GEOBIA TECHNIQUES TO IMPROVE IMPERVIOUS SURFACE CLASSIFICATION BENEATH THE TREE CANOPY FOR ACCURATE IMPERVIOUS SURFACE PER PARCEL CALCULATION IN ATHENS, OH

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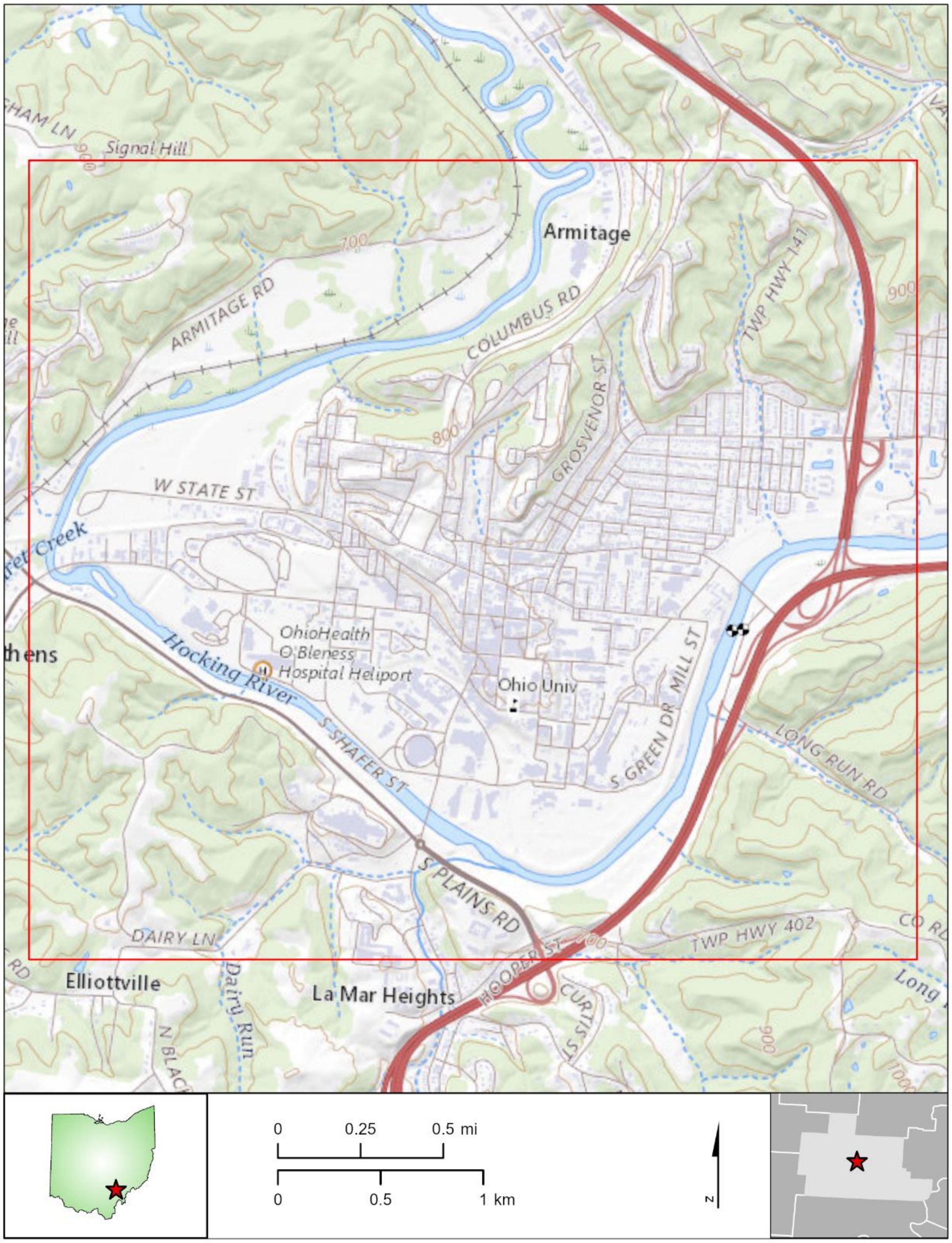
1. INTRODUCTION

With climate change threatening on the horizon, it is more important than ever that cities are prepared to meet the challenges of rapidly changing demographics and increasingly extreme weather events. According to the study, *Causal Effect of Impervious Cover on Annual Flood Magnitude for the United States*, "For every percentage point increase in roads, parking lots and other impervious surfaces that prevent water from flowing into the ground, annual floods increase on average by 3.3%" (Blum 2020). Impervious surface refers to all hard surfaces such as paved roads, parking lots, roofs, and highly compacted soils, that prevent the natural soaking of rainwater into the ground.

Traditional methods of impervious surface calculation are time consuming and expensive; however, the continual rapid advancement in production of high-resolution remote sensing technology is allowing cities and individuals to leverage geos-spatial problem-solving methods that would not have been feasible in past decades, making remote sensing an attractive solution for cities seeking a low cost means of assessing impervious surface.

E-Cognition is a powerful geospatial software that allows users to develop geographic object-based image analysis (GEOBIA) rulesets to segment and classify a wide variety of raster products in to meaningful objects for use in geospatial analysis. While we are in some sense inundated with high resolution lidar and aerial data, access to the highest quality data and software processing licenses are limited, and data available for public use varies widely in terms of quality. E-Cognition and similar data fusion software enables users to make the most out of large scale, state funded data sets and perform accurate land classifications surveys without large teams and traditional survey equipment. However, the ability to remotely sense the ground surface beneath the tree canopy is a benefit of land based surveys that remote sensing techniques have yet to fully compensate for.

In the following document, I examine the uses and limitations of the key lidar, aerial, and thematic data types in assessing the ground surface beath the tree canopy. I then apply that analysis to an examination of the workflow used to extract the impervious surface of the city of Athens, OH, as well as key E-Cognition algorithms that are shown to be effective in producing an impervious surface raster. Finally, I report the results of impervious surface classification and apply it to the calculation of impervious surface per parcel for the city of Athens.



Basemap: USGS National Map (2023)

Figure 1 Study Area: Athens, OH

2. DATA AND METHODOLOGY

The impervious surface model was produced using high quality, publicly accessible datasets. The quality of a dataset as it pertains to its usefulness in a GEOBIA project can typically be expressed in terms of the resolution and positional accuracy of raster data and the completeness and positional accuracy of vector data. High resolution is a variable term that is constantly being redefined as technology advances; 6”, 30cm, and 1m will often all be considered “high resolution” depending on the vendor. As of the writing of this paper, aerial imagery can be said to be high resolution if the resolution six inches or less. The United States Geographic Survey (USG) and American Society for Photogrammetry and Remote Sensing (ASPRS) provide strict guidelines to assess lidar quality based on positional accuracy and nominal point spacing; to be considered high quality (Q1), a lidar dataset should have a .35m (1.14ft)nps and raster data derived from Q1 data may have a resolution no less than .5m (1.6ft) (NGP Standards and Specifications, 2023). Sources for the lidar, aerial, and vector data used in this project include the Ohio Statewide Imagery Program (OSIP), Ohio Geographically Referenced Imagery Program (OGRIP), Unstructured Grid (UGRID), and the USGS Earth Explorer and are summarized in Tables 1-3.

Lidar		
	2007 lidar[4]	**2021 lidar**[1,2]
Projection	NAD 1983 HARN StatePlane Ohio South FIPS 3402 (US Feet)	NAD 1983 (2011) StatePlane Ohio South FIPS 3402 (US Feet)
NPS	1.828 (6ft)	0.35
Quality	2	1
Version	1	1.4
Sensor	Leica ALS50 digital LiDAR Systems	?
Collection Date	March and May 2007	March and April 2021

[3][4]

Table 1 Summary of available lidar data within the Athens, OH study area. The 2021 lidar dataset was selected to create raster data for this project.

1 Ohio Statewide Imagery Program (OSIP) - https://das.ohio.gov/technology-and-strategy/ogrip/projects/osip

2 Ohio Geographically Referenced Imagery Program (OGRIP) - https://temp02.oit.test.ohio.gov/ProjectsInitiatives/OSIPDataDownloads.aspx

3 Athens County Audor Open GIS Data - https://data-athgis.opendata.arcgis.com/

4 UGRID -https://www.ugridd.com/uFIND/@160+W+Union+St+Suite+150+Athens+OH+45701+USA/Ohio+LiDAR+South/data=ZZKuNt1wuMv_8ZmWa7z+t1vLNv_P

Aerial Imagerry						
	2017 NAIP	2021 NAIP	2014 CIR (OSIP*[1,2])	2014 RGB (OSIP)	2020 RGB (OSIP)	2007 RBG (OSIP)
Projection	NAD 1983 UTM Zone 17N	NAD 1983 UTM Zone 17N	NAD_1983_HARN_Ohio_South_ftUS	NAD_1983_HARN_Ohio_South_ftUS	NAD 1983 HARN StatePlane Ohio South FIPS 3402 (US Feet)	NAD 1983 HARN StatePlane Ohio South FIPS 3402 (US Feet)
Resolution	1m	.6cm	6inch	6inch	6inch	1ft
Bands/Classes	4 bands	4 bands	3 (NIR-G-R)	3	3	3
Bit Depth	8	8	8	8	8	8
Sensors	CNIR	CNIR	Leica ADS80-SH81/82 Airborne Digital Sensor	Leica ADS80-SH81/82 Airborne Digital Sensor	VisionMap A3 Edge digital camera systems	Leica ADS40/51/52 digital cameras
Collection Date	Jun-17	Nov-21	Spring 2014	Spring 2014	2020 - no month	March-April leaf off
*OSIP = Ohio Statewide Imagery Program						

Table 2 Summary of leaf-on and leaf-off aerial imagery used.

Vector Data				
	Parcels	Addresses	Road Centerlines	Subdivisions
Projection	NAD 1983 (2011) StatePlane Ohio South FIPS 3402 (US Feet)	NAD 1983 StatePlane Ohio South FIPS 3402	NAD 1983 StatePlane Ohio South FIPS 3402 (Meters)	NAD 1983 (2011) StatePlane Ohio South FIPS 3402 (US Feet)
Type	Polygon	Point	Polyline	Polygon
Source	Athens County Auditor[3]	OGRP[2]	OGRP	Athens County Auditor

Table 3 Summary of vector (thematic) data used.

The quality of the data has a direct impact on the quality of the results. Not only does it allow for more accurate assessments of area, the higher the resolution of the raster data, the easier it is for E-Cognition' s processing algorithms to identify distinct objects. However, access to the highest quality datasets is variable, leaving many communities to rely on data acquired at the state or federal level, which, due to the steep acquisition cost, is often of slightly less quality that can be achieved by a targeted survey at the local level. Therefore, an important aspect of this project is that it can be replicated using data of a quality that can reasonably be expected to be freely available anywhere in the United States.

The project was performed using a combination of E-Cogntion 10.3, E-Cogntion Server, and ArcGIS Pro 3.2. ArcGIS was used to convert the lidar point cloud into the height, slope, and intensity rasters used in E-Cognition and to clip the aerial imagery to the Athens city boundary. However, if licenses are sparse, open-source geospatial software such as QGIS can be used to perform the same functions. Lidar rasterization and area per parcel calculations can also be performed within the E-Cognition environment.

2.1 Data and Useful Attributes

2.1.1 Lidar derived data

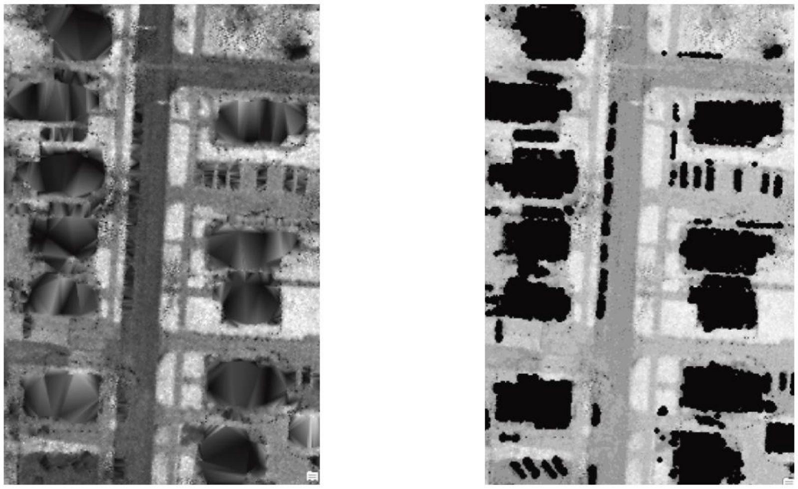
Lidar is a highly valuable data type for performing object-based image analyses because of its ability to assess the environment in three dimensions. Unlike aerial or satellite imagery, lidar can penetrate the tree canopy and provide information on the ground surface beneath. Key landscape feature attributes that may be derived from lidar include height, expressed as a digital surface model and normalized digital surface model (DSM/nDSM) and texture, derived from change in height and expressed as a slope raster and normalized slope raster (Slope_nDSM). This information allows us to map the geometry of the environment and provides key context clues for distinguishing one landscape feature from another (i.e. tree vs building). Additional information regarding the composition of a landscape feature can be inferred by the amount of energy reflected to the sensor after interacting with a surface. This attribute is called intensity and is recorded in the intensity raster. It is the ability to incorporate lidar derived products into the segmentation algorithms that distinguishes E-Cognition from the land classification tools provided in ArcPro., which can only consider the spectral qualities of a single dataset.

Lidar data provided by a vendor will typically undergo a degree of classification prior to being released, whether to the public or to a private entity. Lidar will generally be classified by landscape feature type (ground, vegetation, building, etc) as well as by the number of returns. ASPRS standards describe 20 possible landscape type categories into which lidar returns may be classified, ranging from the broad, ground class category, to categories for specific features, such as bridges and powerlines (American Society for Photogrammetry and Remote Sensing, 2011). However, separating above ground features can be labor intensive, so, in practice, many vendors limit classification to two categories: ground and "not ground". The presence of vegetation can be inferred by the number of returns per pulse, as ground surface and buildings only contain a single return.

The lidar dataset provided by the OSIP contains classification for return values, but no buildings or vegetation classes. Instead, both buildings and vegetation are classified as "Unassigned". This presents a particular challenge for deriving impervious surface, as tree canopy returns need to be removed from the dataset in order to get an accurate determination of the surface underneath. Strategic combinations of number of returns and the ground returns can reduce the amount of tree canopy cluttering the nDSM. A significant portion of the tree canopy was reduced by subtracting a last of many returns normalized surface model (LOM_nDSM) from the nDSM. However, attempts to fully remove the tree canopy from the nDSM without simultaneously removing the buildings were unsuccessful.

For this reason, the use of a lidar intensity raster for impervious surface classification was investigated. Initial results were promising. ESRI defines lidar intensity as "a measure…of the return strength of the laser pulse that generated the point. It is based, in part, on the reflectivity of the object struck by the laser pulse" (ESRI, 2021). Lidar wavelengths are within the near infrared range, and similarly may be used to distinguish vegetation from impervious surface (Figure 1). In theory, lidar intensity can combine the benefits of NIR and NDVI in surface classification with the ability of lidar to penetrate the tree canopy. Multiple studies may be found confirming the effectiveness of lidar intensity in landcover classification (Antonarakis et al., 2008; Song, et al., 2002). However, Kashani et al. note that intensity values are highly susceptible to atmospheric humidity and surface wetness, and often require correctional processing at increasing levels of complexity to remove errors from overlapping swaths, correct for angle of incidence, and make full use of the data (Kashani et al., 2015). The ad hoc normalization method suggested by Kashani was attempted in this study (Figure 2, next page). Although the dataset became more homogeneous, allowing for more intuitive segmentation, the difference in values between road and grass were expressed in decimals. Such as fine threshold was difficult to segment. So, despite the enhanced visual quality of the intensity data, reducing the tree canopy through the creation of a LOM_nDSM was ultimately more effective and less time consuming (Figure 3, next page). It should be noted that, while intensity was not the most useful method for segmentation in this study, the lidar intensity attribute was a useful aid in assigning class values, such as filling in gaps in the impervious surface classification caused by shadows.

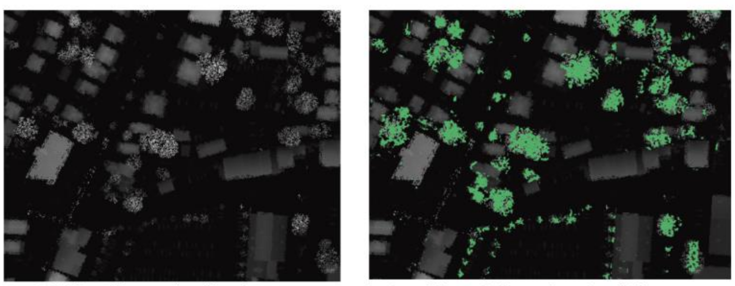
Figure 2 Example of lidar intensity raster showing a portion of downtown Athens, OH, filtered by ground and last of many returns. Bright values represent ground vegetation; darker values indicate paved surfaces. Dark pixel groupings shaped like trees are last of many returns. Light is absorbed when it passes through trees, resulting in a darker value.



a.) Example of ground lidar intensity returns that have not undergone any levels of correction.

b.) Example of ground lidar intensity returns corrected using the ad hoc normalization method.

Figure 3 Example of un-corrected ground lidar intensity return raster (a) and the same ground lidar intensity raster conditioned using the ad hoc normalization method (raster value - min raster value/raster max value - raster min value).



a. nDSM filtered for ground and last of many returns

b. Last of Many nDSM raster (green) overlaid on **a**.

c. Result of subtracting Last of Many nDSM from **a**.

Figure 4 Reduction in tree canopy created by subtracting a last of many returns nDSM (b) from a standard nDSM filtered for ground and last of many returns (a). While some of the tree canopy remains,

2.1.2 Aerial Imagery

Four-band aerial imagery (R-G-B-NIR) captures the spectral qualities of landscape features and has a long history of use in the agricultural industry for assessing the health and species of vegetation.

The two most useful attributes derived from four-band aerial imagery are near infrared (NIR) and normalized differential vegetation index (NDVI). The NIR spectrum falls just outside the visible range and measures the amount of solar radiation reflected from a landscape feature (USDA, 2017). Paved surfaces tend to be darker and therefore absorb more light, while the chlorophyll present in vegetation causes more energy to be reflected back to the sensor. Therefore, NIR values for impervious surfaces tend to be higher than NIR values for pervious surfaces. NDVI is calculated using the formula NIR-RED/NIR+RED where RED refers to the first band in four-band aerial imagery. There is a high correlation between NDVI values and impervious surfaces, with impervious surfaces tending to be negative and pervious surfaces tending to be positive. However, pervious bare earth will sometimes have negative NDVI values as well due to the absence of radiation- reflecting vegetation.

The usefulness of aerial imagery in distinguishing the built environment, vegetation, and water is well established. However, when used to assess impervious surface area, there are three aspects which limit its usefulness. First, aerial imagery is incapable of penetrating the tree canopy, leading to gaps in the data where the ground surface cannot be imaged. As the spectral qualities of the Tree class are similar to other pervious classes such as grass, this is most often a limiting factor when it comes to classifying roads, buildings, and other classes of the built environment. The inability of aerial imagery to penetrate the tree canopy can be mitigated in many regions of the United States by the use of leaf-off four-band aerial imagery. The degree to which this strategy is effective varies regionally and is heavily influenced by the seasonal window and type of tree species common to the survey area – evergreen trees do not lose their foliage. For the study area in Athens, OH 6” color infrared (NIR, R, G) is available. As evidenced in (Figure 4, next page), while the canopy is much less dense in comparison to leaf-on aerial imagery, enough evergreen trees are present to impede impervious surface classification.

June 2020, Leaf on NAIP | Spring 2014, Leaf off CIR (NIR, R, G)

Figure 5 Comparison between Leaf on NAIP imagery and 2014 Leaf-off CIR (NIR, R, G)

The second limiting factor is that there is a tendency for bare earth to be conflated with some types of impervious surfaces, particularly during the "first pass" classification phase which frequently uses NDVI values as a primary attribute for classification (Table 4).

	Level 1 Water		Level 1 Trees		Level 1 Grass		Buildings	
	NDVI	NIR	NDVI	NIR	NDVI	NIR	NDVI	NIR
	-0.54	27	0.29	138	0.11	160	0.02	137
	-0.49	37	0.37	78	0.11	152	0.02	118
	-0.55	31	0.55	61	0.144	162	-0.04	137
	-0.57	28	0.22	145	0.18	153	-0.08	171
	-0.58	28	0.31	117	0.06	147	0.07	58.75
	-0.56	29	0.4	144	0.09	116	-0.01	92.26
	-0.58	27	0.37	134	0.22	171	-0.03	202
	-0.57	28	0.26	123	0.04	160	-0.04	121
	-0.52	25	0.07	124	0.29	161	0.007	119
			0.46	143	0.33	168	-0.03	49
			0.2	126	0.16	150	-0.02	83
			0.49	148	0.12	131	-0.04	129
			0.59	111	0.33	175	-0.04	126
			0.4	131	0.1	129	-0.05	116
			0.15	96	0.28	165	-0.08	123
			0.36	136	0.28	166	-0.02	109
			0.26	116			-0.01	77
							-0.001	82
							-0.03	107
							0.05	111
							-0.07	125
							0.02	83
							0.04	122
Min	-0.59	25	0.07	61	0.01	116	-0.11	49
Max	-0.25	52	0.59	152	0.33	175	0.07	202
Mean	-0.52	31.03	0.3	121.97	0.17	154.37	-0.02	110.04

Table 4 NDVI and NIR values used to find NIR and NDVI ranges. Samples were taken from each tile, when possible.

There are multiple strategies to address this limitation in E-Cognition. For example, if the incorrectly classified bare earth objects are relatively small and/or share a large segment of their perimeter with pervious objects, the bare earth segments may be removed based on area or be merged with the surrounding objects using algorithms such as “grow region” or “remove by relative border”. Alternatively, if there are relatively large regions of bare earth, as is the case in the Athens study area, E-Cognition’ s ability to classify data on multiple levels allows the user to refine the initial classification by means of conditionally re-segmenting the data using the “first pass” impervious surface class as a limiting factor. In the Athens study area, refining the classification on a sub-level using NIR values to re-segment the initial impervious classification was effective.

The final limiting factor is the presence of shadows. Shadowed areas alter the spectral readings of both the NIR and Red bands, resulting in skewed NIR and NDVI readings relative to areas without shadows. Although the lidar intensity raster was ultimately less useful than hypothesized for classifying landcover beneath the tree canopy, the lidar intensity attribute was useful for filling in shadowed areas.

2.1.3 Thematic Vector Files

Thematic Vector files are vector-based data that can aid in the segmentation process by providing pre-existing objects such as buildings or roads. For example, many communities have pre-existing building polygons which could be brought into E-Cognition to define the building class. This would greatly reduce the complexity of the impervious surface classification ruleset and shorten the time needed to create a LOM_nDSM raster, as separating trees and buildings becomes a moot point. Unfortunately, no building polygons were available in Athens. Alternatively, road centerlines may be used to facilitate road classification by searching for objects within a certain distance equal to road width. Road centerlines were obtained from the Athens Open Data website; however, the width of the roads varies frequently throughout the region, reducing their effectiveness. Instead, road edges were created within E-Cognition using the Slope_nDSM raster. Parcel data was also obtained from the Athens Open Data website and used within ArcGIS Pro to calculate the percent impervious surface per parcel.

2.2 Workflow

Ruleset development in E-Cognition is flexible by necessity. Each geographic region has unique properties that will affect not only the attribute ranges for properties such as NIR and NDVI, but which datasets will be most appropriate to use. Different sensor brands will also collect data slightly differently from each other; no two datasets are alike, even if they are collected in the same region during the same time period. As a consequence, there is a trade-off between time spent fine-tuning a ruleset and time spent performing manual corrections, and hours spent creating the perfect ruleset for one project may not translate to hours saved on the next. However, impervious surface classification will follow general patterns, allowing ruleset templates to be transferred from project to project. This section discusses best practices learned from the creation of this ruleset.

2.2.1 Tiling using E-Cognition Server

To begin, the E-Cognition Server extension was used to create 30 2000x2000 pixel sized tiles. Breaking large datasets down into tiles to be processed in the cloud allows E-Cognition software to segment large datasets in a relatively short amount of time. After segmentation is complete, the tiles are stitched together before beginning the initial classification phase. The data was segmented several times across four levels throughout the workflow; each time, the same process of tiling and stitching the data using E-Cognition Server was used to speed up processing times.

2.2.2 Initial Tree Building Segmentation

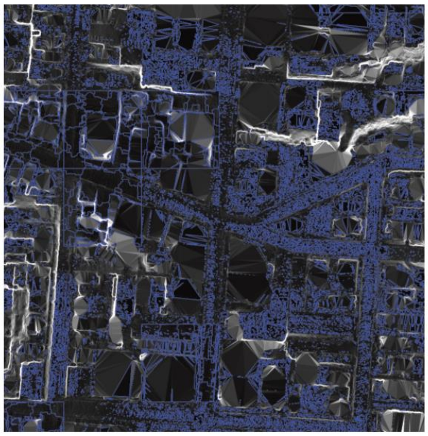
Following industry leader Jarlath O'Neill's advice, the first classification assigned to the data will be to separate tall objects, such as trees and buildings from the ground surface and low vegetation. A nice metric to use is Tall > 2m. From there, the 'Tall' class will be subdivided into Tree Candidate and Building Candidate classes. With that aim in mind, a variety of segmentation algorithms were experimented with to produce the best objects to be used for the initial Tree/Building Segmentation. Objects should ideally be of the largest size possible without containing both trees and buildings. The segmentation preview tool was instrumental in allowing several algorithms with a variety of parameters to be tested on the fly without executing the ruleset. The multi-resolution algorithm based on Slope-nDSM, intensity, and nDSM with additional weight given to Slope_nDSM produced the most natural objects. Note that the Slope_nDSM raster was created by running the slope function in ArcGIS pro against the LOM_nDSM (last of many nDSM) raster described in previous sections. Throughout this workflow, Slope_nDSM refers to that raster, while the Slope raster refers to a Slope surface derived from the digital elevation model (DEM).

Figure 6 Initial Tree/Building Segmentation (multiresolution comp .7 shape .2) showing "buffer object" (green).

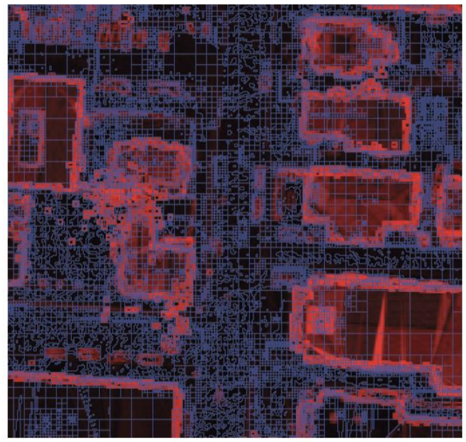
The result is a set of decently well-defined tree and building objects (Figure 5, left). Although the shape will be refined in future steps, the inclusion of a Slope_nDSM has the effect of creating what will be termed “buffer” objects around the perimeter of the buildings. While the work siphoning out high vegetation lidar points through strategic manipulation of last of many returns in ArcGIS Pro has eliminated many trees overhanging buildings, where remaining tall vegetation overlaps buildings, a majority of the overlapping tree objects are connected to the ”buffer object” rather than the central building object. In later steps, the central building object will become the seed to grow the building class the buffer object once the remaining trees have been separated from the buffer.

2.2.3 Initial Ground Classification

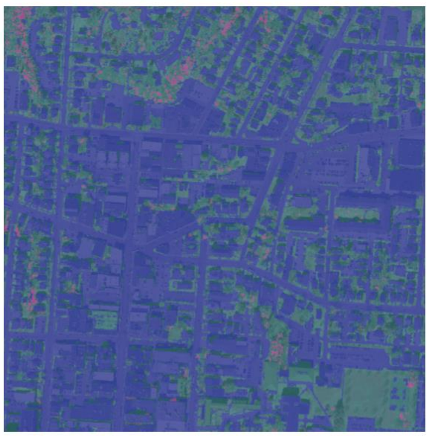
Next, the initial pervious vs impervious ground classification was performed. The primary goal of this step was to create a road classification. In the absence of vector data to use as a thematic layer, the edges of the road were created by segmenting the Slope layer using the contrast split (contrast mode edge ratio, chessboard size 200) algorithm. Then, at a new level, a quadtree segmentation (scale = 60) was performed based on Slope, NIR, Red, and Green (Figure 6, next page). The slope attribute was chosen because paved surfaces tend to have a small change in slope within a single object, as roads are fairly smooth. The two object levels were subsequently merged using the convert to sub-objects algorithm. The sub-objects fleshed out gaps in the edges created by the contrast split algorithm and provided objects that would fill the road area between the edges. A negative NDVI value was the primary method used to fill the road edges. Although not the intention, this method also did a decent job of classifying buildings, sidewalks, parking lots and driveways. Finally, the intensity attribute was used to fill gaps made by shadows.



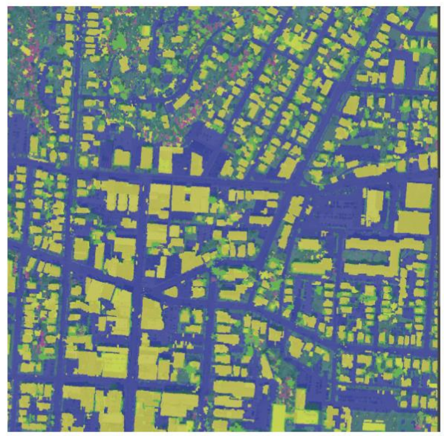
a.) Contrast Segmentation, Edge Split Ration results



b.) Fusion of Contrast Split and Quadtree Segmentation



c.) Results of initial impervious vs pervious classification showing paved areas (purple), pervious (teal), and other (pink).



d.) Results of initial ground and tall classification showing paved areas (purple), pervious (teal), tall vegetation/potential tree of building (light green) and buildings (yellow).

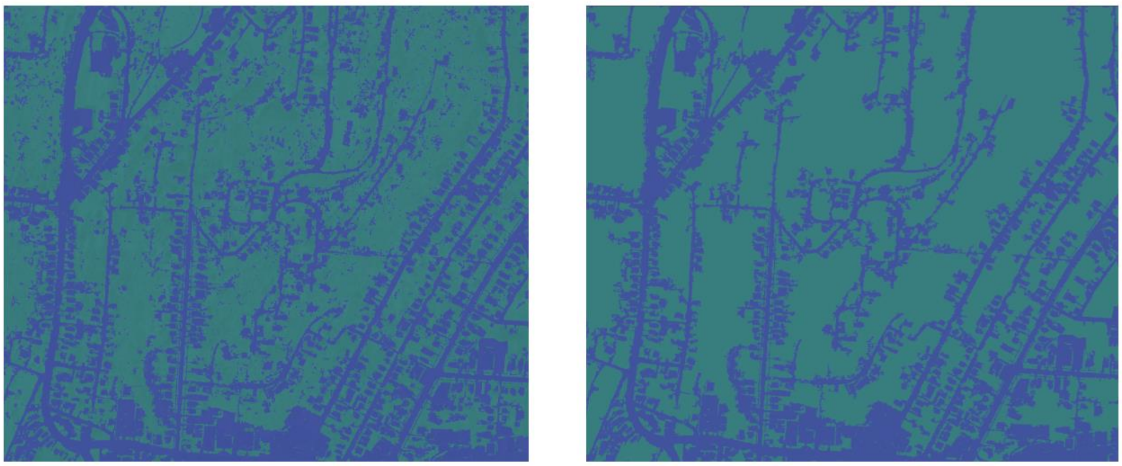
Figure 7 Results of initial classification of both ground and above ground features.

2.2.4 Refining the Initial Tree/Building Classification

Separating the tree objects from the buffer objects was the most difficult step. While slope, intensity, last of many (paired with the height condition), and various geometry attributes were all used at various points during this process, no one attribute stood out as definitive. Rather, removing the overlapping canopy was achieved by breaking up the clusters of objects, based on one of the above attributes, then cycling through successive rounds segmentation, classification, then re-segmentation until a satisfactory border was achieved. This was done primarily through as sort of “push-pull” dynamic between using the remove object algorithm, which allows the user to reclassify objects into the class with which they share the longest border, and then the grow region algorithm, which allows the user to extend the current class into adjoining objects.

2.2.5 Refine Ground Classification

As mentioned previously, several sections of bare earth were mis-identified as impervious based on the lack of vegetation to reflect the NIR and Red band attributes. Small, irregularly shaped, misclassified impervious areas enclosed by the pervious class were reclassified as pervious based on the pixel area, and roundness attributes. At a new level (L3), larger areas of bare soil were corrected by re-segmenting the impervious class using a multi-resolution segmentation algorithm, then using the NIR values to reassign objects to their correct class.



a.) Example of mis-classified bare-earth present in the initial impervious (blue) pervious (teal) classification.

a.) Cleaned data, with most most misclassed bare earth removed.

Figure 8 Example of bare earth areas removed using a combination of area size, re-segmentation, and reclassification based on NIR >150.

The ground classification was then brought back up to Level 1, where the final building class is stored. Once a satisfactory result had been achieved, the building, impervious, and pervious classes were exported as shapefiles to be used in ArcGIS Pro to calculate the impervious surface per parcel.

A copy of the ruleset used to calculate the impervious surface can be found in the Appendix.

3. RESULTS

Approximately 3.5 miles of land belonging to the City of Athens, OH and Ohio University were remotely surveyed to extract impervious and pervious surfaces.

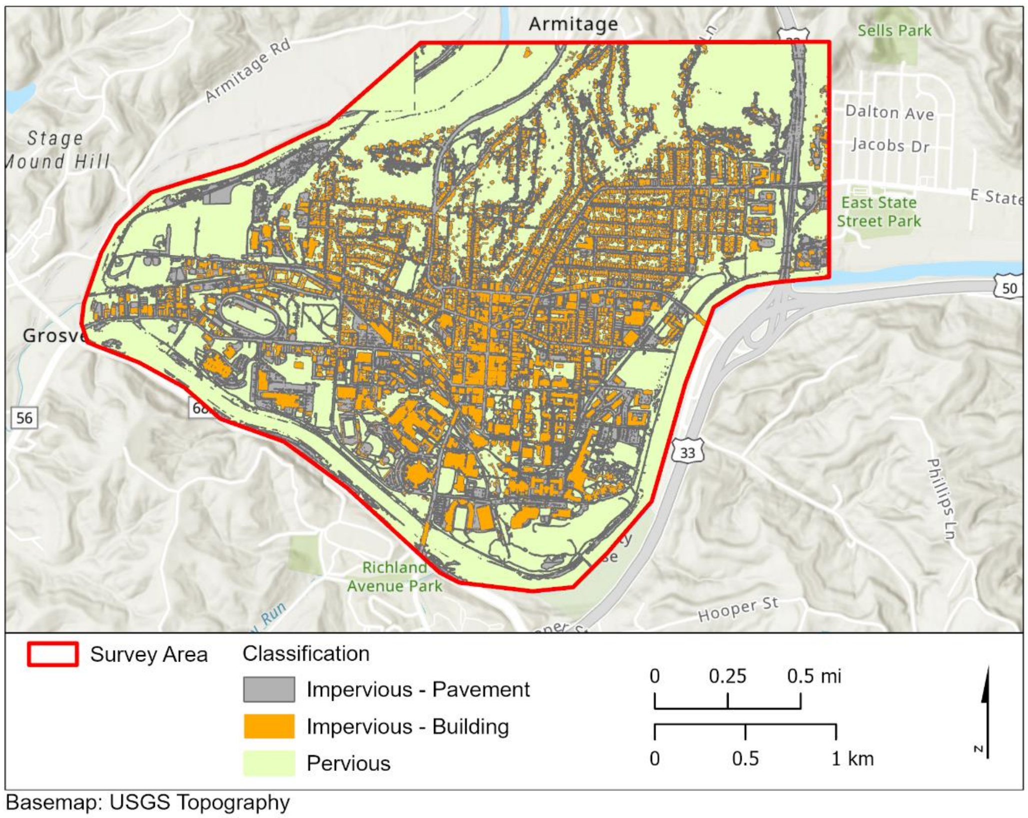


Figure 9 Map showing the extent of the area classified using remote sensing methods (red). Total area ~ 3.5 square miles

The total amount of pervious surface was 2.14mi^2 and the total amount of impervious surface was 1.38mi^2. Of the that area, 3,828 objects totaling an area of 11,279,493.2ft^2 were classified as buildings. A visual inspection of the results indicated that several areas classified as impervious should correctly have been classified as pervious. My hypothesis was that this was due to the conflation of bare earth and impervious land classifications. Bare earth is often misclassified as pavement when performing object-based image analyses if the primary attribute used to distinguish pavement from vegetation is the NIR or NDVI, as these two attributes only indicate the presence of vegetation, and the lack of vegetation does not necessarily equate to the presence of pavement.

Classification	Impervious	Pervious	Total	User Accuracy	Kappa
Impervious	43	7	50	0.86	0
Pervious	4	46	50	0.92	0
Total	47	53	100	0	0
Producer Accuracy	0.91	0.88	0	0.88	0
Kappa	0	0	0	0	0.79

Table 5 Confusion Matrix (sample size 100) generated for the impervious land classification using the strategized random classification method.

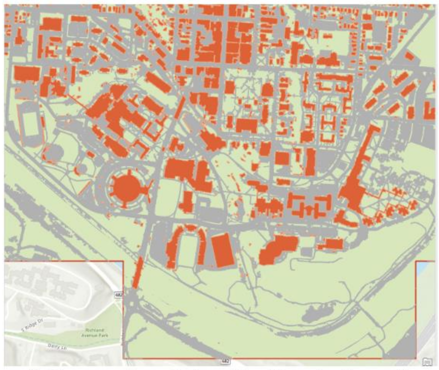
A simple confusion matrix was generated from a set of 100 random points using the random strategized method (Table 5). While the impervious surface producer accuracy was 91%, the user accuracy was only 86%, confirming that several areas classified as impervious were not impervious on the ground. A second statistic was computed for only the objects belonging to the building sub-class to test how many of the building objects were correctly identified (Table 6).

Classification	Building = True	Building = False	Total	User Accuracy
Building = True	46	4	50	0.92
Building = False	4	46	50	0

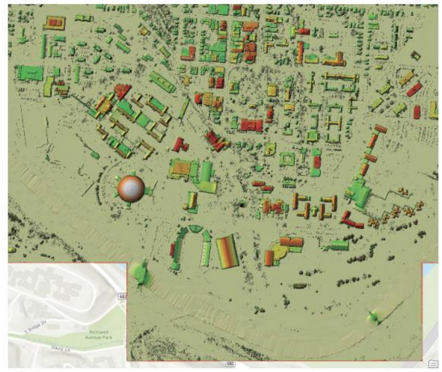
Table 6 Confusion Matrix for building sub-class. Points generated using the random points generator restricted to areas within the building sub-class.

This statistic was only to test whether the object identified at the test point was or was not a building, so only the user accuracy is relevant, as in this case the producer accuracy would equal the user accuracy. The results show that user accuracy for the buildings sub-class was 92%. This is significantly higher than the user accuracy for the overarching impervious class, implying that much of the error was generated from mis-identified ground classes, which supports the initial hypothesis that a large part of the error was a result of the mis-classes bare earth. Three out of the four mis-identified buildings were located in the more rural regions in the north of the study area, which is unsurprising given the higher number of trees in the area (Figure 11, next page).

It should be noted that the sample size of 50 points is smaller than recommended for an area of this size. A larger sample size may give different results and provide additional insights into the data. The decision to use fewer was due to time restrictions.

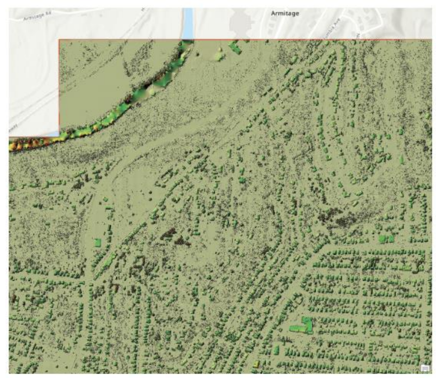


a.) The results of classification in the urban sub-region of Athens.



b.) The Last of May nDSM surface in the Athens urban sub-region.

c.) The results of classification in the northern, rural sub-geion of Athens. Mis-classified impervious surface is clearly visible.



c. The Last of May nDSM surface in the Athens rural sub-region.

Figure 10 Comparison between classified impervious surface (pavement = grey, buildings = orange) and the terrain showing the relative successfulness of the southern, urban regions in comparison with the northern, rural regions.

Overall, the classification in the more urbanized regions of the city was significantly more accurate than the classification in the more rural areas in the north and northeast portions of the city. This disparity can most likely be attributed to using slope data to calculate the road surface, the difficulty in removing the tree canopy in areas of denser growth, and inexperience.

4. CONCLUSIONS

The purpose of this project was to examine the uses and limitations of the key lidar, aerial, and thematic data types in assessing the ground surface beath the tree canopy in order to produce an accurate map of the percent impervious surface per parcel. The results indicated that the rulesets developed to differentiate buildings and trees in an urban environment were largely successful. However, the ruleset process decisions made to do so resulted in a ruleset that failed to differentiate as well between bare earth and impervious surfaces in the more rural regions.

At the start of this project, I focused heavily on methods of removing the tree canopy and did not consider that classifying the surface beneath might prove to be as difficult.

Buildings and trees were distinguished with a relatively high degree of accuracy, particularly in the urban areas, through efforts to remove as much vegetation as possible from the DSM used in E-Cognition. Lidar intensity was also investigated for its usefulness in providing information regarding the sub-canopy surface land class. While I believe that intensity shows great potential to be useful as a primary attribute for classification of impervious surface, it is likely that the process of performing more complex corrections needed to reduce noise in the data would be too time consuming for many projects. When compared to the normalized digital surface raster created by subtracting the normalized last of many returns nDSM from the normalized last of many returns and single returns raster, the lidar intensity raster was less useful for as a primary attribute for segmentation. Nevertheless, lidar intensity was found to be useful for filling in shadows.

The ruleset used to classify the data relied on using slope to create the road edges, then filling in the interior using a combination of slope, NDVI, and lidar intensity. The reason I did not use the road centerline to create a buffer to use as a thematic layer in E-Cognition is that the road widths vary; I was afraid I would mis data due to different road widths. NIR and NDVI could then be used to separate roads from pervious classes. However, many areas beneath the tree canopy had little to no visible vegetation, so neither the NIR nor NDVI attributes, which both emphasize the presence of plants, were as useful as I would have hoped for distinguishing the built environment from bare earth. While successive rounds of classification, segmentation and reclassification based on those NIR and NDVI values were successful in removing the worst of the bare earth classified as impervious during the initial classification, enough mis-classified areas remain to be noticeable.

Finally, more sophisticated E-Cognition rulesets, as well as more familiarity with the available functions would have improved my final classification results. For example, the Region function would have allowed me to apply different routines to different geographic sub-regions of my study area. Additionally, recent E-Cognition releases allow deep learning models to be imported into the software. The use of one of these models would likely facilitate the extraction of building footprints.

Ultimately, E-Cognition was an effective tool for classifying impervious surfaces. A user accuracy of 86% was achieved, and the experience gained investigating how data sources interact with each will prove useful in future ruleset development.

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APPENDEX

Rule set used to extract the impervious surface in Athens, OH.

```
01:45.109 Find Impervious Surface
    01:45.109 Initial Multi-Threshold Segmentation
        01:45.109 multi-resolution: 42 [shape:0.4 compct.:0.9] creating 'Level 1'
05.219 Initial Tree Building Classification
    0.031 unclassified with Mean nDSM > 2 at Level 1: Tall
    02.156 Tall with NDVI > 0.08 and (Mean Slope_nDSM > 60 ) at Level 1: Trees
    0.032 Tall with NDVI < -0.3 at Level 1: unclassified
    02.984 Tall at Level 1: merge region
    0.016 Tall with Mean Slope_nDSM > 2000000000 at Level 1: unclassified
17:03.906 Initial Road Classification
    14:29.766 edge ratio split Slope [0-255:+2] :200-> [creating 'New Level', unclassified,Road, edge]
    30.453 quadtree: 60 creating 'New Level 2'
    03.828 at New Level: convert to sub-objects
    36.500 unclassified at New Level: enclosed by Road: Road +
    26.562 Road with NDVI > 0 at New Level: unclassified
    06.407 unclassified with NDVI < 0.1 at New Level: Road
    14.640 unclassified with Mean Intensity < 2800 and (Mean Slope_nDSM < 20 ) at New Level: Other
    27.844 Other at New Level: merge region
    05.328 Other with Rel. border to Road > 0 at New Level: remove objects into Road (merge by shape)
    02.578 unclassified at New Level: Pervious
04:13.860 Cleanup Trees
    12.359 at Level0: delete
    01:09.250 Trees at Level 1: multi-resolution: 42 [shape:0.1 compct.:0.7]
    0.828 Trees with Mean Last_of_Many > 0 at Level 1: Last of Many
    01.547 Last of Many with Mean nDSM > 2 at Level 1: LOM_TALL
    0.047 Last of Many with Mean nDSM < 2 at Level 1: LOM_GROUND
    02:05.453 Trees at Level 1: quadtree: 60
    01.032 Trees at Level 1: remove objects into Tall (merge by shape)
    01.375 Trees with NDVI > 0.3 at Level 1: unclassified
    0.203 Tall at Level 1: <- Trees
    0.078 Trees at Level 1: unclassified
    0.610 Tall at Level 1: merge region
    0.016 Tall with Area < 200 Pxl at Level 1: unclassified
    Tall at Level 1: erode
    14.141 Road with Mean nDSM > 2 at New Level: Tall Veg
    0.328 Tall Veg at New Level: Road
    19.890 Road at New Level: erode Pervious
    03:02.188 Clean roads
        48.828 Tall at Level 1: export object shapes to ObjectShapes
        <0.001s Road with Mean nDSM > 3 at New Level: Building
        21.297 Road at New Level: <- unclassified
        20.891 Pervious with Mean nDSM > 20 at New Level: unclassified
        46.156 Pervious, Road at New Level: copy creating 'Level0' above
```