Image from NASA:
https://commons.wikimedia.org/wiki/File:Earth_Western_Hemisphere_transparent_background.png#filelinks

Remote Sensing

Geographic Object-Based Image Analysis

In this bonus module, I will provide an introduction to geographic object-based image analysis, or GEOBIA. This material will expand upon the topics covered in the Classification module.

Module Topics

1. Image segmentation algorithms and parameterization
2. Data summarization at object-level
3. GEOBIA and supervised classification

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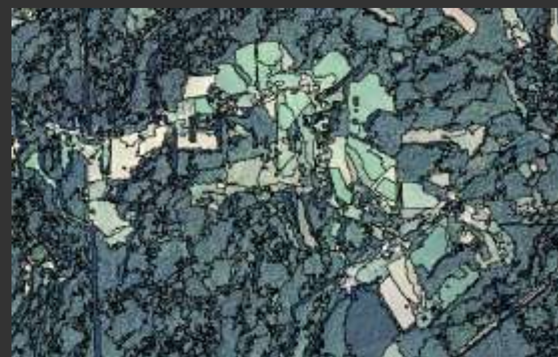
These are the topics covered in this module.

Geographic Object-Based Image Analysis

- GEOBIA
- Commonly used for high spatial resolution data
- Segment image into objects or polygons
- Classify objects as opposed to pixels
- Help remove salt-and-pepper effect
- Potentially a more cartographically pleasing result
- Incorporate ancillary data, textural measures, and geometric measures



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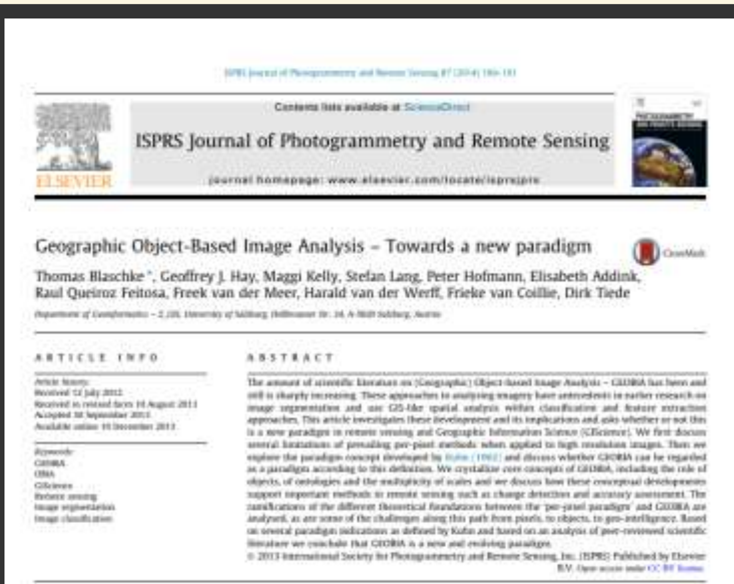
For high spatial resolution data, classifying each pixel individually does not allow for incorporation of spatial context information, which can be of great value for differentiating landscape features, especially when the pixel size or spatial resolution is finer than the average size of the features of interest. GEOBIA allows for the integration of spatial context information. First, input data are segmented into areas or polygons using an algorithm. The goal is to group nearby, similar pixels together to generated objects. These objects then become the unit for subsequent analysis and classification.

For each object, a variety of metrics can be calculated from the pixels within it or from overlapping, ancillary data layers. These include measures of central tendency, variability, texture, and object geometry or shape. These metrics are then used to build rule sets or as predictor variables in supervised classification.

GEOBIA has been documented to reduce the salt-and-pepper issues of pixel-based classification and can yield a more cartographically pleasing output. Although it is commonly applied to high spatial resolution data, it has also been used to analyze moderate spatial resolution data, such as Landsat scenes.

Blaschke et al. (2014)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Geographic Object-Based Image Analysis – Towards a new paradigm

Thomas Blaschke *, Geoffrey J. Hay, Maggi Kelly, Stefan Lang, Peter Hofmann, Elisabeth Addink, Raul Queiroz Feitosa, Freek van der Meer, Harald van der Werff, Frieke van Coillie, Dirk Tiede

ARTICLE INFO

ABSTRACT

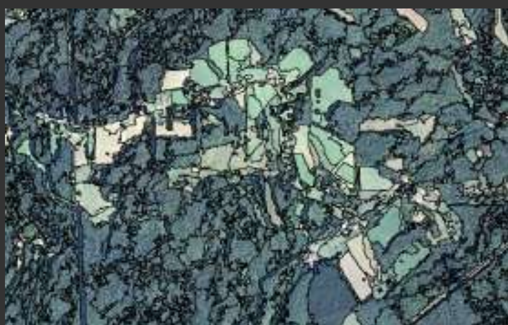
Blaschke, T., Hay, G.J., Kelly, M., Lang, S., Hofmann, P., Addink, E., Feitosa, R.Q., Van der Meer, F., Van der Werff, H., Van Coillie, F. and Tiede, D., 2014. Geographic object-based image analysis–towards a new paradigm. *ISPRS journal of photogrammetry and remote sensing*, *87*, pp.180-191.

GEOBIA has allowed for a major advancement in the analysis and classification of high spatial resolution imagery. It has been described as a new paradigm in the field. Currently, these techniques are used in research and applied mapping studies. GEOBIA has also been integrated into several remote sensing and geospatial software packages.

Image Segmentation

Segmentation Methods

❖ Here we will discuss the multiresolution segmentation algorithm



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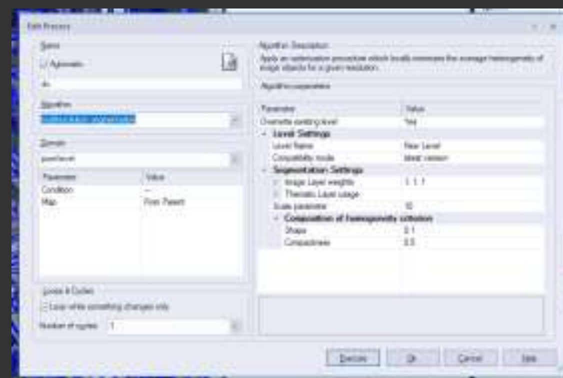
The first step of GEOBIA is to generate image objects, which then become the unit of analysis in subsequent processes.

Different algorithms are available for generating image objects from input raster data. In the eCognition software tool, which is a leading GEOBIA software application, the multiresolution segmentation algorithm has been shown to be very power. I have found that it generally does a very good job generating objects that align or correlate with real-world features. It should be noted that eCognition offers several additional segmentation algorithms including: chessboard, quadtree, contrast split, spectral difference, multi-threshold, superpixel, contrast filter, and watershed.

The multiresolution segmentation algorithm creates objects using an iterative technique, whereby pixels and objects are grouped until a threshold representing the upper object variance is reached. The variance threshold is weighted with shape parameters to minimize the fractal borders of the objects.

Parameters

- Band Weights = relative weights of each input band in the segmentation
- Scale = controls size of objects
  - Larger values produce larger objects on average
- Shape = controls relative weight between the shape in comparison to the spectral properties
  Smaller values mean less influence of shape in comparison to spectral properties
- Compactness = controls balance between the form and edge length of the object
  - Larger values will cause objects to be more rounded or less elongated or irregular



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Several user-defined parameters must be provided that will impact the segmentation result. First, the input data or bands can be assigned different weights. By default, all layers will be weighted equally; however, you can change the weights if you would like certain bands to have a larger or smaller impact on the segmentation result.

The scale parameter generally has the largest impact on the output and controls the size of the resulting image objects. Larger values will produce larger objects, based on area, on average. The shape and compactness parameters tend to have less impact on the output but can be experimented with to potentially improve the segmentation. Shape controls the relative weight between the object shape in comparison to the spectral characteristics. Smaller values result in less influence of shape in comparison to spectral properties. Compactness controls the balance between the form and edge length of the object. Larger values will cause objects to be more rounded, or less elongated or irregular, on average.

Choosing Parameters

- ❖Scale has the largest impact on output
- ❖Can experiment with settings using best judgement or trial-and-error
- ❖Can use Estimation of Scale Parameter 2 (ESP2) Tool: https://cskovi.wixsite.com/fusedem/esp2

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Automated parameterisation for multi-scale image segmentation on multiple layers

L. Drăguț, O. Csillik, C. Eisank, D. Tiede

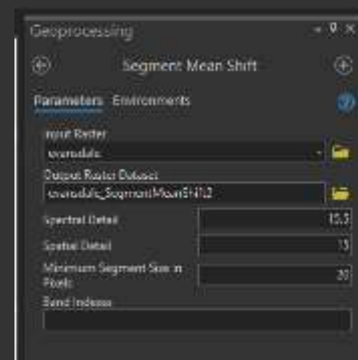
Drăguț, L., Csillik, O., Eisank, C. and Tiede, D., 2014. Automated parameterisation for multi-scale image segmentation on multiple layers. *ISPRS Journal of photogrammetry and Remote Sensing*, *88*, pp.119-127.

It can be difficult to determine the optimal parameter settings. The Estimation of Scale Parameter 2 (ESP2) Tool can be useful for testing a variety of values for the scale parameter.

However, It is common for settings to be selected simply based on trial-and-error.

Other Options

- ArcGIS Pro: provides mean shift algorithm
- QGIS: offers region growing and watershed-based methods
- ENVI



There are other segmentation algorithms available. For example, ArcGIS Pro offers a mean shift method and QGIS offers region growing and watershed-based methods.

Object Variables

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Measure of Central Tendency

- Spectral Brightness = Sum of means of all bands divided by the number of bands
- Band Means
- Band Modes
- Band Quantiles
- Band Medians
- Max Difference = Largest spectral difference between the two most different bands

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Once objects are generated, a variety of variables can be summarized from the associated pixel values. For example, spectral brightness represents the sum of means of all bands divided by the number of bands. For each band, you can calculate measures of central tendency as means, modes, quantiles, and medians. Max difference is the largest spectral difference between the two most different bands.

Measures of Variability

- Band Standard Deviations (first-order texture)
- Gray-Level Co-Occurrence Matrix (GLCM) measures (second-order texture)
  - Measures of contrast = contrast, dissimilarity, and homogeneity
  - Measures of orderliness = angular second moment, maximum probability, and entropy
  - Descriptive statistics = mean, variance, standard deviation, and correlation
  - Hall-Beyer and Warner suggest 1 measure of contrast, 1 measure of orderliness, and at least 2 descriptive statistics


Textural Features for Image Classification

Haralick, R.M., Shanmugam, K. and Dinstein, I.H., 1973. Textural features for image classification. *IEEE Transactions on systems, man, and cybernetics*, (6), pp.610-621.

Warner, T., 2011. Kernel-based texture in remote sensing image classification. *Geography Compass*, *5*(10), pp.781-798.


Kernel-Based Texture in Remote Sensing Image Classification

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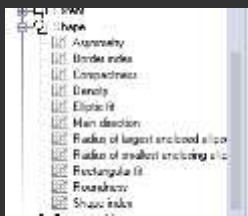
You can also calculate measures of variability for each band. For example, standard deviation, which is a first-order textural measure, can be calculated for each band separately using the pixel values associated with all pixels in an object.

There are also a variety of second-order textural measures that can be calculated for each band. Second-order textural measures, in contrast to first-order measures, do not use all the cells. Instead, only cells that are separated by a defined distance and/or direction are considered. The measures derived from the gray-level co-occurrence matrix (GLCM) after Haralick (1973) are the most commonly used second-order measures. A variety of metrics can be derived. Hall-Baeyer and Warner suggest that 1 measure of contrast, 1 measure of orderliness, and at least 2 descriptive statistics be included.

Measures of Shape and Geometry



- ❖Border Index
- ❖Compactness
- ❖Elliptic Fit
- ❖Rectangular Fit
- ❖Roundness
- ❖Shape Index

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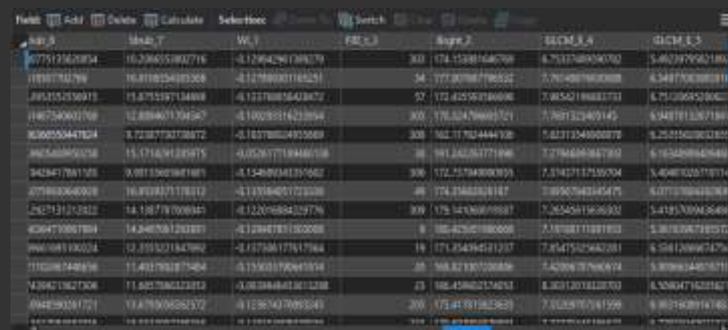
You can also calculate a variety of geometric measures to summarize the shape of each image object.

Additional Measures

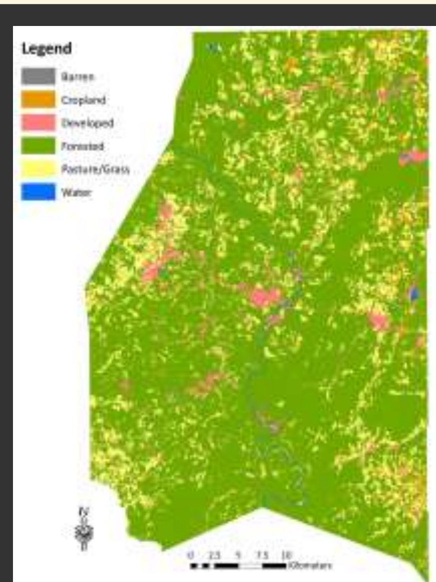
- Summarize ancillary data
- Summarize thematic layers
- Summarize point cloud data
- Comparison to super-objects
- Comparison to neighbors
- Custom variables
- Band indices



It is also possible to summarize ancillary data, such as the density of roads or man-made structures. You could derive metrics from point-clouds, such as LiDAR data, or summarize thematic data, such as soil characteristics or land use. It is possible to generate objects at multiple sizes or scales. If this is undertaken, then you can include measures calculated for larger objects to include with each smaller object that they contain. This can be helpful for summarizing patterns at different scales. You can also include measures associated with differences between objects and their neighbors, generate custom metrics, and include band indices and ratios, such as NDVI.

Variable Examples

Spectral	1st Order Texture	2nd Order Texture	NDVI	Geometry	LiDAR	Road Density	Structure Density
Mean Blue	SD Blue	Homogeneity	Mean	Area	Mean nDSM	Mean 1,000 m radius	Mean 1,000 m radius
Mean Green	SD Green	2nd Angular Moment	SD	Asymmetry	SD nDSM	Mean 500 m radius	Mean 500 m radius
Mean Red	SD Red	Contrast		Border Index	Minimum nDSM	Mean 250 m radius	Mean 250 m radius
Mean NIR	SD NIR	Entropy		Border Length	Maximum nDSM	SD 1,000 m radius	SD 1,000 m radius
		Dissimilarity		Compactness	Mean Slope	SD 500 m radius	SD 500 m radius
		Correlation		Roundness	SD Slope	SD 250 m radius	SD 250 m radius
		Standard Deviation		Width	Minimum Slope		
		* for all 4 bands		Elliptic Fit	Maximum Slope		
				Density	Mean Elevation		
				Rectangular Fit	SD Elevation		
				Length	Mean First Return Intensity		
				Length/Width	SD First Return Intensity		
				Volume	Homogeneity First Return Intensity		
				Shape Index	2nd Angular Moment First Return Intensity		
					Contrast First Return Intensity		
					Entropy First Return Intensity		
					Dissimilarity First Return Intensity		
					Correlation First Return Intensity		
					Standard Deviation First Return Intensity		
4	4	28	2	14	19	6	6
Total: 83 Variables							



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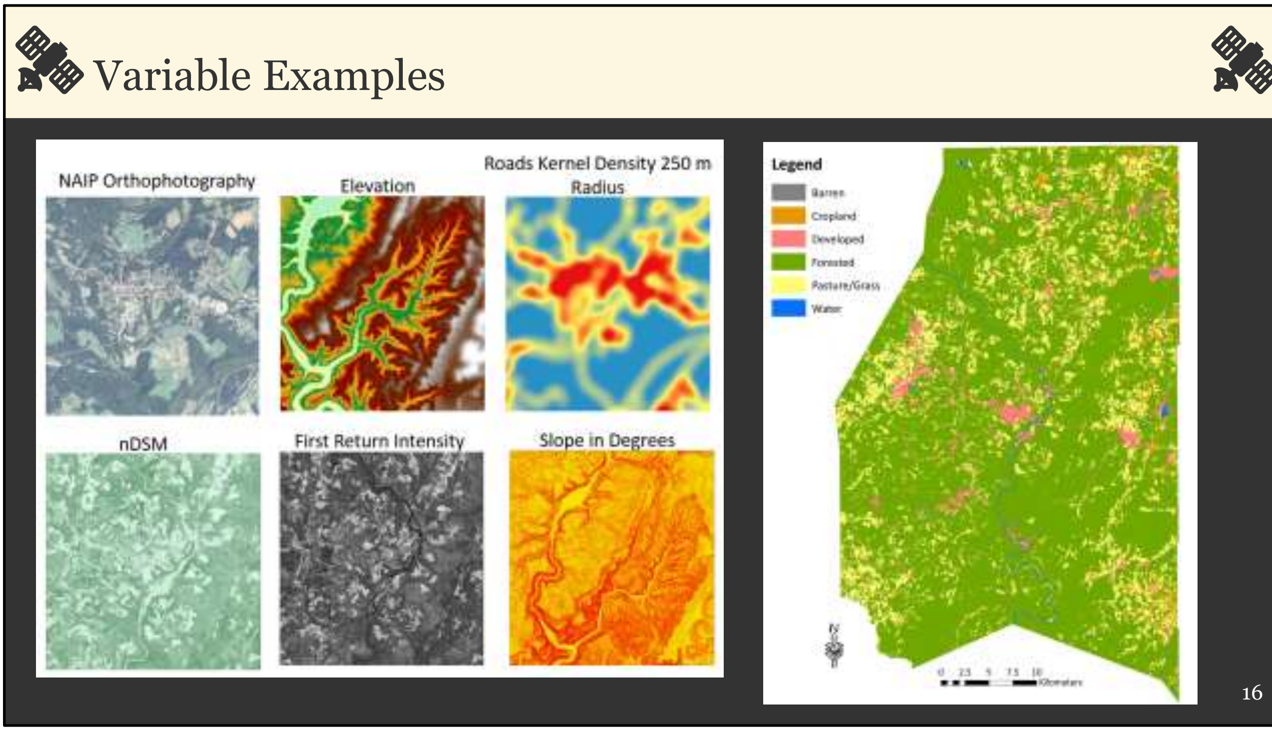
This is an example feature space for an object-based classification of Preston County, West Virginia. Measures of central tendency, first-order texture, and second-order texture are generated from the four input bands. The mean and standard deviation of the NDVI are also included. Object geometric measures are calculated along with LiDAR-derived measures of central tendency and texture. Lastly, kernel density surfaces representing road and man-made structure density are summarized for each object.



This slide shows some examples of the different input datasets summarized for each object.

Using Super-Object Information

- Using features derived for larger objects that contain the objects being classified can improve classification results
- These features can be associated with the smaller objects using a spatial intersection

Johnson, B. and Xie, Z., 2013. Classifying a high resolution image of an urban area using super-object information. *ISPRS journal of photogrammetry and remote sensing*, *83*, pp.40-49.

Johnson, B.A., 2013. High-resolution urban land-cover classification using a competitive multi-scale object-based approach. *Remote Sensing Letters*, *4*(2), pp.131-140.

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Again, it is possible to generate objects at multiple scales and use metrics from larger objects as predictor variables to classify the smaller objects that occur within them. This topic has been explored in the papers referenced here.

Classification

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Rule Sets

- Define classes
- Define rules to differentiate classes
- Input rules as a rule-set
- Rule-set is similar to a dichotomous key
- Rules can be generated based on calculated variables (brightness, mean, standard deviation, GLCM measures, etc.)
- Can incorporate morphological relationships and relationships to other classes

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Image objects can be classified using human generated rule sets. A user will define rules used to differentiate classes that rely on the calculated features. This is similar to a dichotomous key. It is also possible to incorporate morphological relationships, or relationships between adjacent objects, and spatial relationships between the mapped classes. The eCognition software tool provides a workflow for rule set generation, refinement, and deployment.

Supervised Classification

- Select objects to use as training samples
- Randomly select objects to use as validation data
- May need to perform feature selection if you have a large set of variables
- Train a classifier: *k*-NN, random forests, support vector machines, etc.
- Use model to classify all objects
- Can convert to raster

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Image objects can also be classified using supervised classification methods. The variables calculated for each object will serve as the predictor variables and objects will need to be selected to serve as training and validation data. Given the complexity of the feature space, it is generally not appropriate to use parametric classifiers, such as Gaussian Maximum Likelihood. Instead, machine learning methods, such as *k*-NN, random forests, or support vector machines, are preferred. Once a model is generated, it can be used to classify each image object. The result can be maintained as vector data or converted to a categorical raster grid.

Ma et al. (2017) Findings

1. High spatial resolution data commonly used
2. Small study areas (less than 300 ha)
3. Multiresolution segmentation algorithm commonly used
4. Random forests is a good classifier for GOEBIA
5. More class = lower accuracy
6. Great in agricultural settings


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A review of supervised object-based land-cover image classification

Ma, L., Li, M., Ma, X., Cheng, L., Du, P. and Liu, Y., 2017. A review of supervised object-based land-cover image classification. *ISPRS Journal of Photogrammetry and Remote Sensing*, *130*, pp.277-293.

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Ma et al. (2017) reviewed the use of supervised classification for classifying image objects. They noted that these techniques tend to be more commonly applied to high spatial resolution data over small study area extents than coarser data over larger extents. The multiresolution segmentation algorithm, which is made available in the eCognition software, was the most commonly used segmentation method. Random forest was generally a good default classification algorithm for GEOBIA. Attempting to differentiate more classes tended to reduce the classification performance, and GEOBIA was found to be of particular use in agricultural landscapes.

A Note on Accuracy Assessment

- Since objects vary in size, features are commonly weighted by their land area in the confusion matrix and when calculating measures from the error matrix

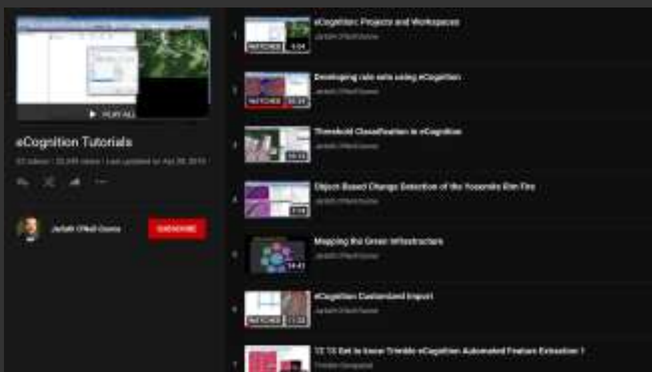
		Reference							
		Barren	Forest	Low Vegetation	Impervious	Mixed Developed	Water	Row Total	User's Accuracy
Classification	Barren	0.201	0.009	0.157	0.149	0.002	0.009	0.527	**38.1**
	Forest	0.014	82.283	1.433	0.055	0.196	0.015	83.995	**98.0**
	Low Vegetation	0.200	0.334	11.021	0.023	0.140	0.000	11.718	**94.1**
	Impervious	0.024	0.007	0.056	0.460	0.020	0.026	0.593	**77.6**
	Mixed Developed	0.000	0.090	0.142	0.111	0.566	0.001	0.909	**62.3**
	Water	0.001	0.063	0.011	0.004	0.001	2.177	2.258	**96.4**
	Column Total	0.439	82.786	12.820	0.803	0.925	2.227	**Overall Accuracy : 96.7%**	
	Producer's Accuracy	**45.7**	**99.4**	**86.0**	**57.3**	**61.2**	**97.7**	**Kappa: 0.856**	

Cells in table represent proportion of the total area of the training objects

Accuracy assessment of object-based classifications can be complex. It is generally recommended to assess both the thematic classification accuracy and the segmentation accuracy.

One complexity relates to the fact that objects vary in size. It is common to weight each validation sample by its land area in the confusion matrix to take these varying sizes into consideration. However, there is still conflicting advice in the academic literature on how best to select validation data and build error matrices for GEOBIA assessment.

eCognition GEOBIA Tutorials



Series created by Jarlath O'Neil-Dunne

https://youtube.com/playlist?list=PLG0a9U3eef7ogzqmj2PwTy2splFdHKe7i

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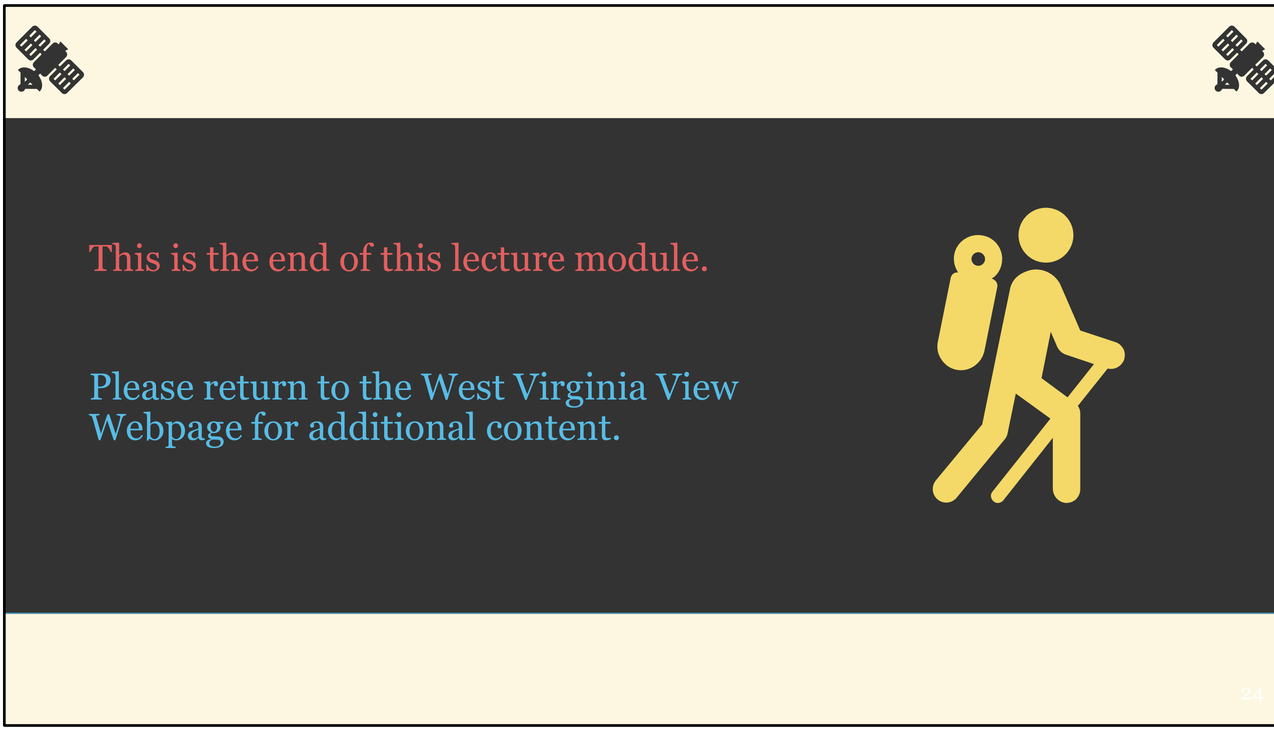

Thanks! Hope you found this useful.