 120 acres
- Grass removed: 58 acres, net reduction of 33% (⅓ reduction)





Results

Estimated Water Savings

Turfgrass irrigation requirements vary in Southern California, but contemporary literature suggests that it can range anywhere from **3-5 acre-feet per year** depending on grass species, climate, and individual landowner irrigation practices (*Costello et al., 2000; WUCOLS IV*). To account for this variation, a calculation was done for each number in that range to produce a low estimate, moderate estimate, and high estimate of water consumption and savings.

Note that 1 acre-foot = 325,851 gallons.

Turfgrass Use	Water Use (AF/Year)	Grass Area Removed	Estimated Water Saved Annually (AF/Year)	Estimated Water Saved Annually (Gallons/Year)
Low estimate	3	58	174	56.7 million gallons / year
Mid-estimate	4	58	232	75.6 million gallons / year
High estimate	5	58	290	94.5 million gallons / year

Estimated Monetary Savings

To translate these findings into economic value, we applied two cost scenarios. The lower estimate cites the Southern California wholesale cost of treated imported weather $1,395 per acre-foot, and the higher estimate cites the “retail” cost of delivered water, $2,000 per acre-foot, which accounts for pumping, treatment, and distribution (*Metropolitan Water District of Orange County, 2025*).

Turfgrass Use	Estimated Water Saved Annually (Acre-Feet/Year)	Cost Savings ($1,395 / AF)	Cost Savings ($2,000/AF)
Low estimate	174	$242,730 per year	$348,000 per year
Mid-estimate	232	$323,640 per year	$464,000 per year
High estimate	290	$404,550 per year	$580,000 per year

Social Implications

On average, one acre-foot of water is the equivalent of usage for 1 household (on average 2-3 people) per year. The reduction in turfgrass is thus the equivalent of supplying water for roughly 172-290 households, or up to 870 residents per year.

Turfgrass Use	Estimated Water Saved Annually (Acre-Feet/Year)	Equivalent Residents (if 2 people per household)	Equivalent Residents (if 3 people per household)
Low estimate (174 AF/year)	174 households	348 residents	522 residents
Mid-estimate (232 AF/year)	232 households	464 residents	696 residents
High estimate (290 AF/year)	290 households	580 residents	870 residents

Discussion

The results of this study quantify the efforts of the City of Beverly Hills to reduce turfgrass and save water within their city limits. Our object-based classification approach effectively delineated grass versus other land cover types, producing a final estimate of 178 acres of grass in 2009 and 120 acres of grass in 2022, totaling to a net decrease of 58 acres (roughly 33% of Beverly Hills Turf). These numbers correspond to up to 290 acre-feet / 94.5 million gallons of water saved every year, and up to $580,000 saved annually. Between 2009 and 2022, that is a total of at least 2,262 acre-feet and at most 5,510 acre-feet of water saved total. Within the broader context of water conservation efforts in Southern California, this landscape-level shift is a triumph for the city of Beverly Hills.

When interpreting these results, it is important to note the intentional conservatism that went into this analysis. Our workflow relied on a strict definition of turfgrass to distinguish it from other objects that, in an urban environment, appear spectrally similar. In similar studies, tree canopy, hedges, shrubs, and synthetic grass are easily mistaken for turfgrass. Because these urban environments are so complex, we prioritized classifying grass accurately over maximizing acreage detection. Thus, borderline and ambiguous patches of what "could have been grass" were excluded unless they could be confirmed with the vegetation mask or NAIP imagery.

As a result, our recorded grass estimate is lower than similar studies. However, the magnitude of change (roughly 33% or a ⅓ reduction) is consistent with similar studies and publicly reported turf loss estimates in the greater Southern California area, especially in regions that adopted incentive programs. So, even though our map is more conservative than others with grass identification, it still aligns with turf and water-use reduction trends.

Assuming that the typical turfgrass lawn requires 3-5 acre-feet of water per acre annually, the removal of 58 acres corresponds to an estimated annual saving of 174-290 acre-feet of water, which is enough to supply up to 290 households, or up to 870 residents with water for an entire year. Considering that the population in Southern California continues to rise as water availability declines, savings like this are imperative (and effective) for the coming years.

It is also important to note potential sources of error. When comparing two NAIP images acquired on different dates, seasonal effects, shadows, image quality, and vegetation vigor can differ, all of which are factors that can impact image classification performance. Further, although the accuracy assessments for both years returned a strong overall accuracy of 90%, certain classes, like bare soil, demonstrate greater confusion with woody vegetation and impervious surfaces. While these types of errors are to be expected when remote sensing in an urban environment, they should still be considered when interpreting the final results.

Even with these uncertainties, the patterns observed through this analysis are irrefutable. The loss of turfgrass from 2009 to 2022 is widespread and aligns with the general magnitude of change in similar studies. When compared to state-wide water estimates, these findings suggest that Beverly Hills has experienced meaningful progress towards water conservation though xeriscaping over the studied 13 year period.

Conclusion

Through various remote sensing techniques, including supervised object-based classification and vegetation-index analysis, this study quantified the landscape level shift from irrigated turfgrass lawns to xeriscaping in Beverly Hills between 2009 and 2022. The city reduced grass cover by an estimated 58 acres, which corresponds to an estimated range 174 to 290 acre-feet of water annually (at least 2,262 acre-feet and at most 5,510 acre-feet of water saved between 2009 and 2022) or 56.7 million to 94.5 million gallons saved every year. This has saved the city of Beverly Hills up to $580,000 per year. These findings demonstrate the effectiveness of xeriscaping and conservation-forward incentive programs, providing a technical foundation and motivation for future xeriscaping initiatives. This analysis produced a repeatable workflow for tracking urban landscape change in Beverly Hills, and can be referenced when making policy decisions with regard to individual landowner impact.

Xeriscaping - image from Urbafloria Landscape Designers

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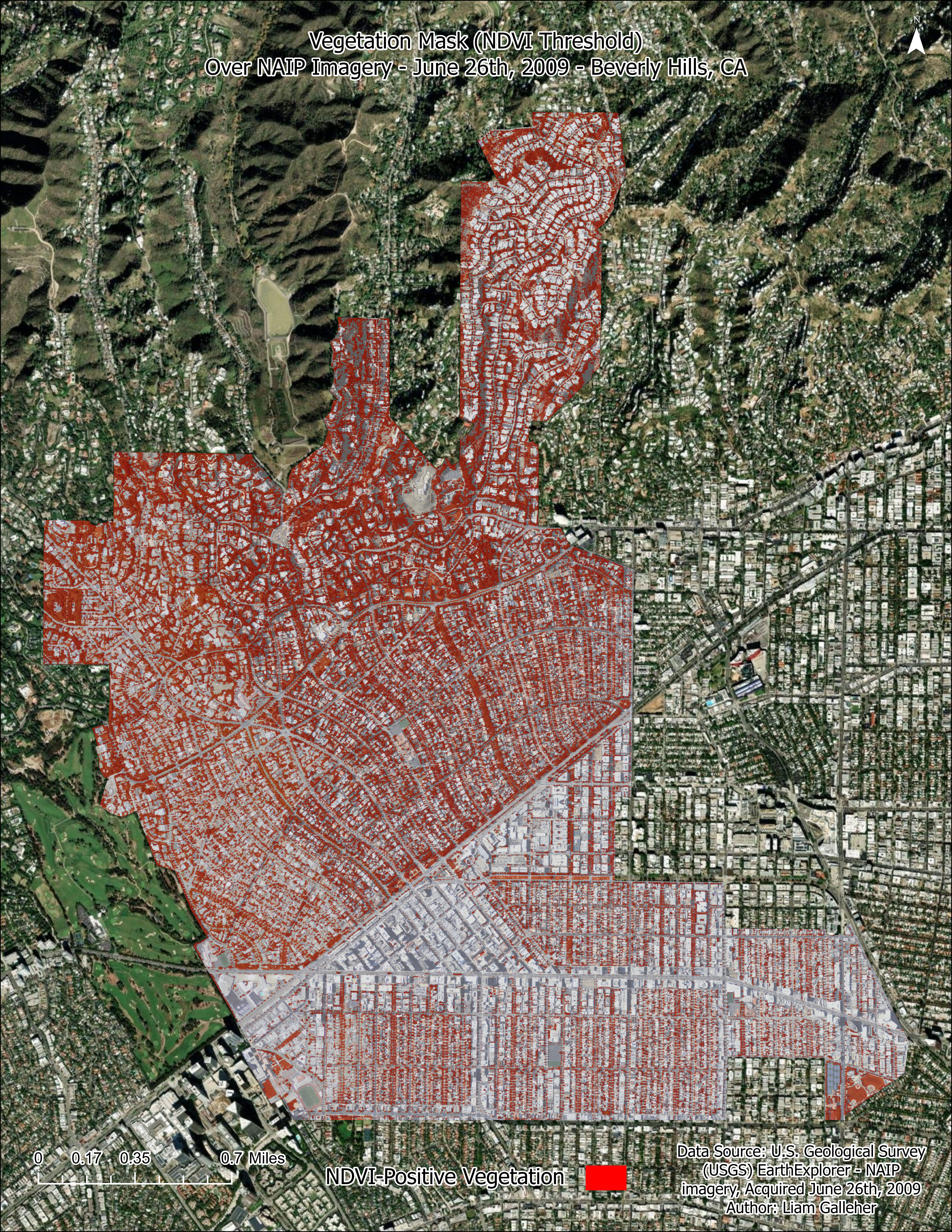

Vegetation Mask (NDVI Threshold)
Over NAIP Imagery - June 26th, 2009 - Beverly Hills, CA
N
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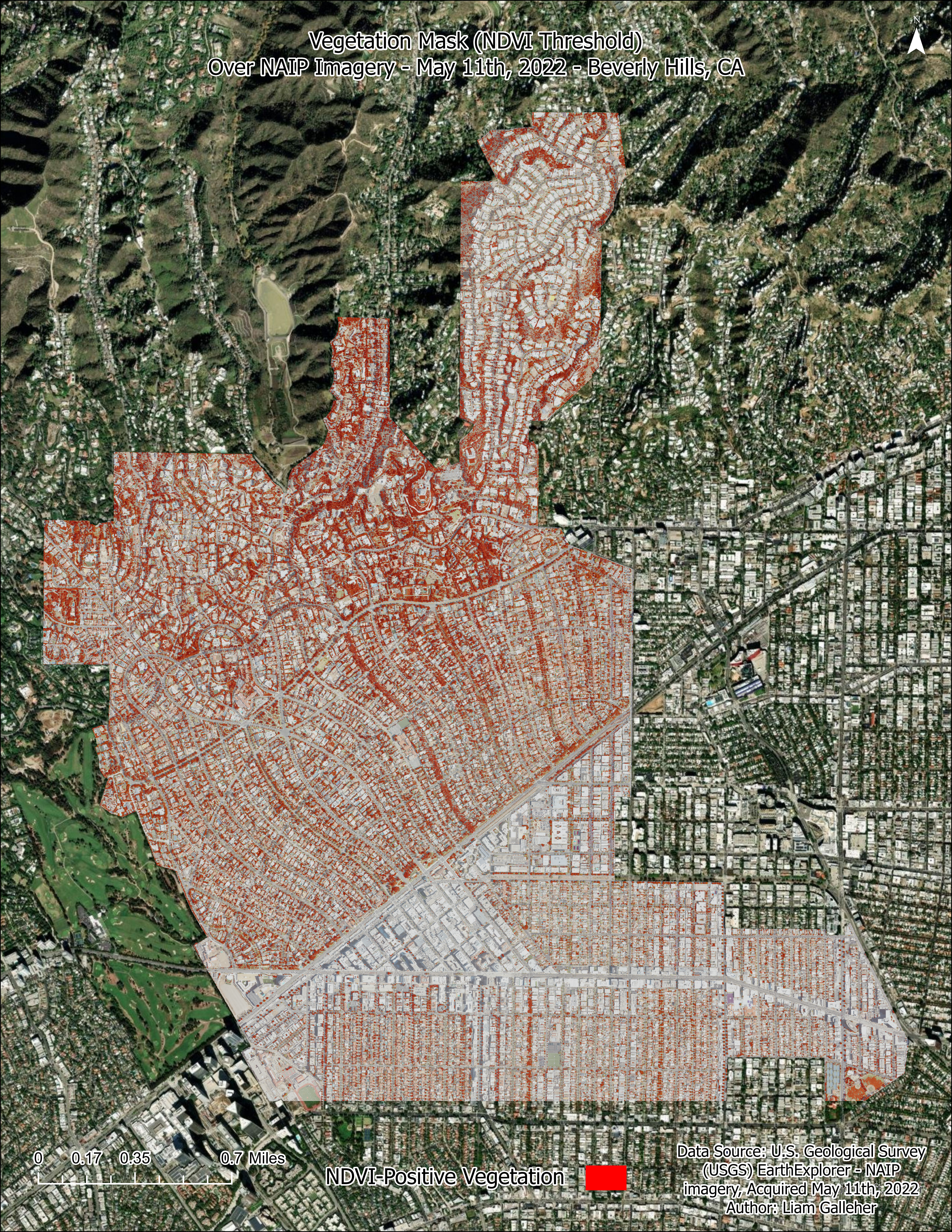
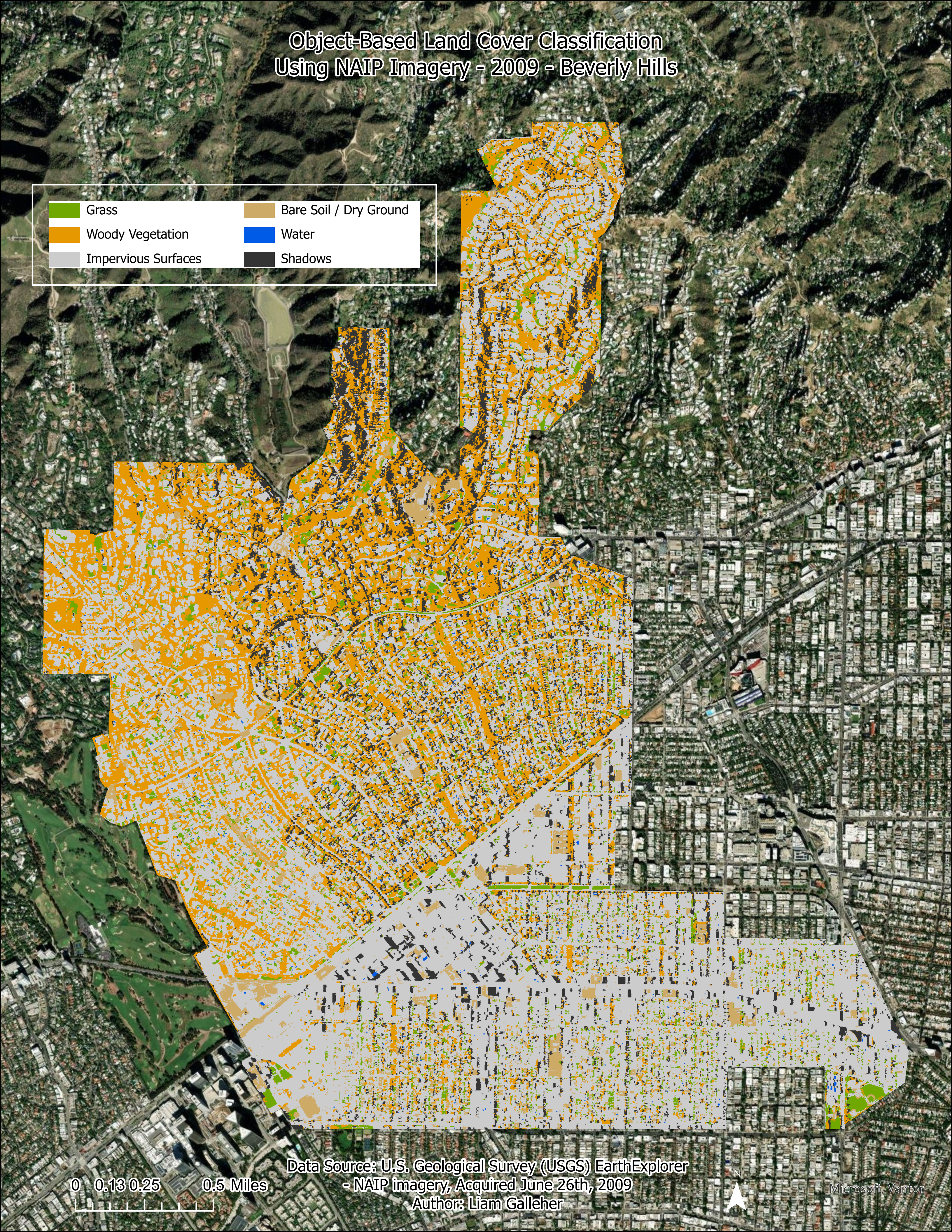
NDVI-Positive Vegetation
Data Source: U.S. Geological Survey (USGS) EarthExplorer - NAIP imagery, Acquired June 26th, 2009
Author: Liam Galleher


Vegetation Mask (NDVI Threshold)
Over NAIP Imagery - May 11th, 2022 - Beverly Hills, CA
N
0 0.17 0.35 0.7 Miles
NDVI-Positive Vegetation
Data Source: U.S. Geological Survey
(USGS) EarthExplorer - NAIP
imagery, Acquired May 11th, 2022
Author: Liam Galleher


Object-Based Land Cover Classification
Using NAIP Imagery - 2009 - Beverly Hills
Grass
Woody Vegetation
Impervious Surfaces
Bare Soil / Dry Ground
Water
Shadows
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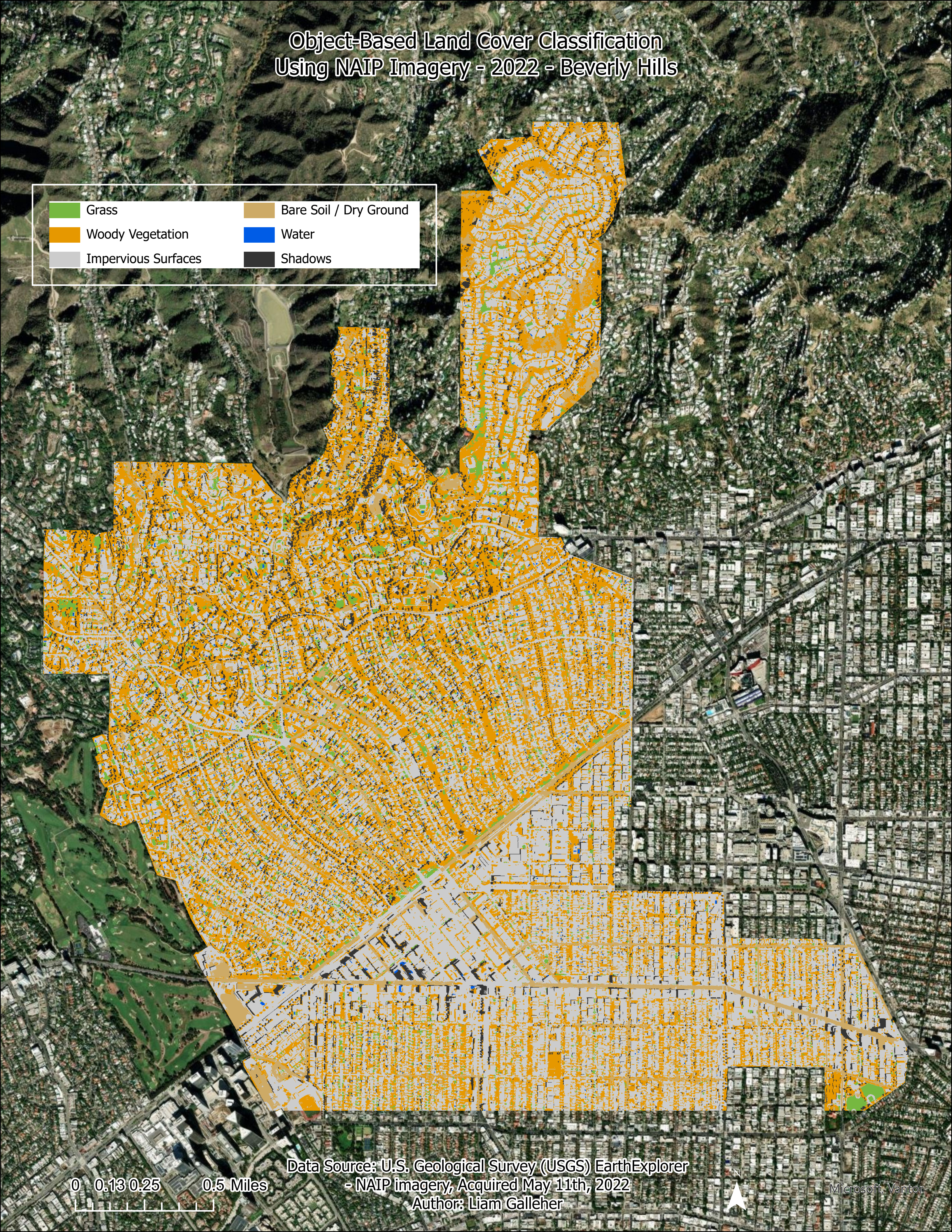
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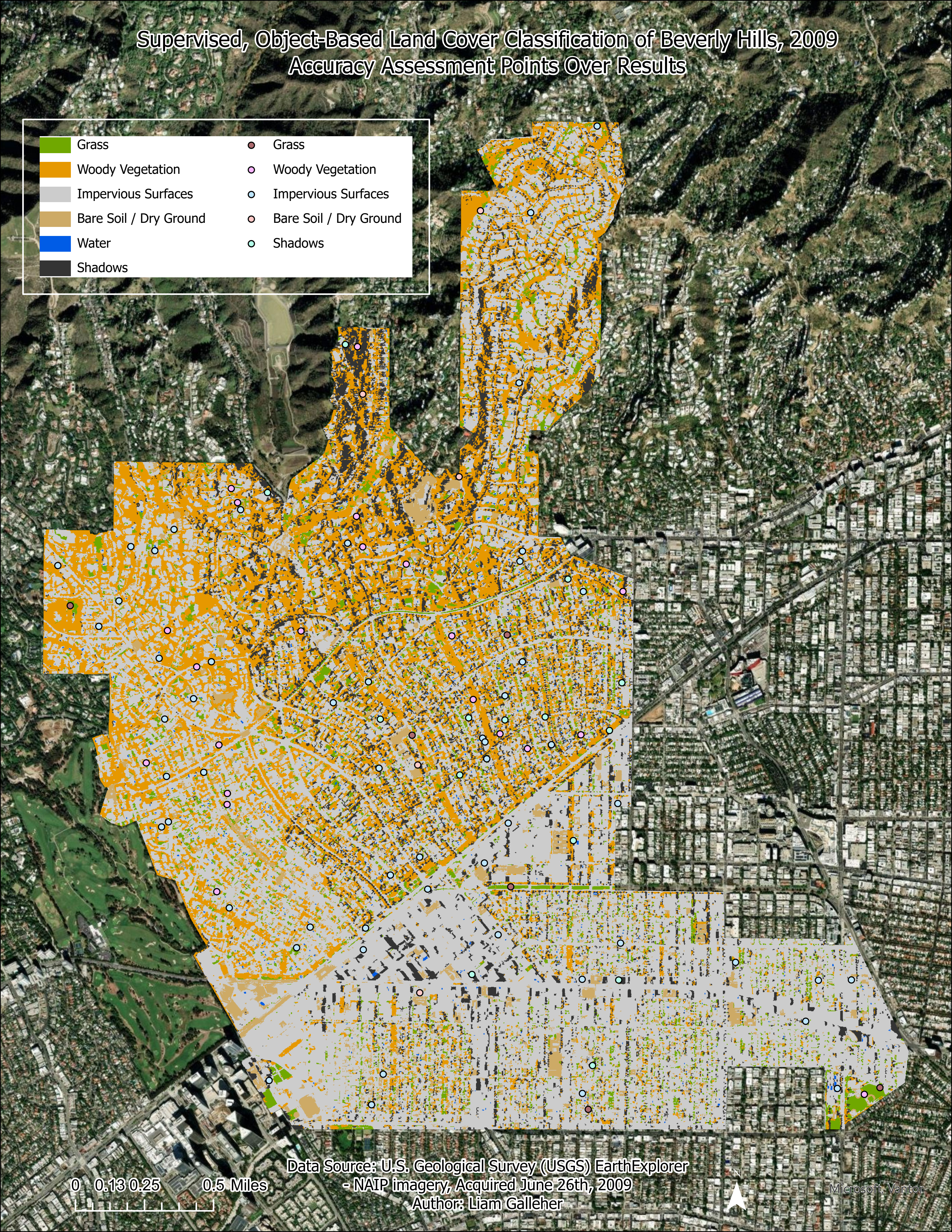
Supervised, Object-Based Land Cover Classification of Beverly Hills, 2009
Accuracy Assessment Points Over Results
Grass
Woody Vegetation
Impervious Surfaces
Bare Soil / Dry Ground
Water
Shadows
Grass
Woody Vegetation
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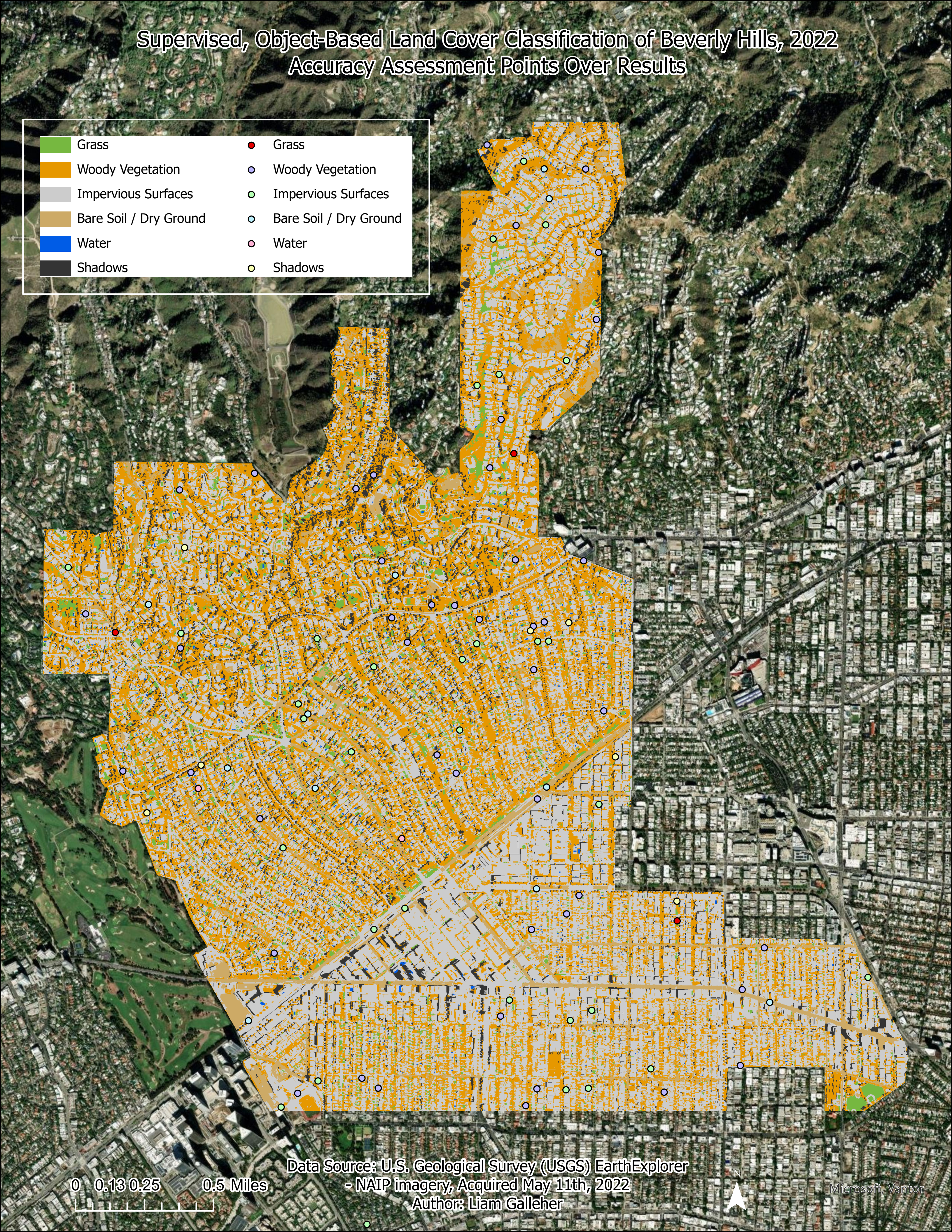

Supervised, Object-Based Land Cover Classification of Beverly Hills, 2022
Accuracy Assessment Points Over Results
Grass
Woody Vegetation
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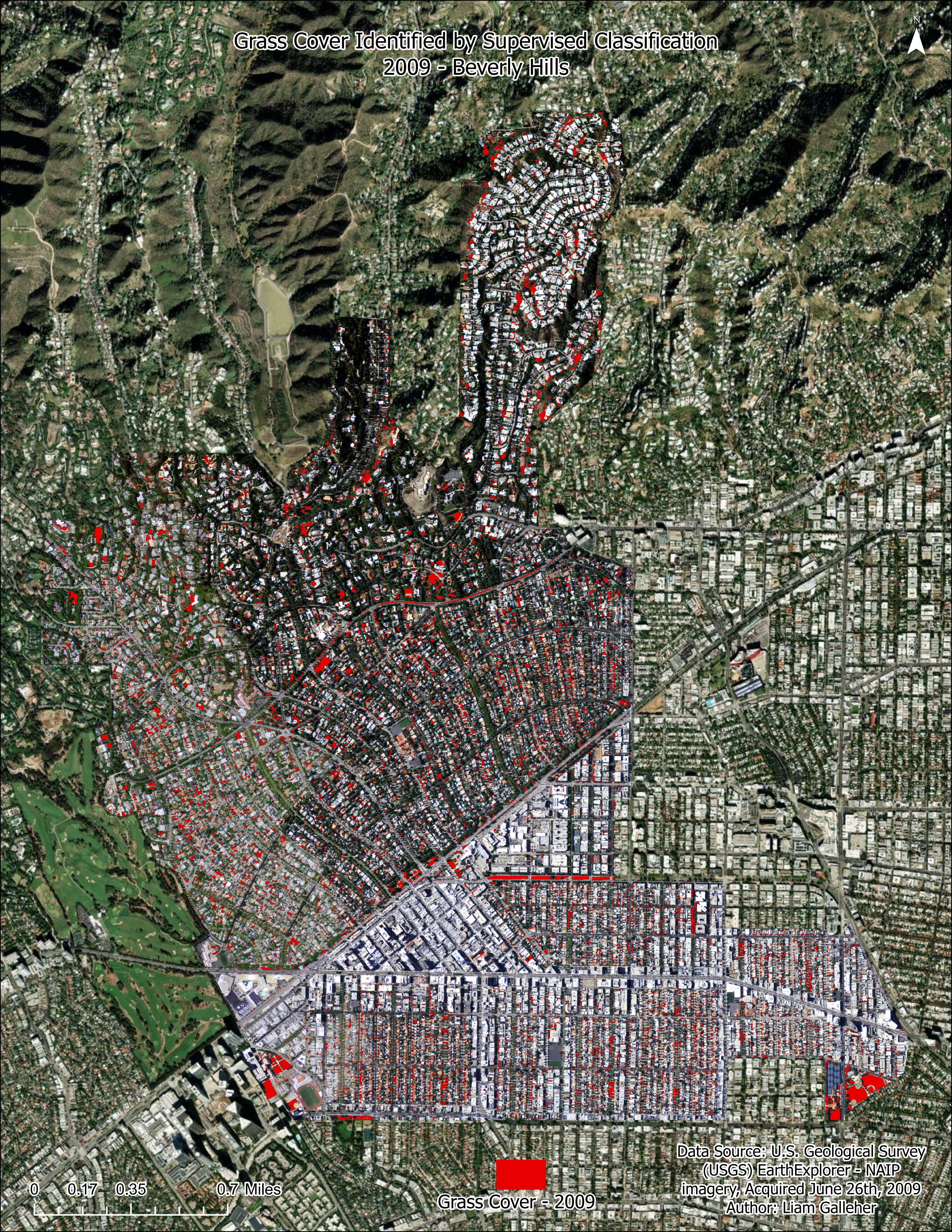
Grass Cover Identified by Supervised Classification
2009 - Beverly Hills
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Grass Cover - 2009
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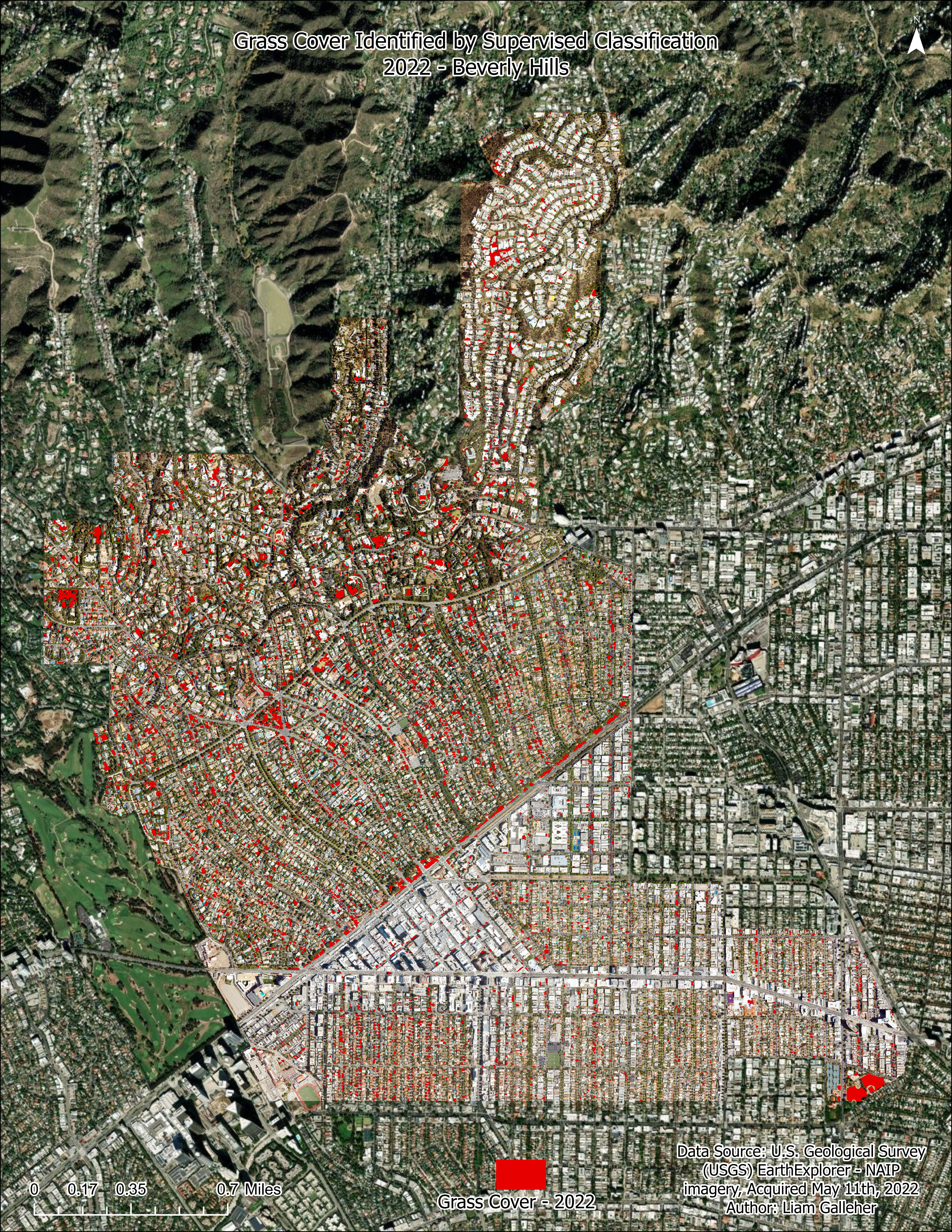
Grass Cover Identified by Supervised Classification
2022 - Beverly Hills
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Grass Cover - 2022
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(USGS) EarthExplorer - NAIP
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