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# Object-Based Supervised Land-Cover Classification of High-Resolution Imagery Using ArcGIS Pro Segmentation and scikit-learn Random Forest

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Abstract: Object-based image analysis (OBIA) can improve high-resolution land-cover mapping by grouping pixels into meaningful image objects before classification, thereby reducing the salt-and-pepper noise common in pixel-based methods. This paper presents a reproducible OBIA workflow that integrates mean-shift image segmentation in ArcGIS Pro, rasterization of training polygons and segment identifiers, and supervised machine-learning classification using a Random Forest model implemented in Python (GDAL, NumPy, and scikit-learn). Training labels were transferred to segmented objects using a majority-label rule, while object-level features were computed as mean spectral values from a three-band (RGB) image. The workflow produces a classified raster map with spatially coherent objects, suitable for exploratory land-cover mapping in an urban park. It provides a foundation for adding richer features and formal accuracy assessment in future work.

**Keywords:** Object-Based Image Analysis; Segmentation; Mean Shift; Random Forest; scikit-learn; ArcGIS Pro; Supervised Classification; Raster Processing.

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# I. INTRODUCTION

High-resolution aerial imagery resolves fine-scale landscape elements such as rooftops, sidewalks, and small vegetation patches. Still, pixel-level classification often produces fragmented results because individual pixels vary due to shadows, mixed materials, and sensor noise. Object-based image analysis (OBIA) addresses this limitation by first segmenting imagery into homogeneous objects that better correspond to real-world features, and then classifying those objects using spectral and contextual attributes. This study documents an ArcGIS Pro + Python workflow for OBIA that (i) prepares object and label rasters from segmentation outputs and training polygons and (ii) trains a supervised classifier in scikit-learn to produce an object-consistent land-cover classification map.

# II. DATA AND STUDY INPUTS

The workflow uses four primary inputs: (1) a high-resolution three-band image (Portland Fine. tif), (2) a mean-shift segmentation raster (arcpy\_ seg\_ index. tif) representing image objects, (3) training polygons (Portland Training Samples. shp), and (4) rasterized class labels derived from the

training polygons (Portland Training Samples\_ label. tif). Two intermediate rasters are generated to support OBIA sampling: an object identifier raster (sample\_ id. tif) and a label raster aligned to the reference image.

# III. METHODS

# ➤ Preprocessing in ArcGIS Pro

Preprocessing steps were completed in ArcGIS Pro to ensure that the segmentation objects and training labels were rasterized at a consistent cell size, extent, and spatial reference. The key objective was to create (i) an object ID raster for sampling and (ii) a label raster aligned with the imagery for supervised learning.

# • Task A: Create an Object ID Raster (Sample\_Id. Tif)

The segmentation raster was converted to vector polygons using the Raster to Polygon tool. Segmentation polygons intersecting the training polygons were selected using Select by Location and exported to a new feature class. The exported polygons were then converted back to raster using Polygon to Raster to produce sample\_id.tif. Raster environment settings (including cell size and extent) were

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controlled to match the imagery and to prevent misalignment during sampling.

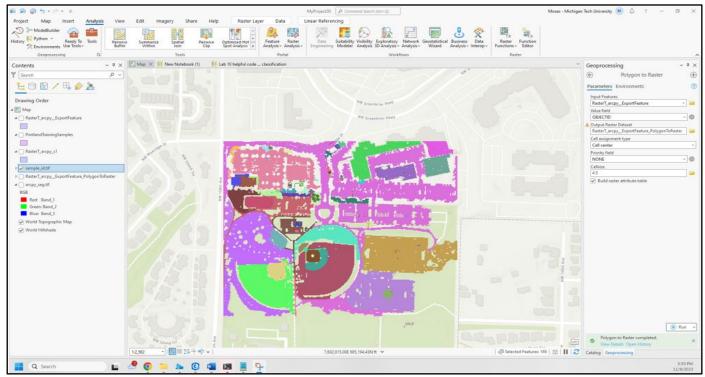


Fig 1 ArcGIS Pro: Converting Segmentation Polygons Intersecting Training Samples to An Aligned Object ID Raster (Sample\_id. Tif).

• Create a Rasterized Training Label Layer (Portland Training Samples\_Label. Tif)

Training polygons were rasterized using Polygon to Raster to create PortlandTrainingSamples\_label.tif. The rasterization environment was set to match the reference image (PortlandFine.tif) so that training labels align with image pixels and derived object features.

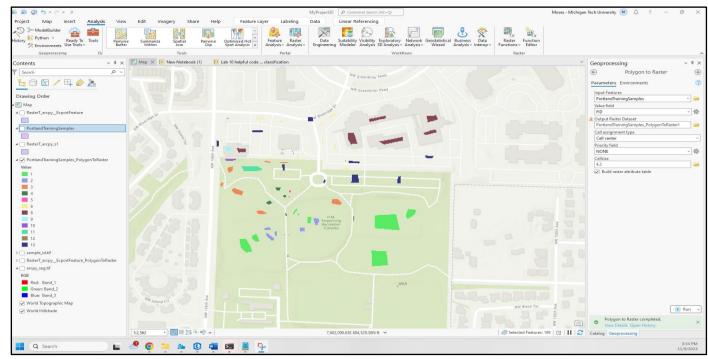


Fig 2 ArcGIS Pro: Polygon-to-Raster Conversion of Training Samples to Create an Aligned Label Raster (Portland Training Samples\_ Label. Tif).

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# ➤ Object-Based Feature Extraction and Supervised Classification (Python)

A Jupyter notebook was used to extract object-based features and train a supervised classifier with scikit-learn. Raster data were read with GDAL and processed as NumPy arrays. For each training object (a unique value in sample\_id.tif), the mean RGB values were computed as the feature vector. Labels were obtained by extracting the training-label pixels within the same object and assigning a single object label using a majority (most common) rule. A Random Forest Classifier with 100 trees was trained on the object feature matrix and applied to all unique segmentation objects to generate a predicted class map, with predicted labels written back to all pixels belonging to each object.

## IV. RESULTS

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The preprocessing workflow produced two aligned rasters essential for OBIA: sample\_id.tif, which encodes object identifiers for training objects intersecting the training polygons, and Portland Training Samples\_label.tif, which encodes training class labels aligned with the imagery. The trained Random Forest model produced an object-consistent classification map in which predicted classes follow segmentation boundaries, reducing pixel-level speckling. Because the feature set in this implementation is limited to mean RGB values per object, some confusion is expected between spectrally similar materials (e.g., light roofs and concrete, dark pavement and shadowed vegetation). Formal quantitative validation (e.g., an object-level confusion matrix using withheld objects or independent reference data) is recommended for research-grade assessment.

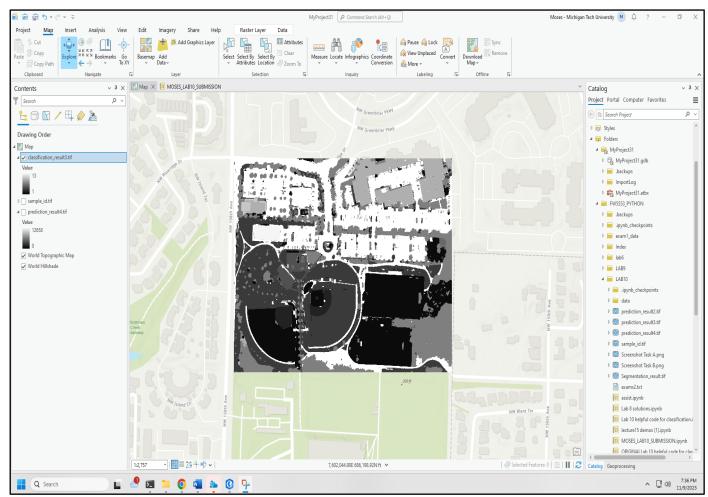


Fig 3 Object-Based Supervised Classification Results in ArcGIS Pro (Predicted Class Map).

# V. DISCUSSION

This study presents a practical OBIA workflow that integrates ArcGIS Pro raster/vector processing with a Python-based supervised classifier. The approach benefits from spatial coherence introduced by segmentation and from transparent, reproducible feature-extraction and model-training steps. However, OBIA performance depends strongly on segmentation quality and the richness of object

features. Using only mean RGB values limits separability across heterogeneous urban classes. Future work should incorporate additional features (within-object standard deviation, texture measures, object-shape metrics) and, when available, spectral information (e.g., near-infrared bands or vegetation indices). Accuracy assessment should be conducted using object-based validation to avoid spatial autocorrelation and to provide defensible per-class performance metrics.

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# VI. CONCLUSION

An ArcGIS Pro-Python OBIA workflow was implemented to produce an object-based supervised land-cover classification map from high-resolution imagery. The workflow creates aligned object-identifier and training-label rasters, extracts object-level features, trains a scikit-learn Random Forest model, and maps predicted labels back to image objects. The resulting classification demonstrates the value of OBIA for producing spatially coherent thematic maps and provides a baseline framework for more advanced feature engineering and validation in future applied studies.

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