

Center pivot irrigation feature extraction in the Chesapeake Bay Watershed using an object-based image analysis (OBIA) approach

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The Pennsylvania State University | Advisor: Jarlath O'Neil-Dunne



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2018 Irrigation and Water Management Survey

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Table Number and Description

Entire Farm Data

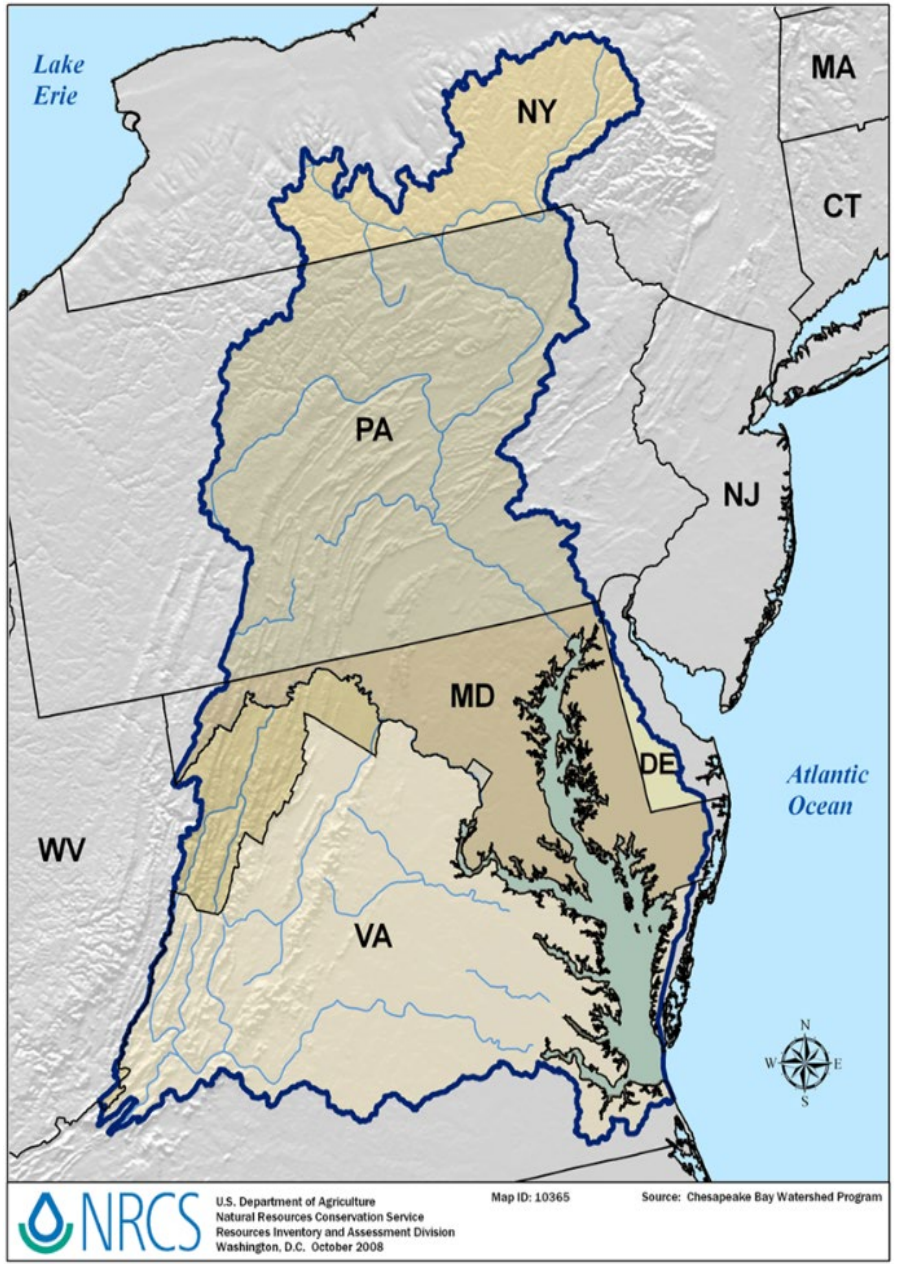
[Table 1. Irrigated Farms in the Censuses of Agriculture: 2017 and Earlier Censuses](#)

[Table 2. Irrigated Farms by Acres Irrigated: 2018 and 2013](#)

Table 2. Irrigated Farms by Acres Irrigated: 2018

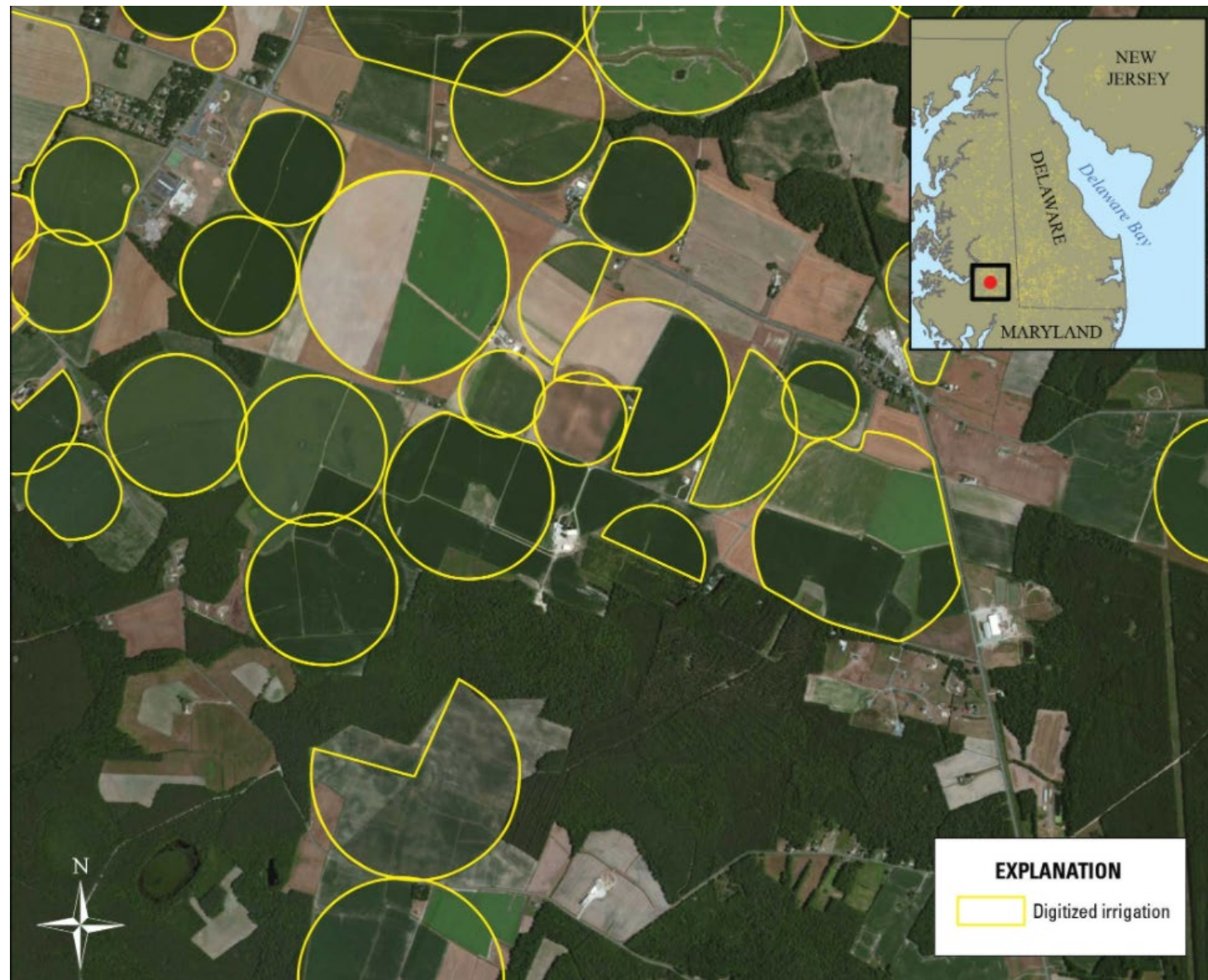
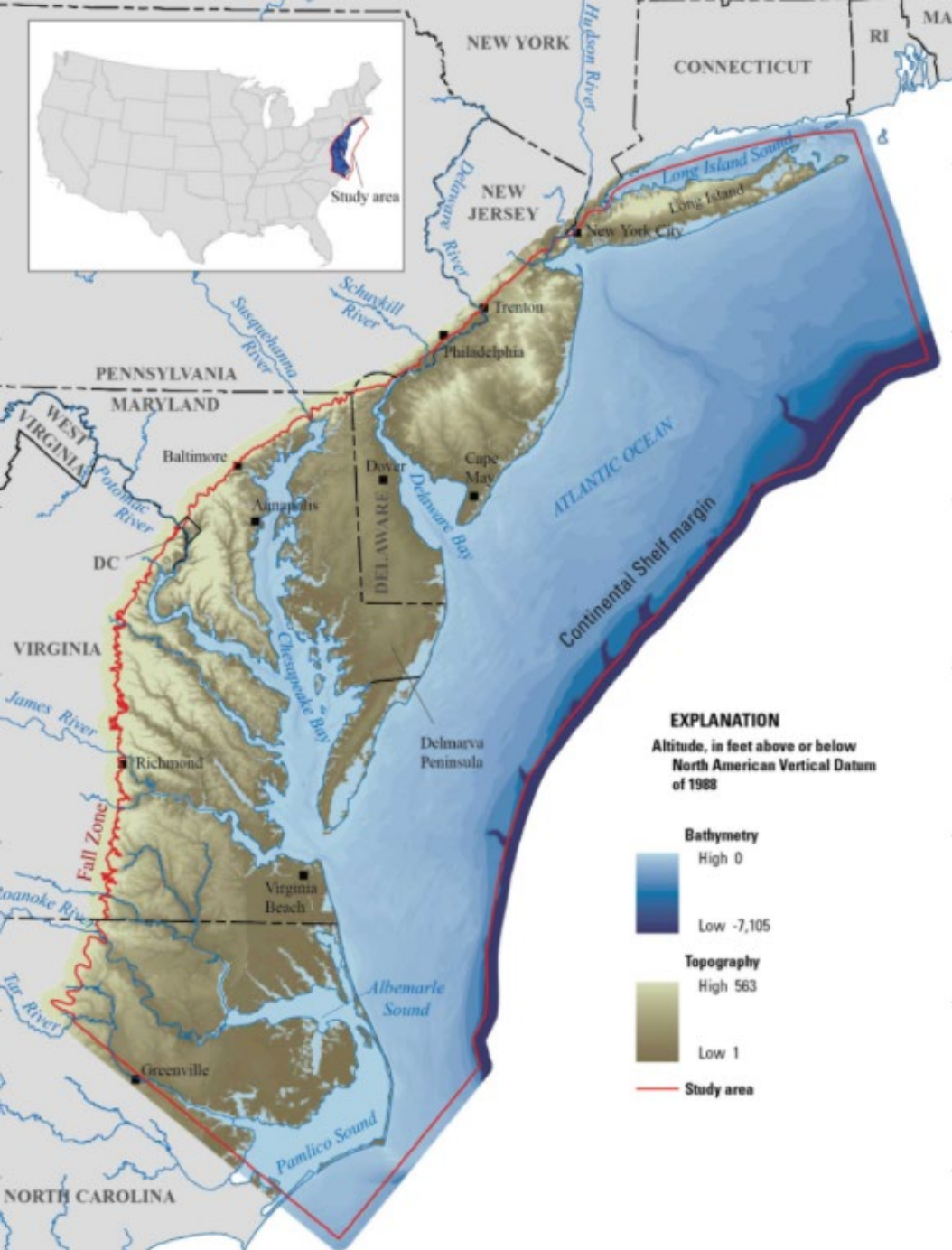
[Excludes institutional, research, and experimental farms. For meaning of abbreviations

Geographic area		Total		
		Farms	Land in farms (acres)	Acres irrigated
United States	2018	231,474	222,028,954	55,938,795
	2013	229,237	213,993,983	55,319,417





Milligan, C. (2016, April 12). *Irrigation systems: Real rainmakers for farmers*. Retrieved June 29, 2020, from Delaware Business Times: <https://delawarebusinesstimes.com/news/industry/agribusiness/irrigation-systems-real-rainmakers-farmers/>





Power lines

Access lane

Wheel tracks

Irrigation arm

**Center pivot
tower and
well/pump**

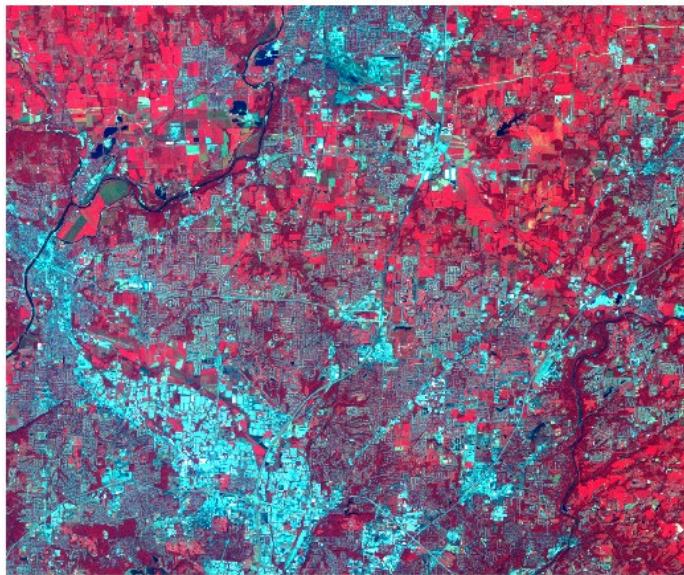
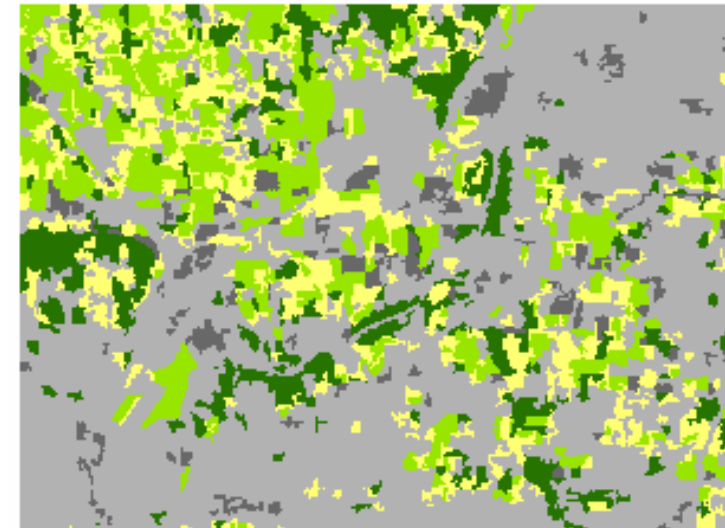


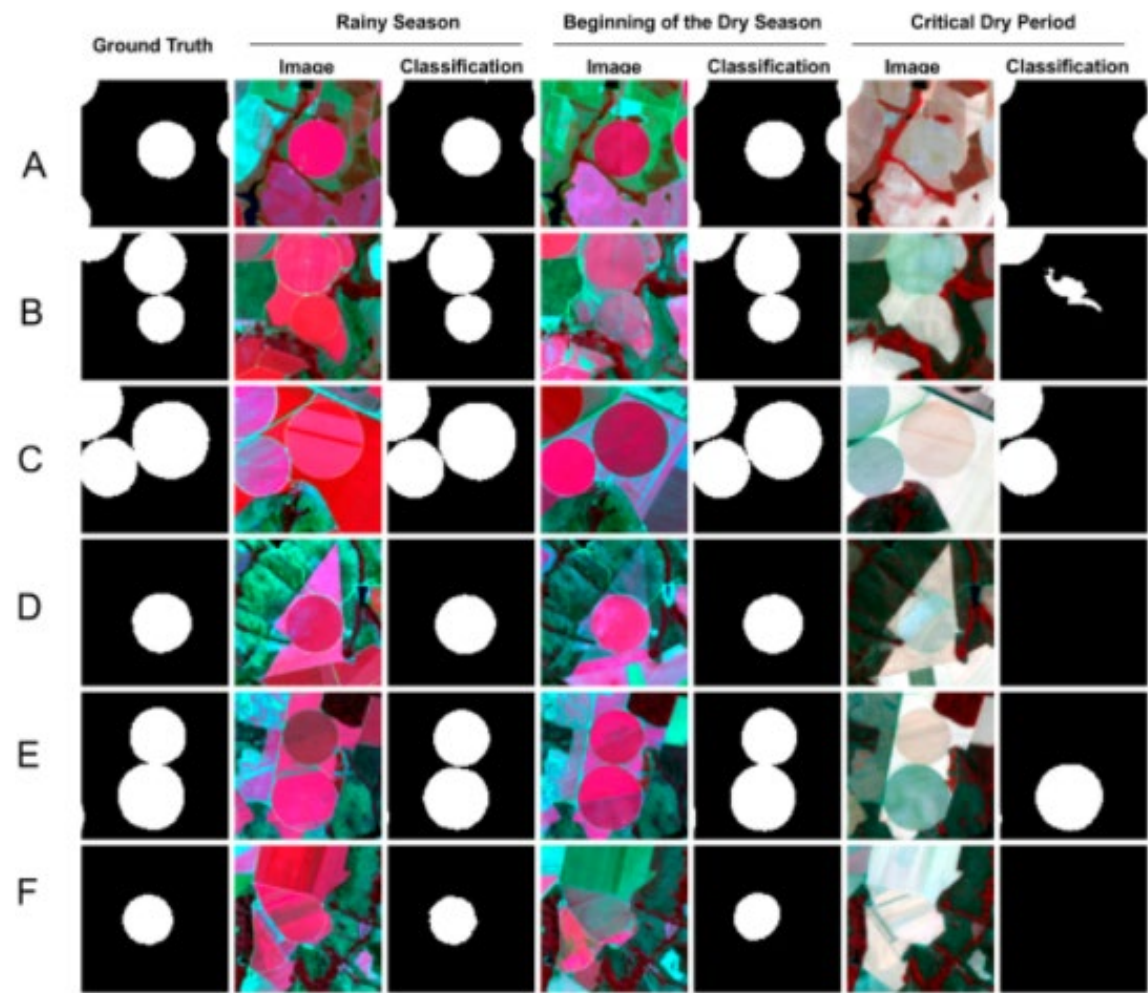
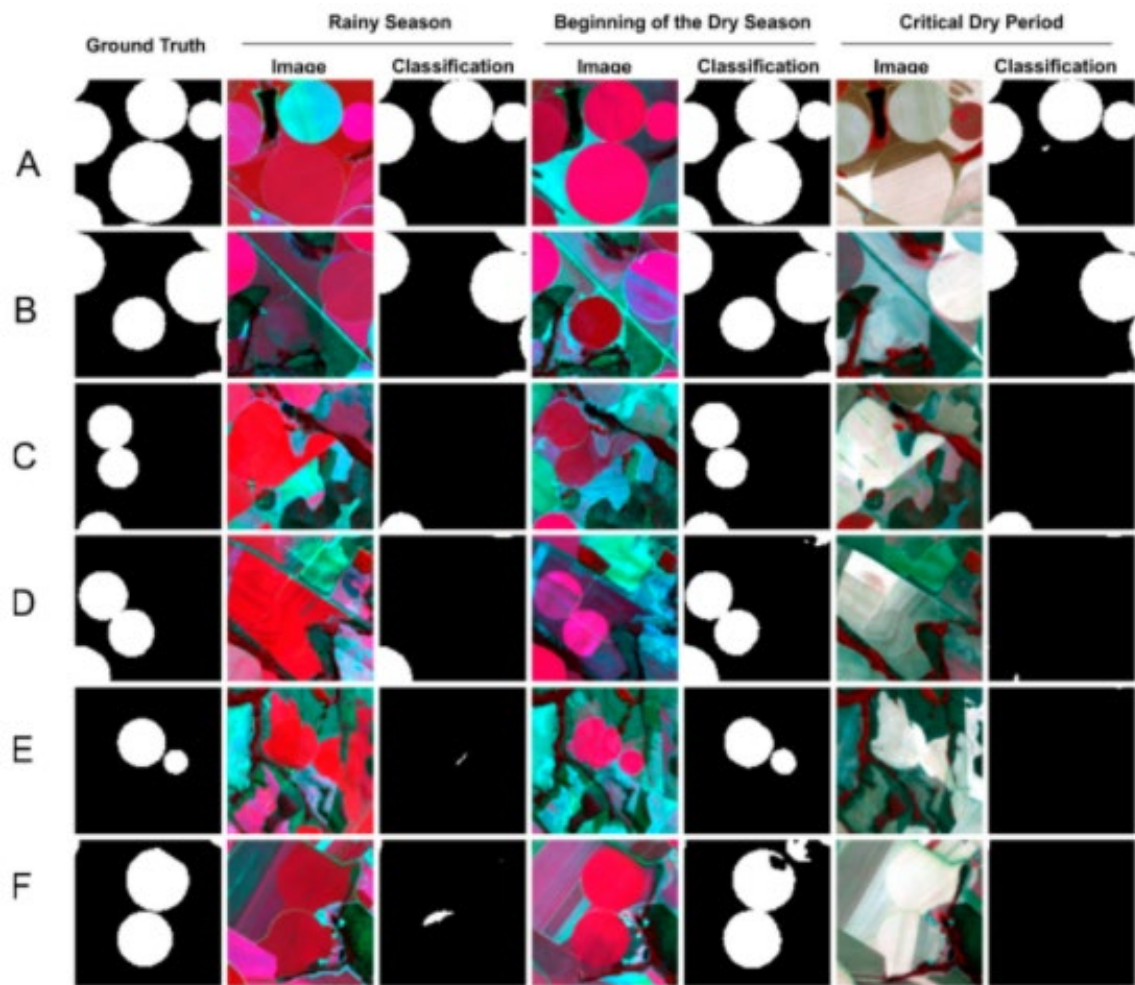
Image Classification

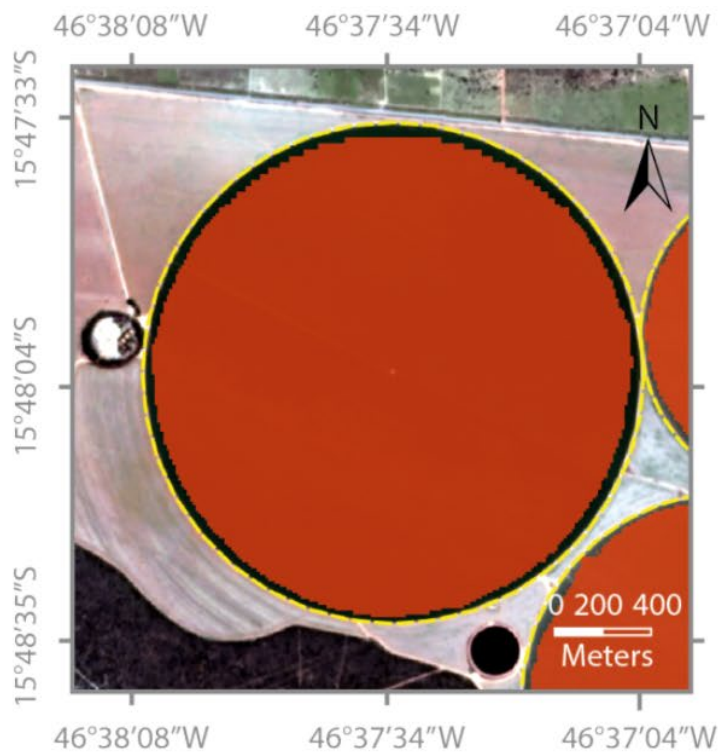
Classification: NorthernCincy

Training Sample Manager

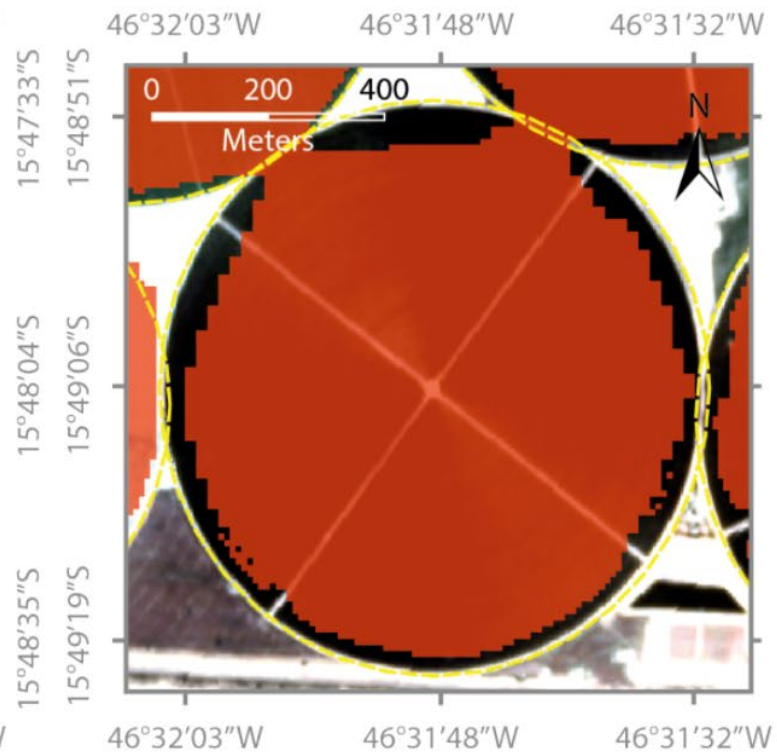
ID	Class Name	Value	Color	Count
1	Commercial / Industrial	1	Grey	991
2	Residential	2	Light Green	1249
3	Cropland	3	Green	940
4	Forest	4	Dark Green	441
5	Pasture	5	Yellow	547



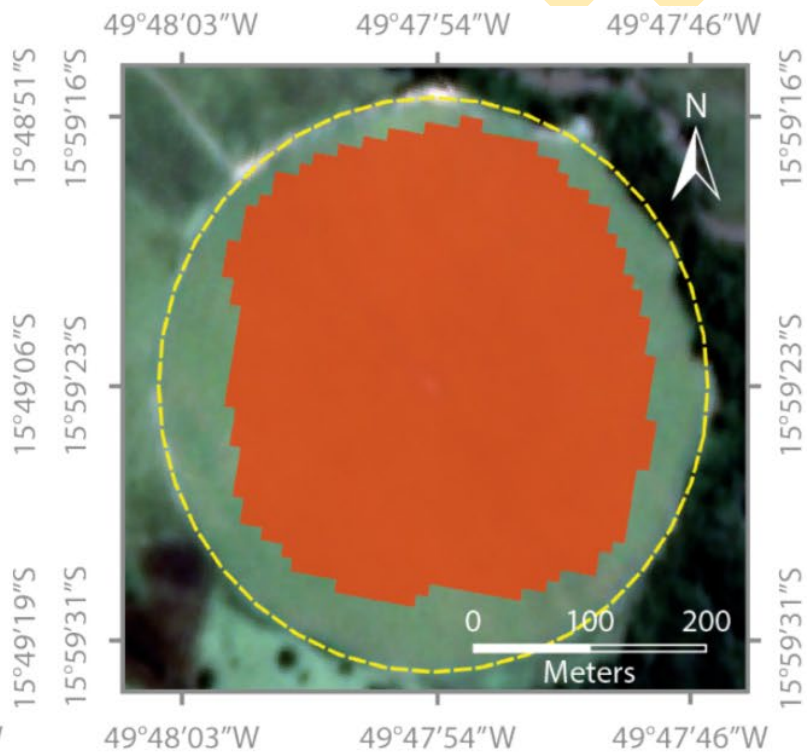




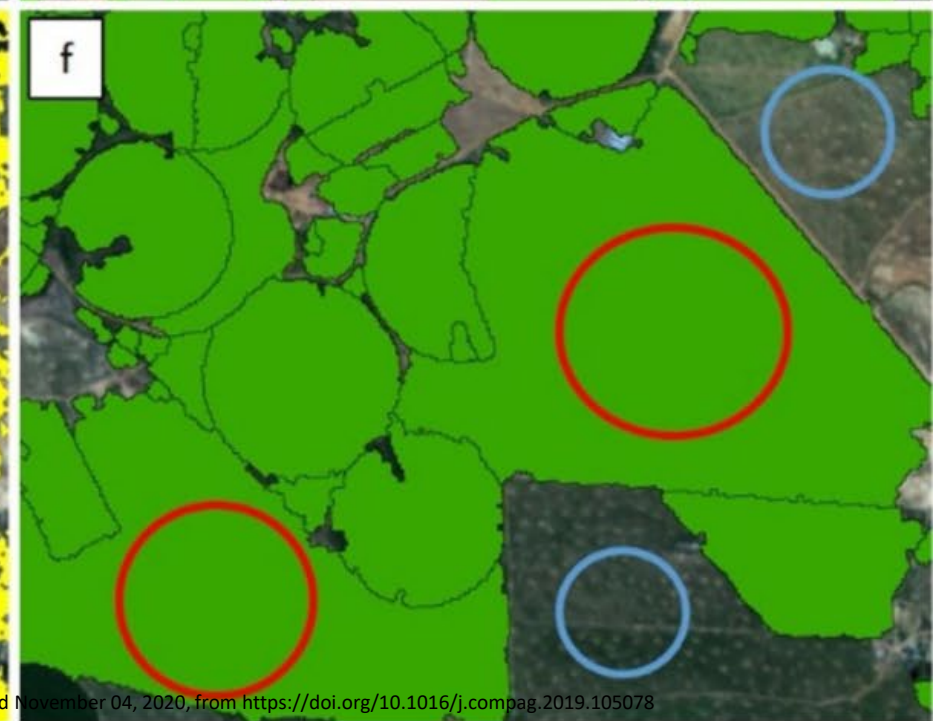
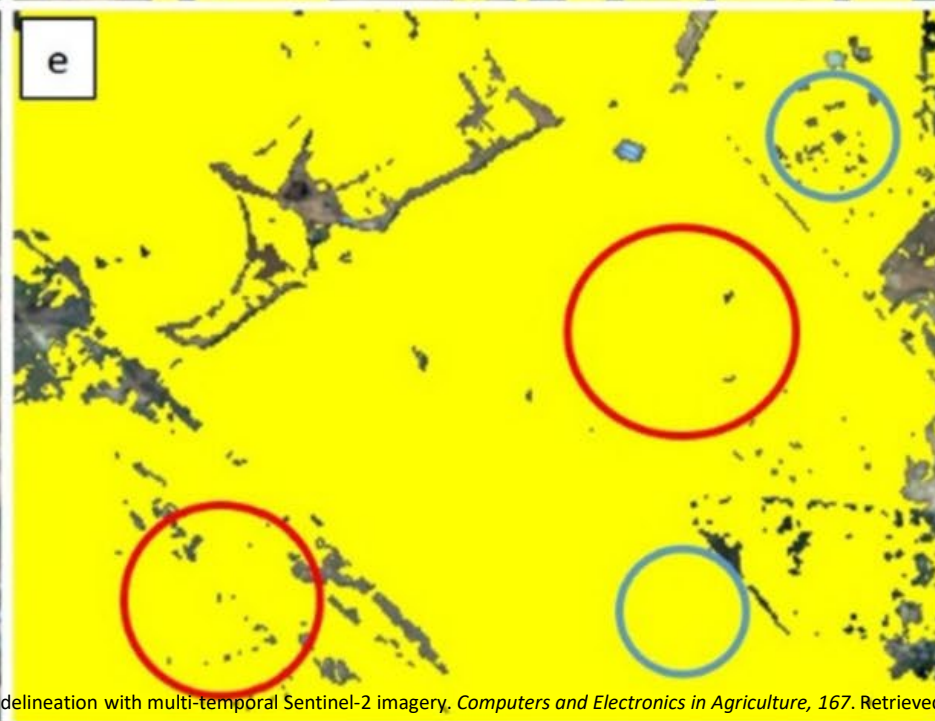
(a)

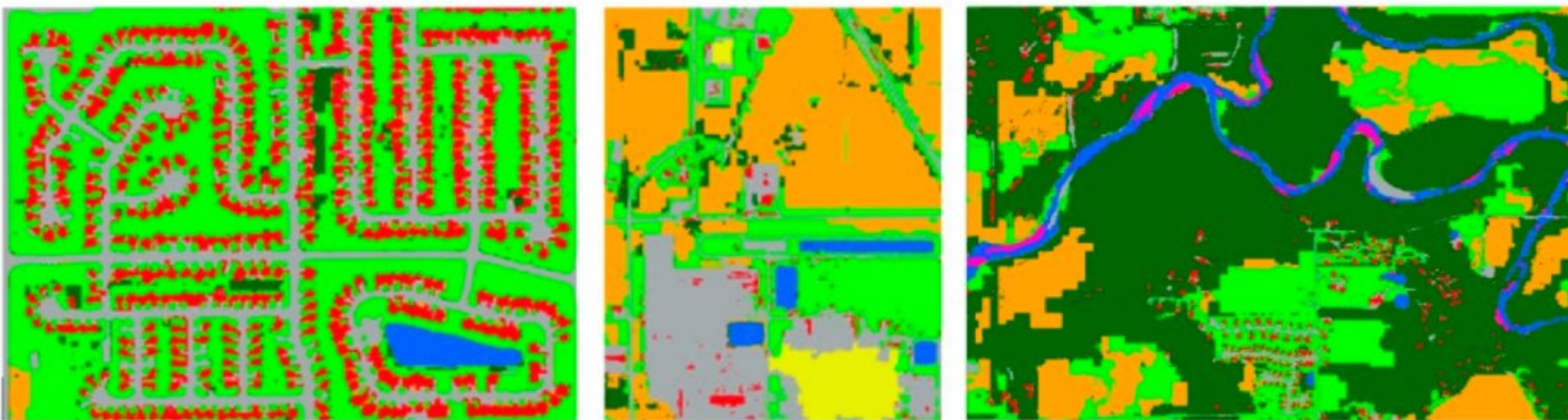
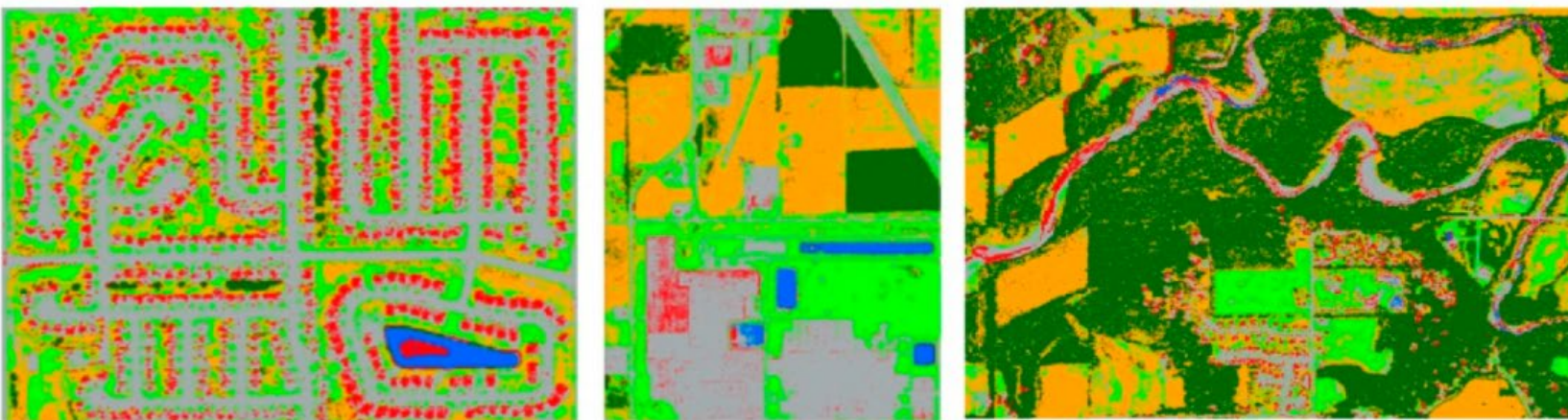


(b)



(c)





- Tree
- Water
- Crop
- Road
- Building
- Grass



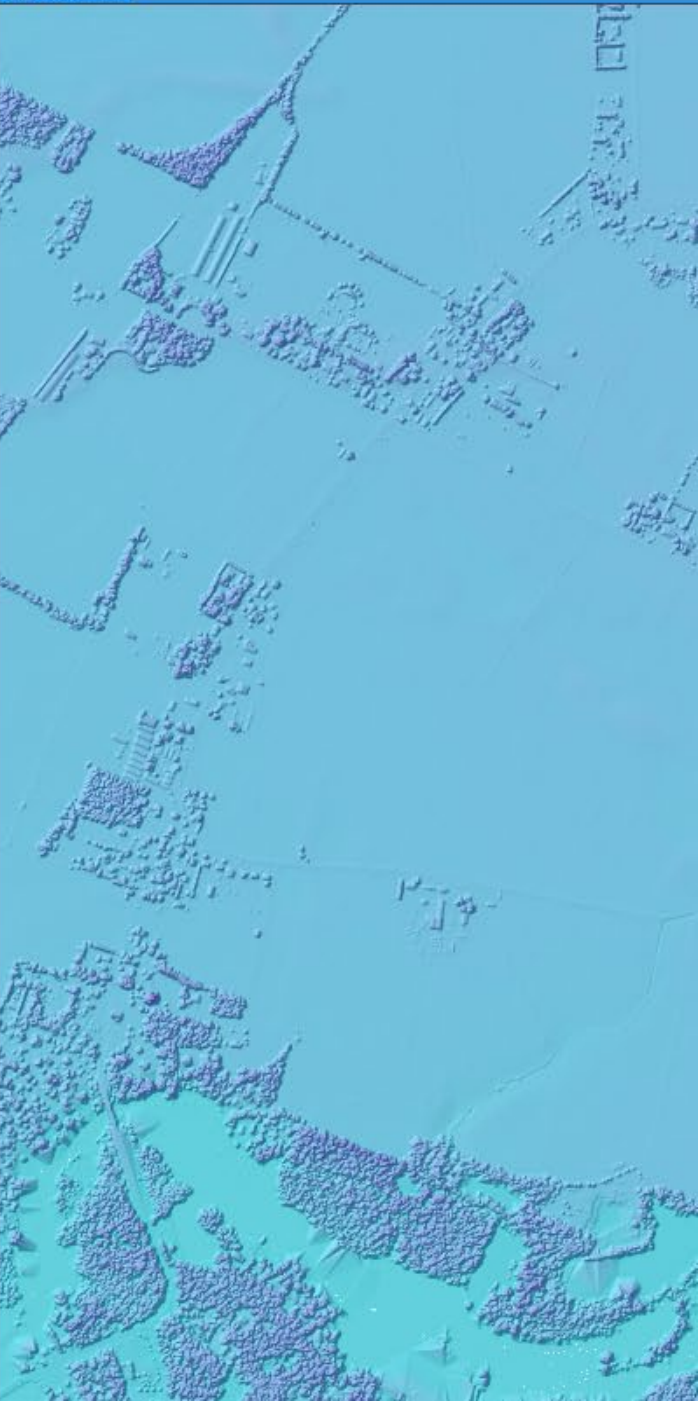












ELEMENTS OF IMAGE INTERPRETATION

by

Charles E. Olson, Jr.

Supplementary notes prepared for use in image interpretation training programs of the University of Michigan School of Natural Resources, Ann Arbor, Michigan.

Nine elements of image interpretation are described in the following paragraphs. This discussion is not intended to be exhaustive. In fact, a separate book could be written about each of the elements mentioned. Appreciation of the importance of these elements will grow with experience and practice. This description serves as an advance look at what is considered in more detail later.

1. Shape. The shape or form of some objects is so descriptive that their images may be identified solely from this criterion. The Pentagon Building near Washington, D.C. is a classic example.

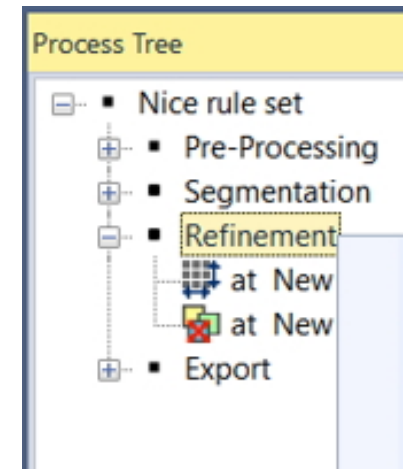
2. Size. In many cases length, width, height, area, or volume are essential to accurate and complete interpretation. The volume of wood which could be cut from the stand in Figure 1 is dependent upon tree-size, stand density, and size (or age) of the stand.

3. Tone. Different objects reflect and emit different amounts and wavelengths of energy. These differences are recorded as tonal, color, or density variations in the record. The stand of mixed hardwoods shown in Figure 1 was photographed in late October at the peak of the fall color change. Species differences show clearly in different tones or shades of gray.

4. Shadow. Shadows can help or hinder the interpreter, for they reveal invisible silhouettes but hide some detail. Shadows in Figure 2 provide information on the size and shape of this building which is not apparent from the image of the building alone. These same shadows obscure detail in the lawn and sidewalk areas in front of the building.

5. Pattern. Pattern, or repetition, is characteristic of many man-made objects and of some natural features. The land-use pattern shown in Figure 3 is typical of areas of deep, wind-blown soils. Orchards and strip cropping are particularly conspicuous because of pattern.

6. Texture. The visual impressions of roughness or smoothness created by some images is often a valuable clue to interpretation. Tree size is often interpreted on the basis of apparent texture. Smooth, velvety textures are commonly associated with young saplings, while rougher, cobbled textures usually indicate older trees of sawtimber size.



Edit Process

Name

Automatic

42 [shape:0.1 compact:0.5] creating "New Level"

Algorithm

multiresolution segmentation

Domain

pixel level

Parameter	Value
Condition	---
Map	From Parent

Loops & Cycles

Loop while something changes only

Number of cycles 1

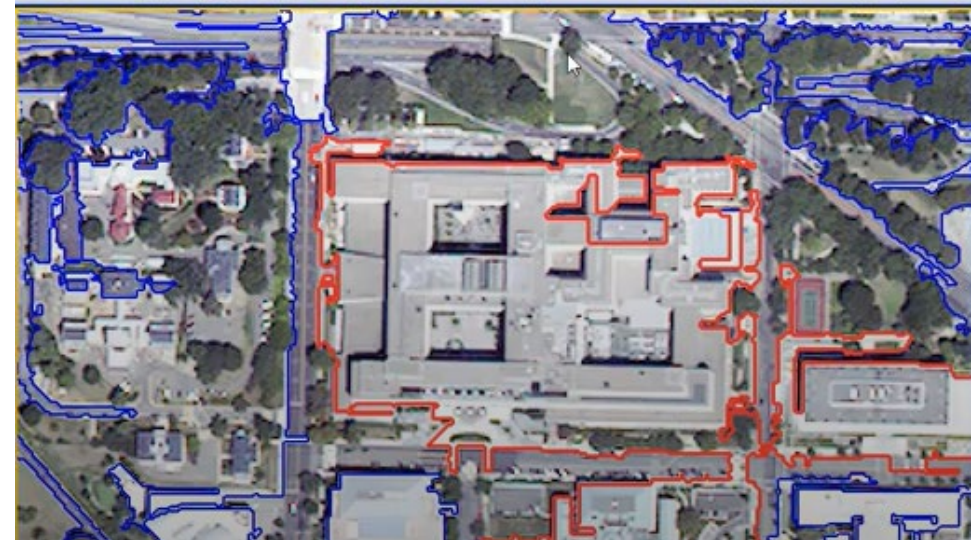
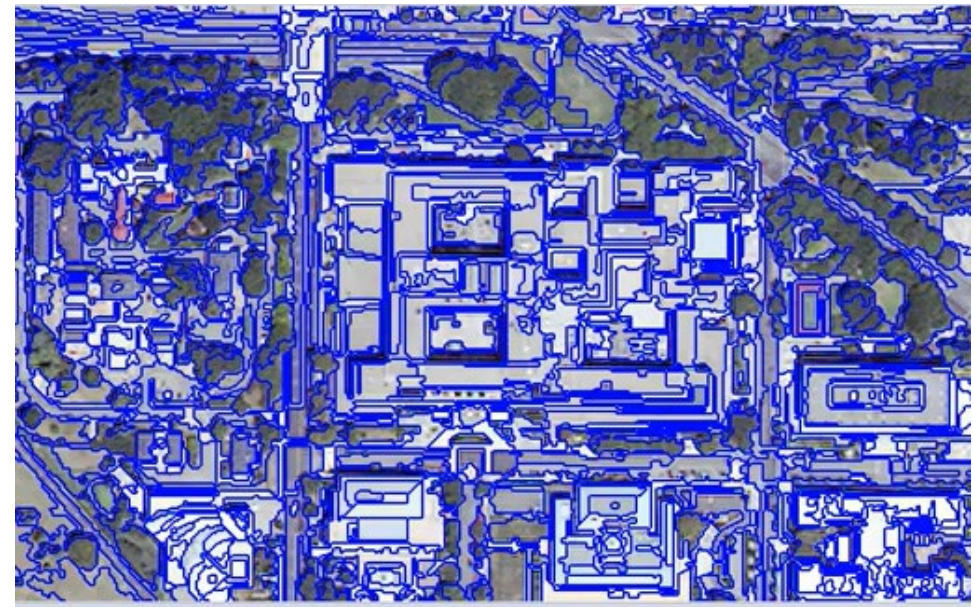
Algorithm Description

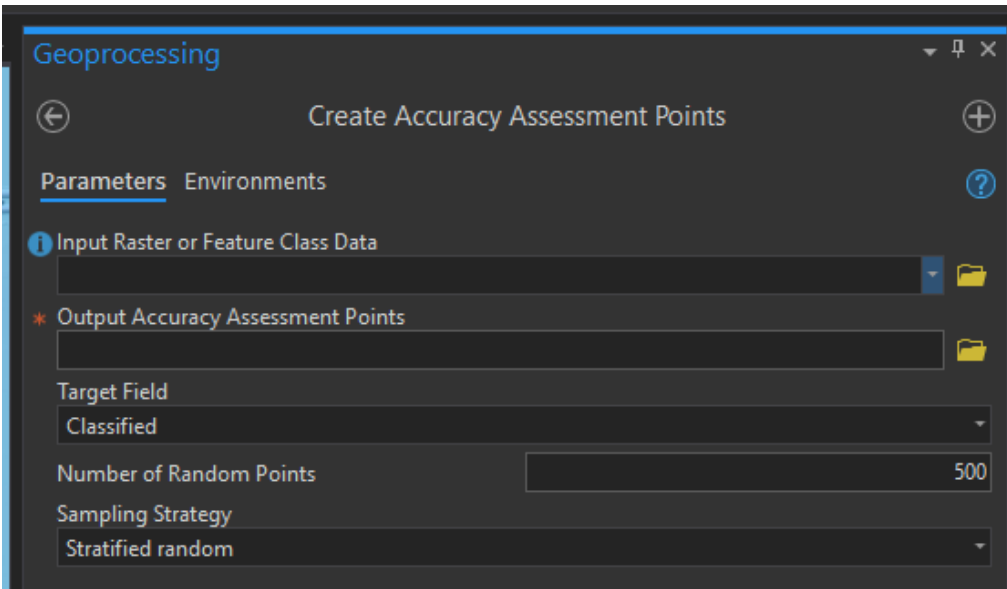
Apply an optimization procedure which locally minimizes the average heterogeneity of image objects for a given resolution.

Algorithm parameters

Parameter	Value
Overwrite existing level	Yes
Level Settings	
Level Name	New Level
Compatibility mode	latest version
Segmentation Settings	
Image Layer weights	1, 1, 1, 1, 1, 1, 1, 1
Thematic Layer usage	No
Scale parameter	42
Composition of homogeneity criterion	
Shape	0.1
Compactness	0.5

Execute Ok Cancel Help



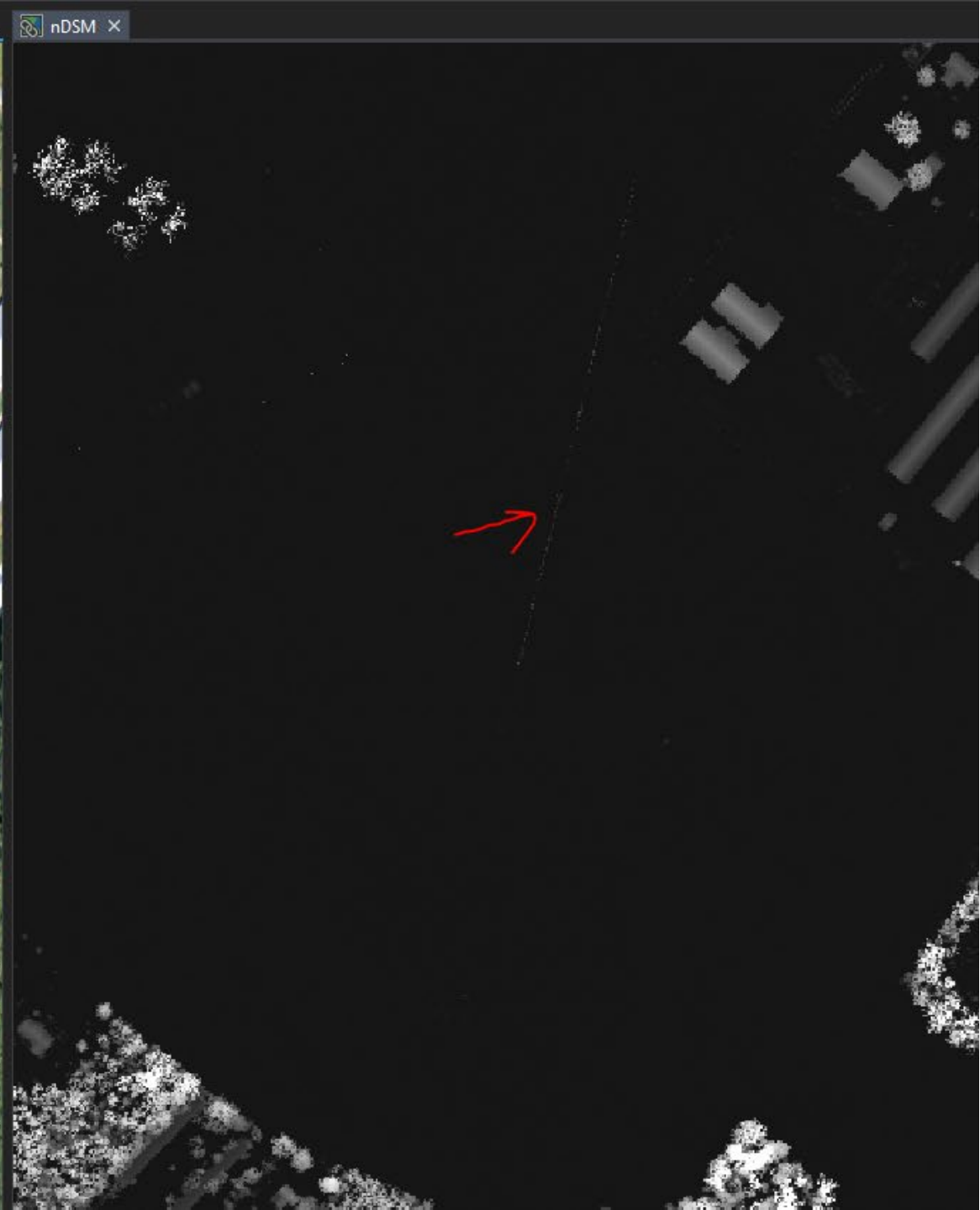


A Review of Assessing the Accuracy of Classifications of Remotely Sensed Data

Russell G. Congalton

Department of Forestry and Resource Management, University of California, Berkeley

Class/Value	Class 1	Class 2	Class 3	Class 4	Class 5	Grand Total	User's Accuracy	Kappa
Class 1								
Class 2								
Class 3								
Class 4								
Class 5								
Grand Total								
Producer's Accuracy								
Kappa								



Agricultural Center-Pivot Irrigation System Identification in the Chesapeake Bay Watershed

Data Input: Lidar

Data Input: 4-Band National Agriculture Imagery Program (NAIP) Imagery

Trimble's eCognition Object-Based Image Analysis Software

Create Algorithm-Based ruleset effectively segmenting, identifying, extracting and classifying individual and groups of image objects across the study area

Classified Image Objects: Water, Structures, Trees, Agricultural Fields, and Center-Pivot Irrigation Systems

Enhanced Informed Decision Making for Planners and Policy Makers

Natural Resource Management

Protection

Mitigation

Task	Time	Date
Define Problem and Propose Project	3 Months	October 2020 - December 2020
Data Acquisition	1 Month	December 2020
Feature Extraction Development and Execution	3 Months	December 2020 - March 2021
Accuracy Assessment	1 Month	March 2021
Create Final Report	1 Month	April 2021
Submit Abstract to Conference	1 Month	April 2021
Present at Conference	1 Month	May 2021

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