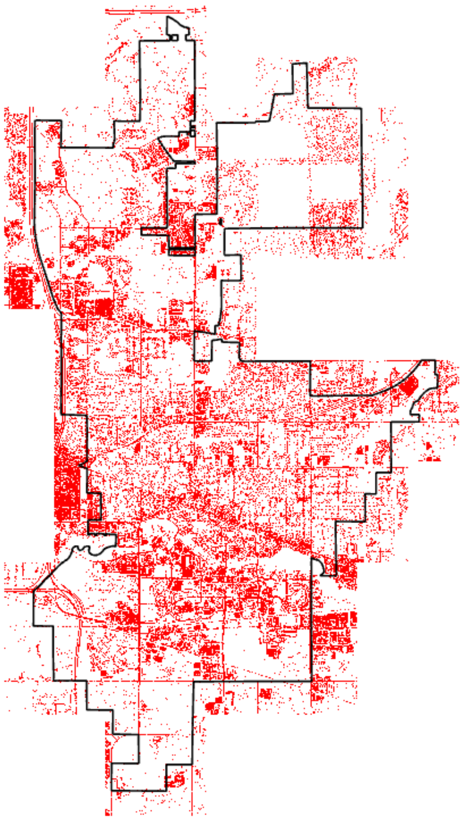

Procedure for Impervious Surface Mapping

A GIS-based Approach

Prepared by
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Table of Content

This material is based upon work supported by the Department of Energy and the Michigan Energy Office (MEO) under Award Number EE00007478 as part of the Catalyst Communities program. Find this document and more about the CLC Fellowship that supported this project at graham.umich.edu/clcf.

Background and Scope

Urbanization brings forth the replacement of natural landscapes with built-up surfaces, often compromising the environmental quality. Other consequences of impervious surface extension are increased flooding susceptibility, diminishing groundwater recharge, and pollution of receiving water, thus raising environmental, infrastructural, and health concerns. As billions of gallons of stormwater runoff and snowmelt that flow from impervious surfaces must be treated, social demand for flood protection and mitigation rises. To address the issue, cities are increasingly turning to green infrastructure (GI) [1]as an environmentally viable option for increasing their capacity to manage stormwater. GI is scalable and mimics natural processes such as infiltration and evapotranspiration. It has a distinctive advantage over aged grey infrastructure—systems of gutters, pipes, and tunnels including hydrological function restoration, and ecosystem services while accounting for the least carbon footprint (Figure 1).

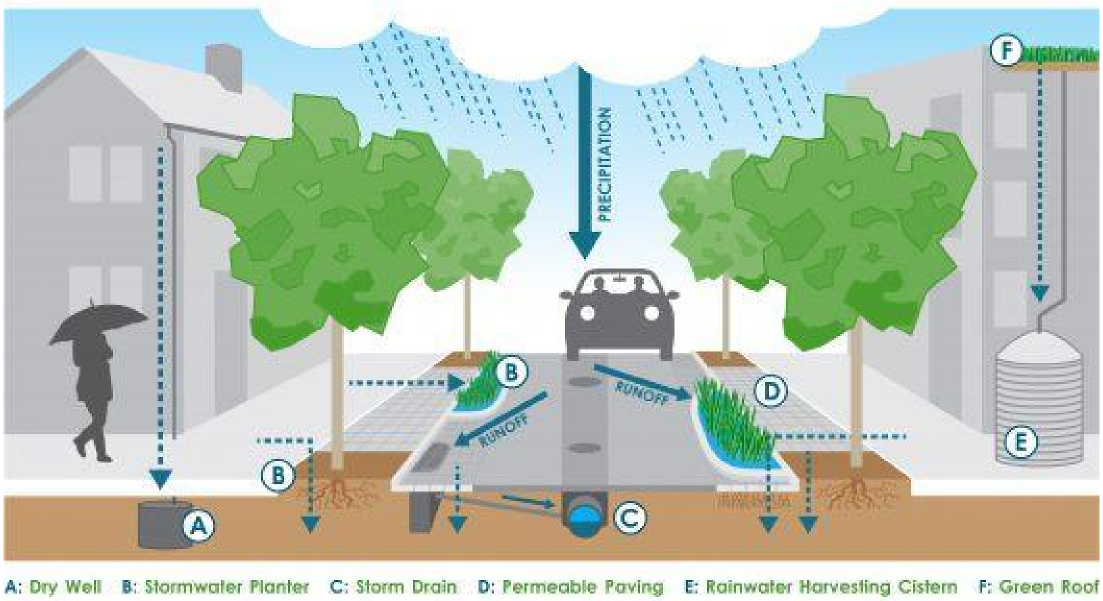

Figure 1: GI type (source: …………)

GI planning requires a thorough analysis of the surface features and impervious condition inventory helps to identify best management practices for determining stormwater utility fees, and emergency management planning. Innovative advances in ortho imagery and LiDAR have recently enabled the production of more precise impervious-surface maps of areas ranging from large cities to rural landscapes. These new technologies generate data that can be used for multiple purposes while requiring fewer resources.

Although field measurements and manual digitization can be used to quantify impervious surfaces, however, these processes can be time and resource demanding. As such, a robust methodology, based on data availability, was adapted that leverages machine learning for

[1] https://www.epa.gov/green-infrastructure/what-green-infrastructure

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impervious surface identification and extraction from orthoimaginary. This document is the workflow of the process undertaken. It is intended for knowledgeable users familiar with technical aspects of land use modeling in an ArcGIS Pro environment.

This guidance is prepared as a revision to the impervious surface mapping[2] by Esri's Learn ArcGIS team. This guidance will serve as an accompanying document to the GI feasibility and inventory mapping. To facilitate its use, this guidance is divided into sections that contain description of each stage on the flowchart. In addition, pre-processing (before the execution of classification) and post-processing (after the execution: map composition) stages guidance is also added to this guidance.

The prerequisite computational system to initiate the process includes-

- Windows 10, 64 bits or higher
- Central processing units (CPUs) multicore processor (atleast i5-i7 series or 10th generation)
- RAM capacity higher 16 GB
- Enough physical space available

In addition, having a solid-state drive (SSD) and dedicated graphics processing unit (GPU) will expedite the computation significantly. Although the process can run directly on the CPU, it will take longer to run, and the workflow can be overwhelming to the CPU.

Classification and Segmentation

Land Use/Land Cover (LULC) data are an important input for ecological, hydrological, and agricultural models. Most LULC classifications are either created using pixel-based analysis of remotely sensed imagery which are often supervised or unsupervised. These pixel-based procedures examine the spectral properties[3] of each pixel in interest without considering the associated spatial or contextual information. Using pixel-based classification on high-resolution imagery may produce a "salt and pepper" effect, which contributes to inaccuracy (Gao and Mas, 2008). In contrast, segmentation, an object-based approach, produces a spectrally homogenous object where every pixel in an image is given a label of a corresponding class. The object-based image analysis aggregates pixels based on a segmentation algorithm such as the mean shift function which groups neighboring pixels that are similar in color, shape, and spectral characteristics together (Blaschke, 2010). The comparison between the two processes can be explained as,

- Pixel-based classification: Classification is performed on a pixel-by-pixel basis, using only the spectral information available for that specific pixel (i.e., values of pixels within the locality are ignored).
- Object-based segmentation: Classification is done on a localized group of pixels, considering the spatial properties of land-based features as they relate to each other.

In supervised image classification, the user trains computer algorithms to extract features from an imaginary. These training samples are drawn as polygons, rectangles, or points, and the computer learns and scans the rest of the image to identify similar features. However, the

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[2] https://learn.arcgis.com/en/projects/calculate-impervious-surfaces-from-spectral-imagery/
[3] Spectral resolution describes the ability of a sensor to define fine wavelength intervals.

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decision to select classification relies upon the spatial resolution, computational capacity, and desired output. Although the object-based approach is expected to perform better, however, the process requires higher computational capacity and is not immune to over-segmentation and under-segmentation errors (Lui, 2010).

Here, we apply a hybrid approach that augments the segmentation with supervised classification.

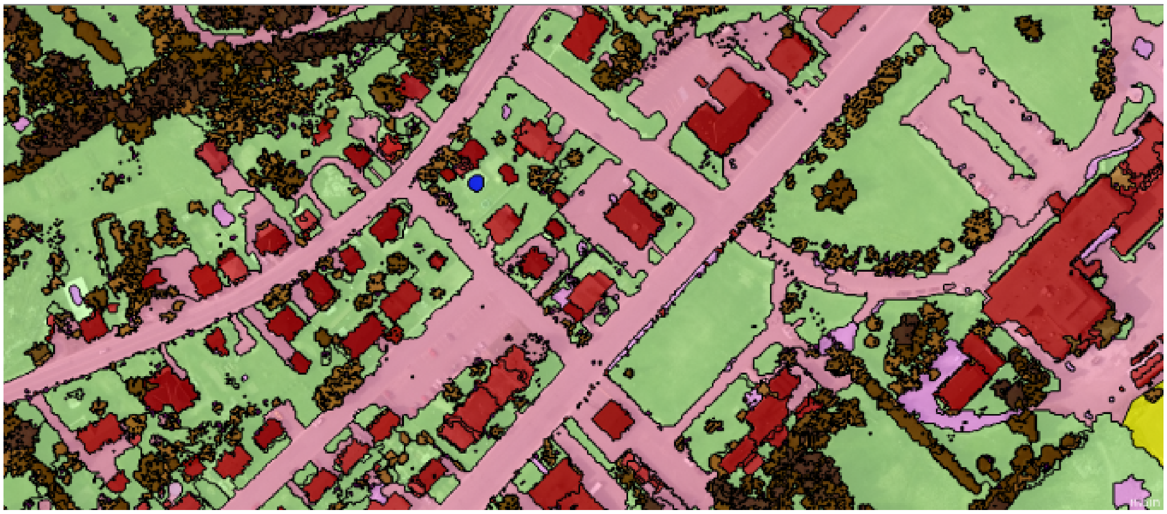

Figure 2: Object-based classification (https://gisgeography.com/obia-object-based-image-analysis-geobia/)

Data Compilation

The dataset used was captured in East Lansing, spanning across Ingham and Clinton counties in Michigan. Numerous datasets were used for the analysis, and they are enlisted as follows.

- 2020 Ortho Imagery: A 3-inch (leaf-off) true color multispectral imagery consisting of four bands was used for imperviousness analysis. In total, 94 raster files, each of dimension 1000*1000, were used for the city of East Lansing, Michigan. This dataset was obtained from the DPW East Lansing.

- Parcel layer: A city-wide feature class of land parcel vector dataset was obtained from DPW East Lansing.

- Ancillary datasets: These include city boundary, road, and building footprint vector data that were compiled from various sources including Open Street Maps.

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Method

Land use classification can be accomplished using one or more of the following methods, or in combination: supervised classification is performed by an interpreter; unsupervised classification (the entire classification process is performed with computation); and object-based visual interpretation (interpreter sets all objects manually). To determine the impervious surface features from the imagery, a supervised object-based segmentation approach was applied. Instead of classifying each pixel, generalized segments will not only reduce the number of spectral signatures but also addresses the errors and inaccuracies. A snippet of the overall procedure is presented in figure 3.

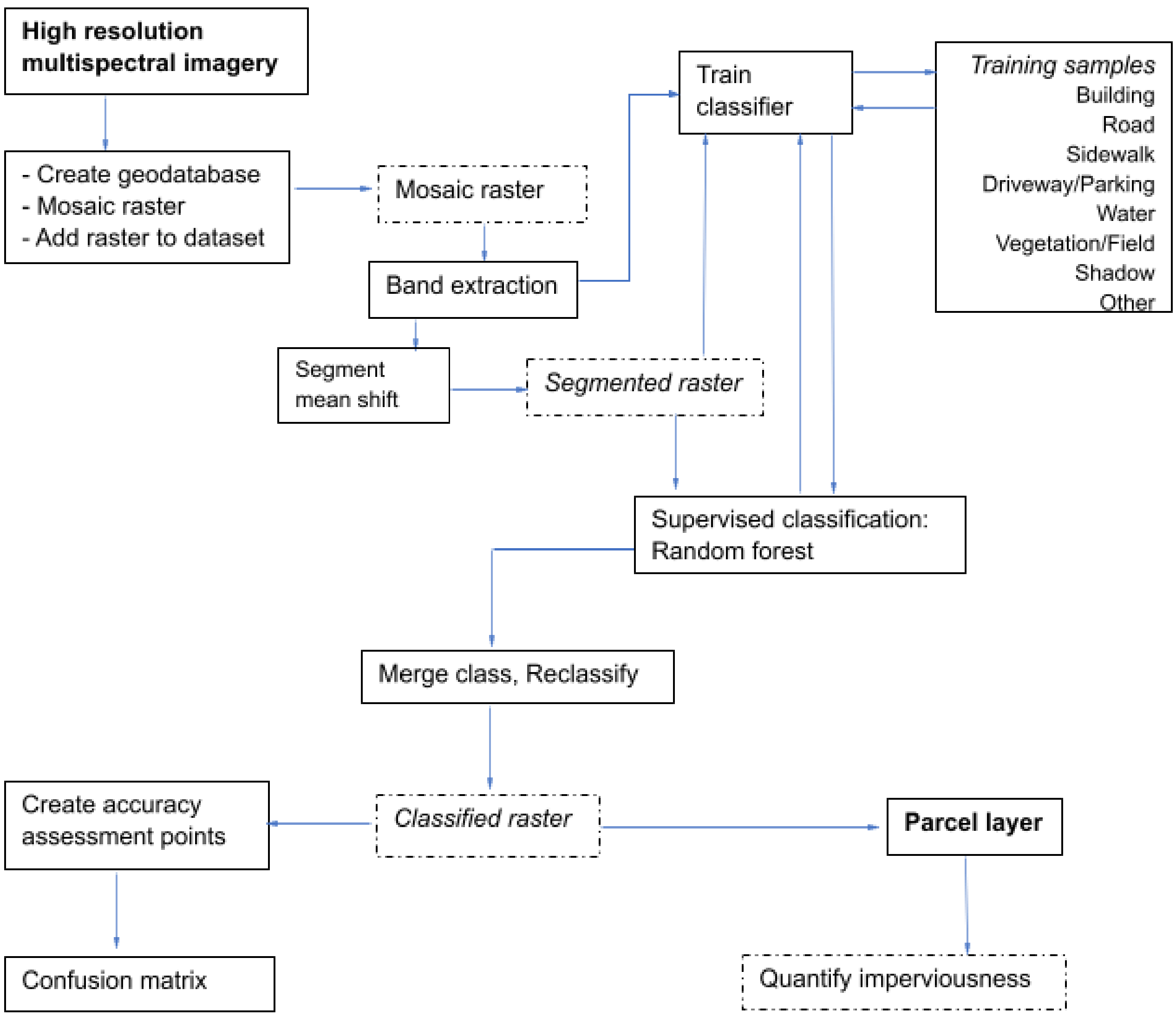

Figure 3: Detailed methodology flowchart for impervious surface mapping

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Pre-processing

1. Image pre-process

All satellite image data are biased (due to error or distortion), including geometric and radiometric distortions. This is because the data recorded by the sensor is greatly influenced by atmospheric conditions, the angle of data capture from the sensor, and the time of data collection. During the image pre-processing stage, this distortion must be addressed before it can be used as the basis for interpretation and classification. The raw ortho-image obtained for the exercise was already corrected and projected to NAD1983 as the datum.

2. Develop mosaic

Before proceeding with the image classification, a mosaic dataset[4] is developed which is a type of geodatabase structure to manage imagery and raster data effectively. This process not only addresses the challenge of working with multiple images individually but also helps in developing a dataset that can be easily accessible for both visualization and analysis.

- After creating a File Geodatabase, from the Geoprocessing panel, type “create mosaic dataset” and select the first option. Alternatively, from the Catalog pane, right-click on the geodatabase file with the extension (.gdb), then point to New, and choose Mosaic Dataset.
- In the Create Mosaic Dataset window, give the name and location for the dataset, and define its coordinate system. The coordinate system should be consistent with those on multispectral imagery. **Product Definition** field is left blank.

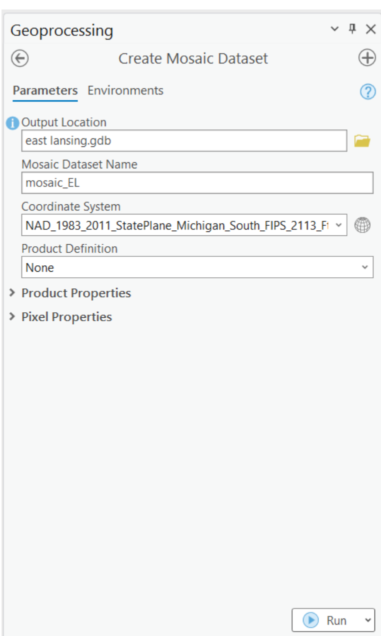

Figure 4: Parameters for creating a mosaic dataset

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[4] A mosaic dataset is a well-defined geodatabase structure optimized for working with large collections of imagery and raster.

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The tool executes and creates a new mosaic dataset in the project geodatabase and adds a mosaic dataset group layer to the contents pane of the map. Next, the multispectral imagery is associated with the mosaic dataset.

- In the geoprocessing panel, type "Add Rasters to Mosaic Dataset", hit enter, and select the first option. Alternatively, From the Catalog pane, in the file geodatabase, right-click on the mosaic_EL dataset and choose Add Rasters.
- In the Add Rasters to Mosaic Dataset window, the default **Raster Dataset** raster type is selected from the dropdown option.
- Click the Input Data drop-down menu and choose **Folder**.
- Click the **Browse** button. Browse to and choose the folder containing imagery.
- Under Raster Processing, select **Build Raster Pyramids.**
- Under Mosaic Post-Processing, select **Build Thumbnails**, **Update Overviews** and click **Run**.

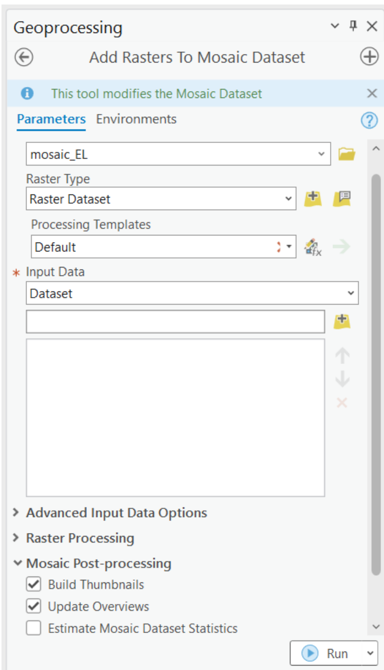
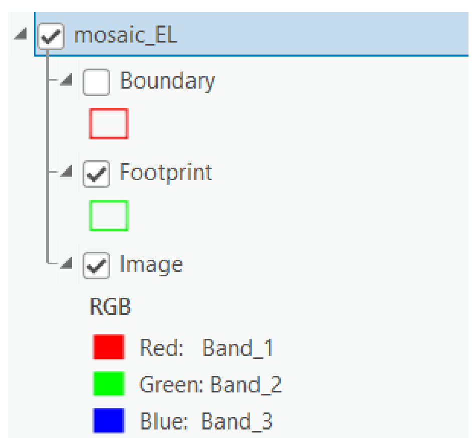


Figure 5: Parameters for adding raster to the mosaic dataset

This process will add references to the images on the disk to the attribute table of the mosaic dataset. Once the tool is finished, it creates three sublayers in the contents panel, namely Boundary, Footprint, and Image.



If all images added to the mosaic dataset are not displaying, from Catalog, right-click on the mosaic dataset and click **Properties**. In the **Mosaic Dataset Properties** pane, click

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the **Defaults** tab. Expand **Image Properties** and change the **Maximum Number of Rasters Per Mosaic** to 100.

If all run well, the final layout should appear in Figure 6.

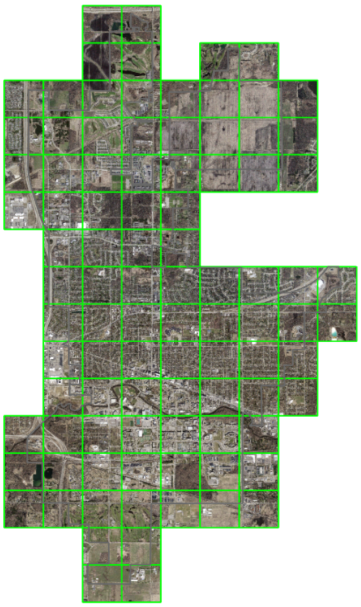
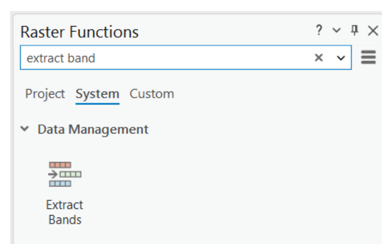


Figure 6: Final mosaic with multispectral imaginary (in natural color)

3. Band extraction



Impervious surfaces comprise human-made structures including buildings, roads, parking lots, and pathways. Pervious surfaces include vegetation (trees, grass), water bodies, sand, and bare soil. To distinguish between natural and urban features, band combination change is applied.

- Select the mosaic dataset and from the ribbon, click the **Imagery tab** and in the Analysis group, click **Raster Functions**.
- In the Raster functions, type “extract bands” and hit enter.

- In the Raster functions window, in the Parameters tab, set the **Method** to Band IDs, for **Combination**, delete the existing text and type 4 1 3 (with spaces)[5] and click **Create New Layer**.

[5] This band combination includes Near Infrared (Band 4) for emphasizes vegetation, Red (Band 1) for human-made objects and vegetation, and Blue (Band 3) that emphasizes water bodies.

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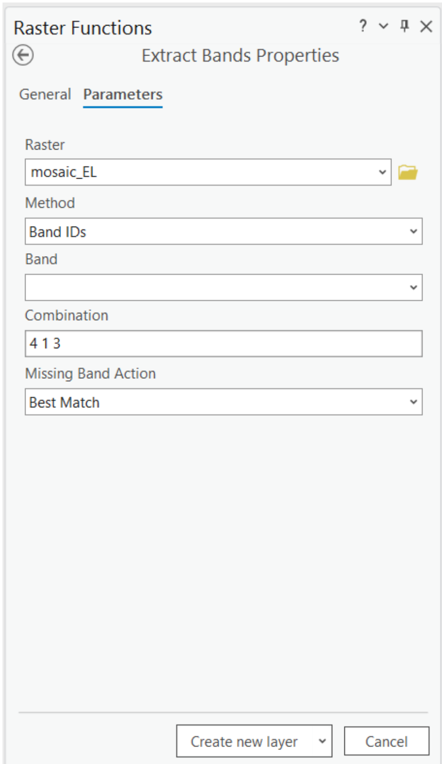

Figure 7: Setting parameters for band extraction

After the process executes, a new layer, named Extracted Bands_mosaic_EL is added to the map. Although a layer appears in the Contents pane, however, it is not added as data and will be lost if the layer is removed, or if ArcGIS Pro session terminates for any reason. The whole classification process runs on the extracted layer.

Processing

1. Segmentation

The object-based classification workflow relies heavily on segmentation. Segmentation is the outcome of three parameters namely spectral detail, spatial detail, and minimum segment size which determines how an image is segmented, efficiently. The detail of these parameters can be found here. Because impervious surface features can include spatial objects of varying sizes and shapes, spectral information is more important than spatial information.

It is a resource-intensive process of the entire workflow. The image segmentation is based on the Mean Shift approach.

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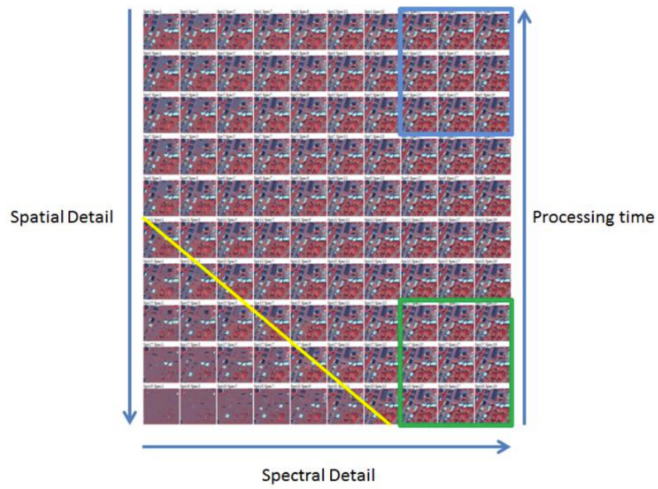

Figure 8: Interrelation between segmentation parameters (Butler, ESRI, 2005)

- In the ribbon, on the Imagery tab, in the **Image Classification** group, **Classification Tools**, click **Segmentation**.
- In the Segmentation panel, default values are modified as, Spectral detail: 18, Spatial detail: 12, and Minimum segment size pixel: 3.
- Leave **Show Segment Boundaries Only** unchecked and click Preview.
- A new layer segmented_181203 is added to the content panel.
- Inspect the segmented image. This image is being generated on the fly, so the processing will vary depending on the map extent.

If you are dissatisfied with the segmentation result, you can always return to the previous page of the wizard, change the parameters, and re-run the preview until a satisfactory result is achieved. A good rule for naming the preview image is using segmented values.

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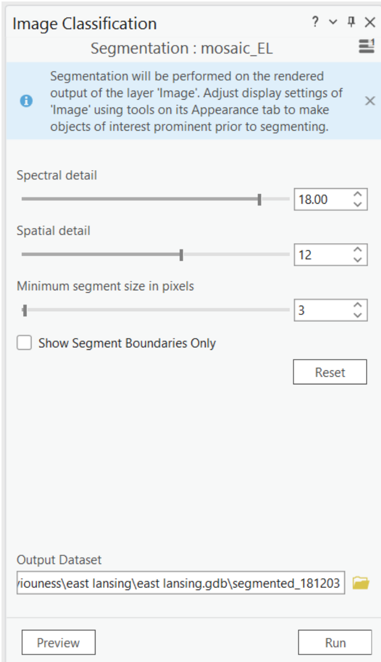

Figure 9: Parameters for segmentation

2. Training samples

This is the most important step in classification, as the quality of training samples serves the machine learning algorithm with the necessary information to carry out the classification. Training samples are polygons that represent distinct sample areas of the imagery's various land-cover types. The training sample guides the classification tool about the various spectral properties each land cover exhibits.

- In the ribbon, on the Imagery tab, in the **Image Classification** group, click the **Training Samples Manager**. By default, the training sample manager is populated with NLCD 2011 and therefore this needs to be modified to contain two parent classes: Impervious and Pervious. Following, subclasses are added to each class that represents types of land cover. The list of classes is presented in table 2.

Table 2. Land cover classes used for analysis

Value	**Class Name**	**Description**
20	*Impervious*	
21	Building	Houses, apartments, or any elevated concrete structure
22	Road	Highways, feeder roads, or concrete linear structure
23	Driveway/Parking	Parking structures
24	Sidewalk	Walking or running trails with concrete paving
30	*Pervious*	
31	Vegetation/Field	Trees, grassland, cropland, and fields
32	Water	All water bodies including rivers, canals, and lakes
33	Shadow	Shadows do not represent actual surfaces. However, shadows are usually cast by tall objects such as houses or trees and are more likely to cover grass or bare earth, which are previous surfaces.
34	Other	Includes bare earth, barren surface, and any landcover class that is not impervious but cannot be classified as water, or vegetation

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- All classes are deleted by right-clicking and selecting **Remove class**.
- After all, classes are removed, right-click on NLCD2011, and select **Add New Class**
- In the **Add New Class** window, for Name: “Impervious”, Value: 20, and Color: Gray 20%, and Click OK.
- Select Impervious, right-click, select **Add New Class,** and add a class named Building with a value of 21 and a color of Mango.
- The above steps are repeated until all the desired classes are created, each with unique value and color.
- Right-click on the NLDC2011, click **Edit Properties**, and change the name to “Impervious_Pervious”. Click **Save** the current classification schema at the top of the Training Samples Manager panel.

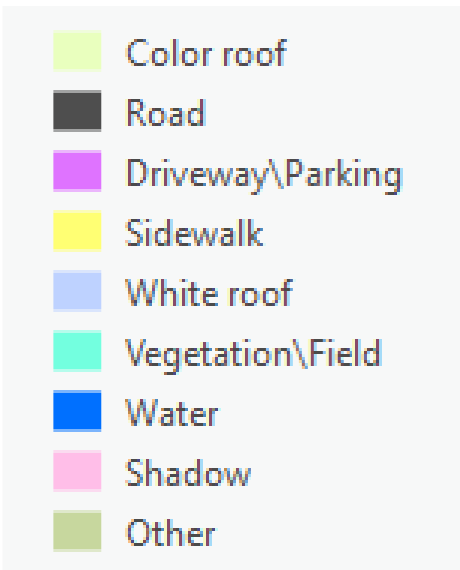

Figure 10: Land use class defined for classification

Now training samples are generated on the segmented image using the aforementioned land use classes or segment Picker  can be used to choose segments directly.

- Select **Building,** click the **Polygon** button, and zoom in on an area in the image that has building clusters.
- Next, collect training data for all the classes. This can be done by selecting a class from the list, with the **Segment Picker** active, and clicking on an area in the display to create a new sample polygon segment or draw a polygon that only comprises a particular land use class, double click to finish drawing. This adds a row to the wizard for a new training sample. Repeat this process for numerous buildings in the image.
- In the wizard, select all the building polygons by pressing Shift (on the keyboard), and above the list of training samples, click the **Collapse** button 

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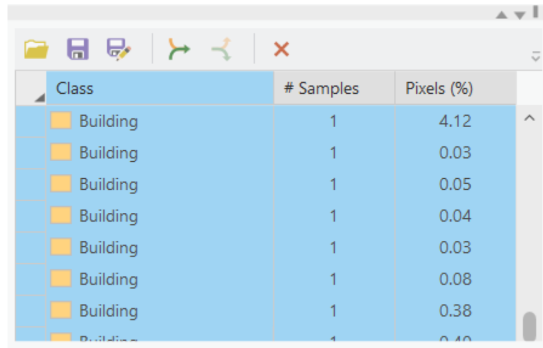
- The above steps are repeated for each land use class.
- After all training samples have been developed, save the training data as a feature class in the same geodatabase.



When creating training samples, depending on the spatial resolution of the image, it is rational to create a high number of samples to represent each land-use type. In addition, the original image displayed in natural color or infrared can be used for drawing polygons.

- Zoom into the image and choose an area that represents a class from the list.
- Pan and zoom around to collect as many samples as possible for each class. In the classification phase, having a few training samples in each part of the image will yield good results. Use the keyboard shortcuts available to help you navigate and select classes. The C shortcut key switches your cursor to the Pan tool.

Important consideration

i. Avoid mixing different classes while drawing polygons.
ii. Capture the full range of spectral signatures for each class.
iii. Collect training data across the entire image, not just focused on a limited spatial extent.
iv. As a rule of thumb, collect 100 or more for each class.

3. Train classifier and run classification

There are several machine learning classifiers[6] to choose from depending on the classification type intended to use. Random Trees[7], a non-parametric classifier, is one of the most accurate learning algorithms available in the discipline, with a reduced need for normal distribution and a constant training sample size, and runs efficiently on large databases. Additionally, lighter computation requirements, insensitivity to overfitting, and adaptability with segmented images are some of its attractive characteristics. Henceforth, the segmented images and classification schema developed in the preceding step will be used.

- In the ribbon, on the Imagery tab, in the **Image Classification** group, click the **Classification Wizard**.
- In the Configure window, Classification Method is selected as **Supervised** from the drop-down, classification type as **Object-based**, classification schema is previously developed “Impervious_Pervious”, output location is the file geodatabase.

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[6] https://pro.arcgis.com/en/pro-app/2.8/tool-reference/image-analyst/understanding-segmentation-and-classification.htm

[7] https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-analyst/train-random-trees-classifier.htm

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- Optionally, Segmented Image is selected as segmented_181203, Reference Dataset is selected as DEM.
- After obtaining all the parameters values, click Next

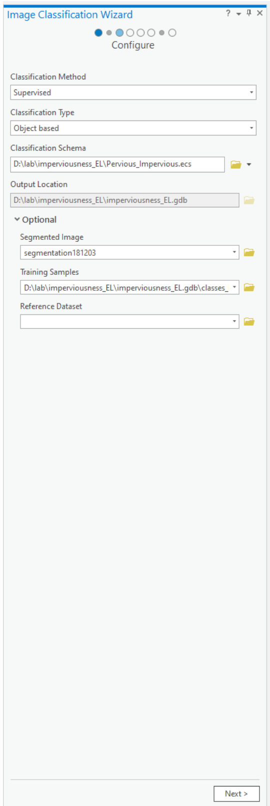

Figure 11: Parameters for Configure window in classification

- Escape the training sample manager. Click Next.
- Next train classifier, In the Image Classification Wizard pane, in the Train page of the wizard, select Classifier as **Random tree**. Under the Segment Attributes, choose Mean digital number and Standard Deviation, and use the remaining default parameter values and then click **Run**.
- Once the training has been completed, the classification preview will be displayed.
- If the classification looks relatively accurate, click **Next** to save the classification.

Alternations in the training samples can be made by clicking the Previous button, if unsatisfied. This takes you back to Training Samples Manager where editing of samples can be done. Generally, collect training samples of misclassified features and assign them to the appropriate class.

- Once satisfied, click **Next** and then Run on the Training Samples Manager page to reclassify using the updated training sample file and again **Next** to classification preview.
- Click **Run** on the Classify page to create classification outputs.
- After the process executes, a thematic classified raster is added to the content panel. Before moving to the **Merge Classes** page, export the classified raster for later.

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- On the Merge Class page, you can choose to merge your subclasses into their parent class or keep it as it is. Since we only want impervious and pervious surface features, we can use the dropdown arrows to choose *Impervious* and *Pervious* as the new classes. When all is done Click **Next** to generate the updated Impervious Surface map.
- The final page is Reclassify, here you manually edit classes that are visually incorrect using **Reclassify within a region** tool to delineate a region where all the class polygons of one class type are reassigned to another class, or **Reclassify an object** tool to select a single class polygon and reassign it to another class.
- Once you have reclassified any incorrect pixels, click **Run** to generate and **Finish** to save the final classification output.

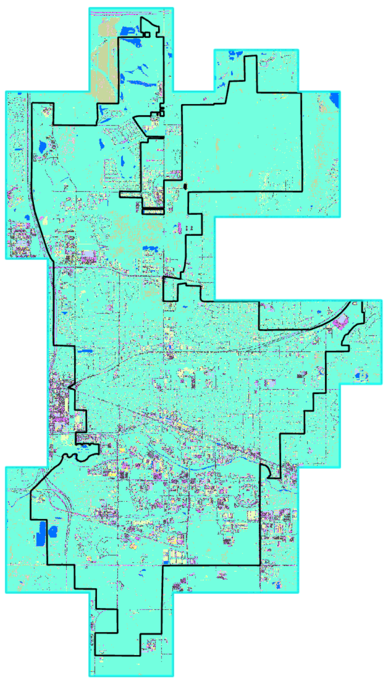

Figure 12: Output obtained from classification wizard

Post-processing

1. Assess classification

To determine the quality of the classified image, an accuracy assessment needs to be conducted using the statistical procedure. To perform the assessment, first randomly generated accuracy assessment points are placed throughout the image and a comparison is made with the classification value (pervious or impervious) to the actual land cover from the original imagery. Second, a matrix is calculated to determine percent accuracy.

- In the Geoprocessing pane, type “Create accuracy assessment points”, and press Enter.
- In the results list, click **Create Accuracy Assessment Points** (for Image Analyst or Spatial Analyst Tools).
- In the Create Accuracy Assessment Points tool, fill the parameters as in figure 14.

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- Select input raster as Classified raster layer Output Accuracy Assessment Points, click browse button, and browse to Project, Databases, and double-click mosaic_EL.gdb.
- Give it a name, **“accuracy point”** and save.
- In Target Field, confirm that **Classified** is selected.
- For Number of Random Points, type 200, and sampling strategy as **Equalized stratified random**[8].
- Click **Run**.

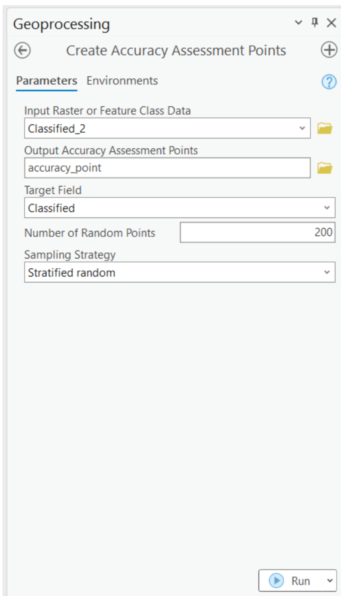


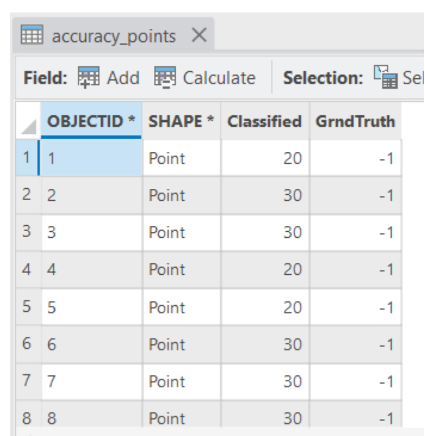
Figure 13: Accuracy assessment parameters

This will add a new layer with 200 accuracy points to the map.

- In the Contents pane, right-click the **accuracy_point** layer and choose **Attribute Table**.

The attribute table contains information for each point location including ObjectID, Shape fields, Classified, and GrndTruth (or Ground Truth). The Classified field has values that are either 20 or 40. These numbers represent the classes determined by the classification process, as they appear in the Classified raster layer where 20 is impervious and 30 is pervious.

In the GrndTruth field, every value is -1 by default, signaling that the value is still unknown, and the point needs to be ground truther. Manual inspection of the imagery for each point is done and the GrndTruth attributes are edited to either 20 or 30, depending on the type of land cover found.



	OBJECTID *	SHAPE *	Classified	GrndTruth
1	1	Point	20	-1
2	2	Point	30	-1
3	3	Point	30	-1
4	4	Point	20	-1
5	5	Point	20	-1
6	6	Point	30	-1
7	7	Point	30	-1
8	8	Point	30	-1

[8] Sampling Strategy parameter determines how points are randomly distributed across the image. It can be distributed proportionally to the area of each class (Stratified random), equally between each class (Equalized stratified random), or randomly (Random).

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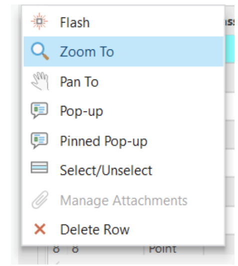

- In the attribute table, click row header **1** to select the feature and right-click the row header, and choose **Zoom To**.
- The map zooms to the selected point., zoom in close enough to the point, depending on the extent of your map and the location of the point.
- Back in the attribute table, in the **GrndTruth** column, double-click the value for the selected feature to edit it. Replace the default value with either 20 or 30, depending on your observation, and press Enter.
- Repeat the above procedure for all points.
- On the ribbon, click the **Edit** tab, in the Manage Edits group, click **Save** to save all the edits you made in the attribute table. When prompted to confirm, click **Yes**.

<u>Confusion matrix</u>

- In the **Geoprocessing** pane, search for and open the **Compute Confusion Matrix** tool (for either Image Analyst Tools or Spatial Analyst Tools).
- In the Compute Confusion Matrix tool, for Input Accuracy Assessment Points, choose accuracy_point, for Output Confusion Matrix type “Confusion_Matrix” and click **Save**.
- Click **Run**.
- A confusion table is created in the Contents pane, under Standalone Tables. Right-click Confusion_Matrix and choose **Open**.

An illustration of the confusion matrix is shown in figure 16.

OBJECTID	ClassValue	C_20	C_40	Total	U_Accuracy	Kappa
1	C_20	47	3	50	0.94	0
2	C_40	1	49	50	0.98	0
3	Total	48	52	100	0	0
4	P_Accuracy	0.979167	0.942308	0	0.96	0
5	Kappa	0	0	0	0	0.92

Figure 14: Confusion matrix (ESRI)

The values in the **ClassValue** column serve as row headers in the table. **U_Accuracy** is for user's accuracy and represents the fraction of pixels classified correctly per total classifications. **P_Accuracy** is the producer's accuracy and represents the fraction of pixels classified correctly per total ground truths. **Kappa**[9] is an overall assessment of the classification's accuracy. Generally, if the Kappa value were below 70 percent, the classification would probably not be accurate enough and would need to be revisited to be improved.

Two aspects of the workflow may contribute to classification error and lower Kappa value. First is an error in segmentation where features may be misclassified if the segmentation parameters generalize the original image too much or too little. Second, the training samples may have caused the majority of errors by having too few training samples or training samples that cover a

[9] Follow the article to learn on Kappa coefficient.
https://towardsdatascience.com/cohens-kappa-9786ceceab58

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wide range of spectral signatures. Increasing the number of samples or classes may improve accuracy.

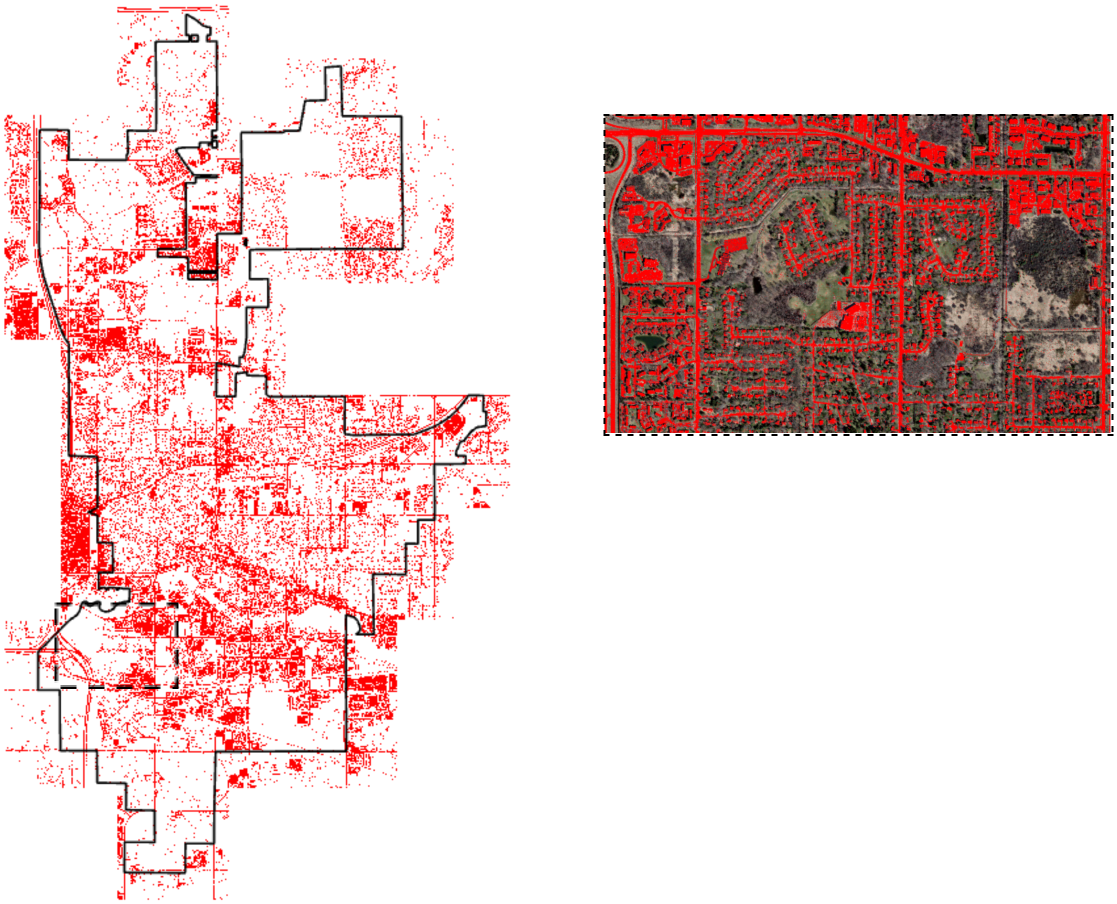

Figure 13: Finalized image showing impervious objects

Conclusion

Land cover classification can be difficult, and it is not always easy to map or separate land cover categories with high accuracy. However, there are ways to potentially improve the result by incorporating more data into the analysis, improving training samples, or possibly redefining the classes of interest. The incorporation of machine learning capabilities into geospatial technologies makes mapping the impervious surface area in an urban landscape cost-effective, consistent, and repeatable. Furthermore, one can always investigate other ML algorithms and platforms (Python, R, QGIS).

The imperviousness layer is the first of its kind for East Lasing, Michigan. Further improvisation can be made as per the requirement. The layer is based on a solid methodology, up-to-date data, and improved technology, making it an important policy and planning tool. This data can be used in conjugation with the hydrological model for flood estimation and forecasting,

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demonstrating the effectiveness of green infrastructure in stormwater management, and urban landscape research.

Limitations

Despite its capacity for automating impervious surfaces, the process has some limitations that users need to be cognizant of beforehand. Many factors can affect classification accuracy including image quality, the reliability of training data and reference/field data, and the accuracy of the assessment method.

- Although object-based classification, in theories, is expected to perform better, however, the bottleneck is it drains computer memory and processing time may take hours if not days.
- While creating training samples, care must be given to collect enough samples for the class of interest and to make it representative as well as fairly spaces.
- Because no single classifier has yet been demonstrated to satisfactorily classify all of the land cover classes, there is no best classifier for both performance and accuracy. Individual evaluations, along with the pros and cons of each method could, however, provide insight into the applications of the methods compatible with the intent.

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