

Iterative Target Detection for Detection and Classification in Hyperspectral Images with an Application to a Landsat 8 Image of Lake Chelan, WA USA.

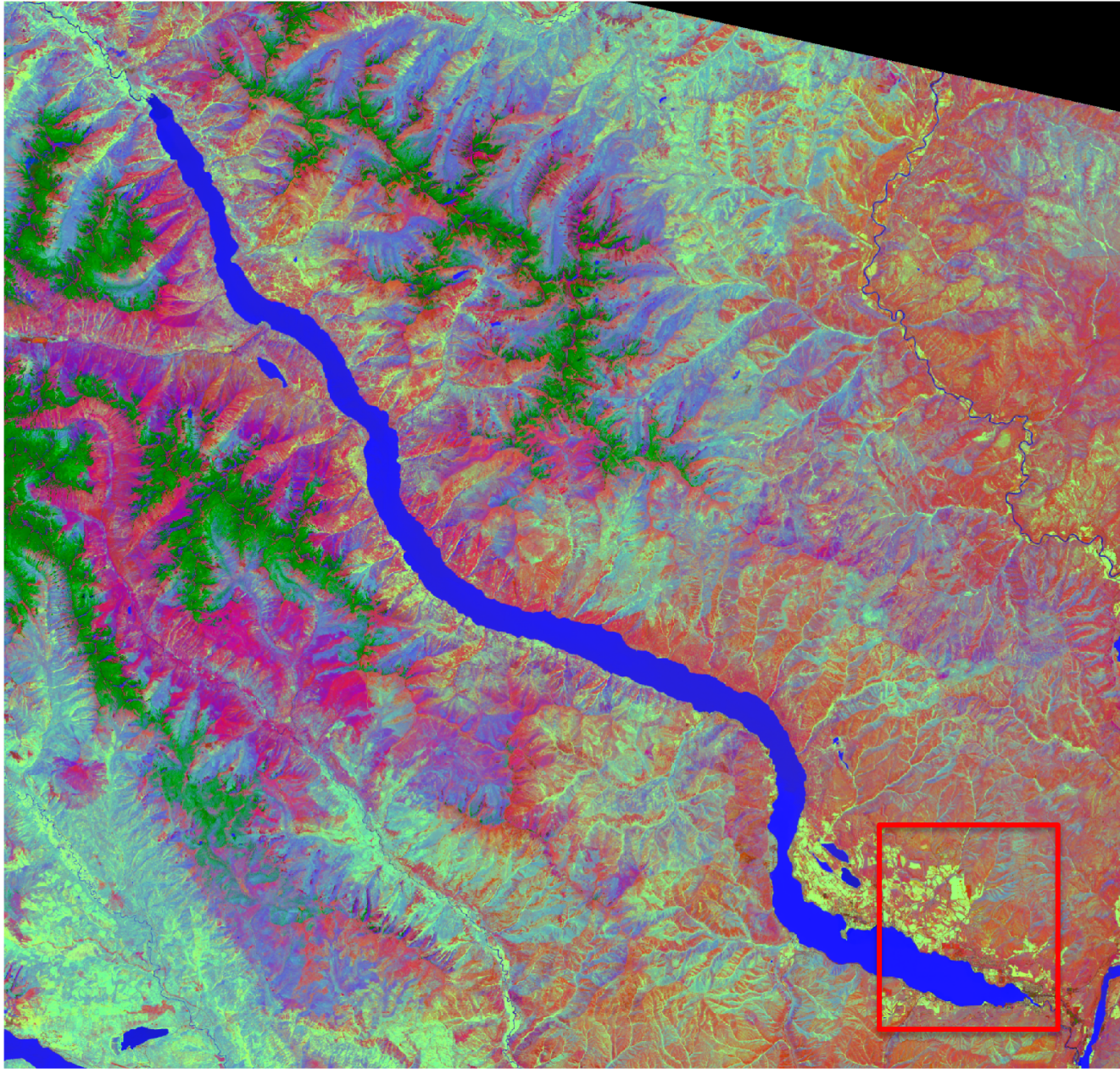
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“Iterative Target Detection for Detection and Classification with an Example Application in Hyperspectral Imaging.” Neal B. Gallagher, Eigenvector Research, Inc.

Abstract: Classical least squares (CLS) is the tool of choice for detection and classification in hyperspectral images because often target spectra are known but reference values for each pixel are rarely available. Generalized least squares (GLS) is a weighted CLS model used to suppress clutter signal (interferences and noise) while enhancing minor target signal. (GLS is also known as the matched-filter.) An iterative target detection approach exhibits synergy between GLS and the extended mixture model (extended least squares, ELS) to further improve discrimination. The approach is relevant for chemical imaging, medical imaging and remote sensing. An example is shown for a Landsat 8 image of Lake Chelan, WA USA. GLS was used iteratively in a hierarchical approach to classification and GLS combined with ELS was used to further split a single class that was otherwise difficult to classify.

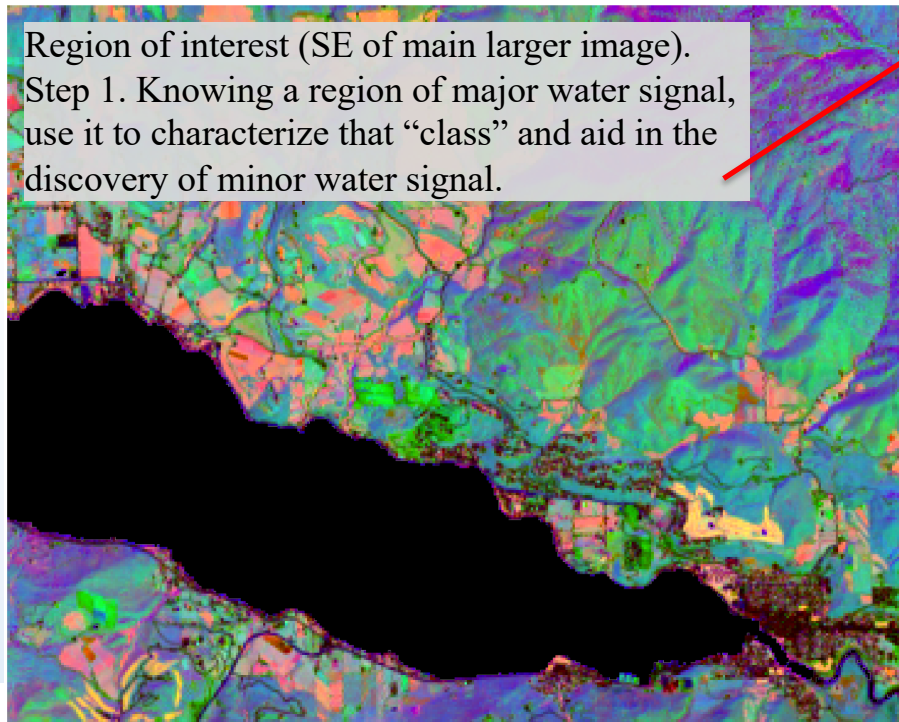
The first task used GLS iteratively to create global classes in the image associated with Water, Green (orchards, vineyards and lawn), Bare Earth, three types of forest, Road, Buildings and Other (corresponding to no specific class). The second task used GLS/ELS to split Class Green into signal attributable to lawn (e.g., associated with the municipal golf course) from cherry orchard (and other agricultural land including vineyards and other orchard types). Both objectives were complicated by the presence of a large number of pixels associated with water, forest, rough terrain, dry scrubland, homes, roads and buildings. The local GLS/ELS model showed good results that were verified in many cases using ground truth.



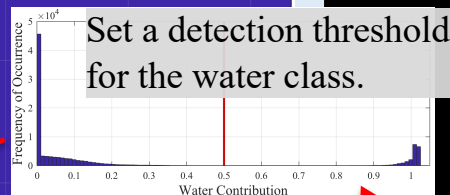
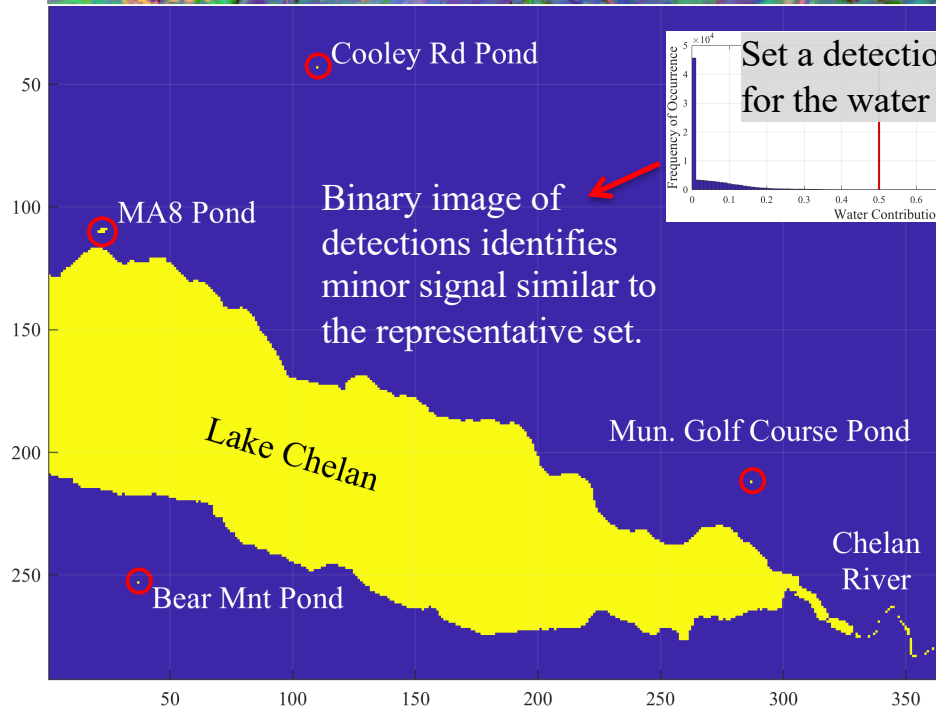
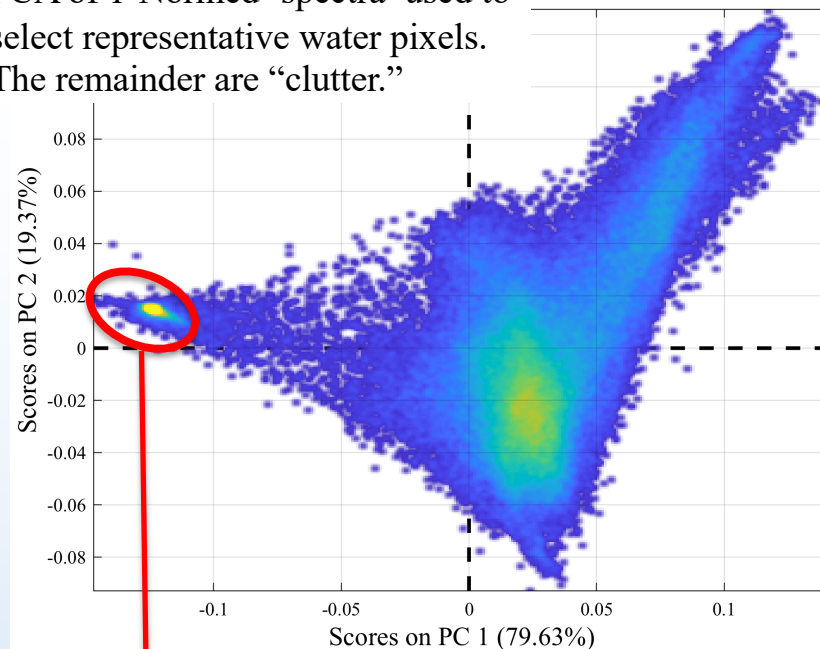
Analysis Objective

- Hyperspectral images can be characterized by spatial “regions” or “classes.”
 - The present example shows how a hyperspectral image can be segmented into regions using an interactive approach and clutter suppression techniques.
 - Significant signal due to known regions can be used to aid in the discovery of minor signal that is otherwise less easy to find.

Region of interest (SE of main larger image).
Step 1. Knowing a region of major water signal, use it to characterize that “class” and aid in the discovery of minor water signal.

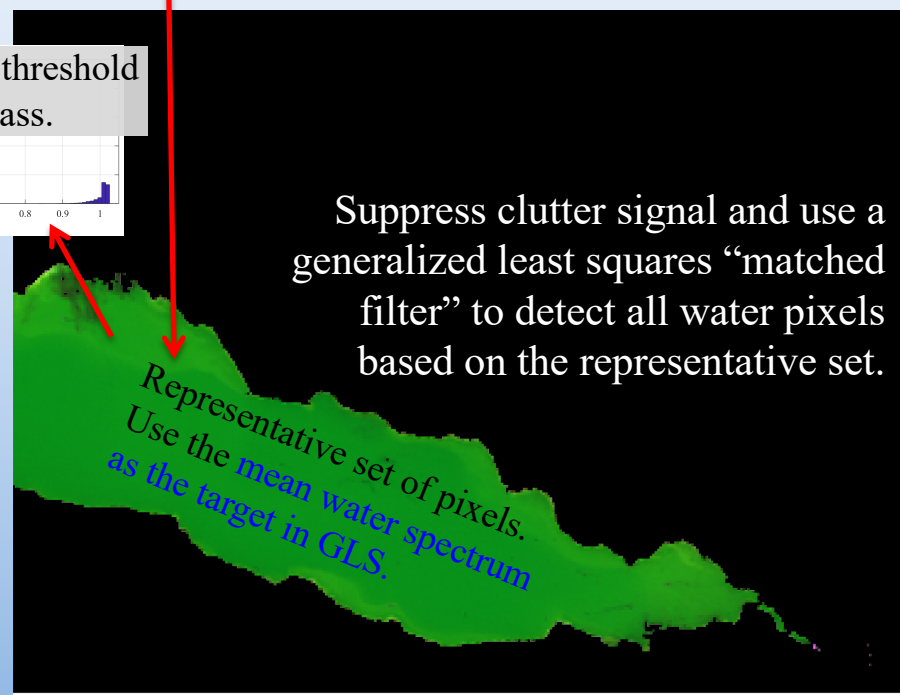


PCA of 1-Normed ‘spectra’ used to select representative water pixels. The remainder are “clutter.”



Binary image of detections identifies minor signal similar to the representative set.

Suppress clutter signal and use a generalized least squares “matched filter” to detect all water pixels based on the representative set.



GLS for Water

Measured Image

Water Target (from representative pixels).

Water Contributions

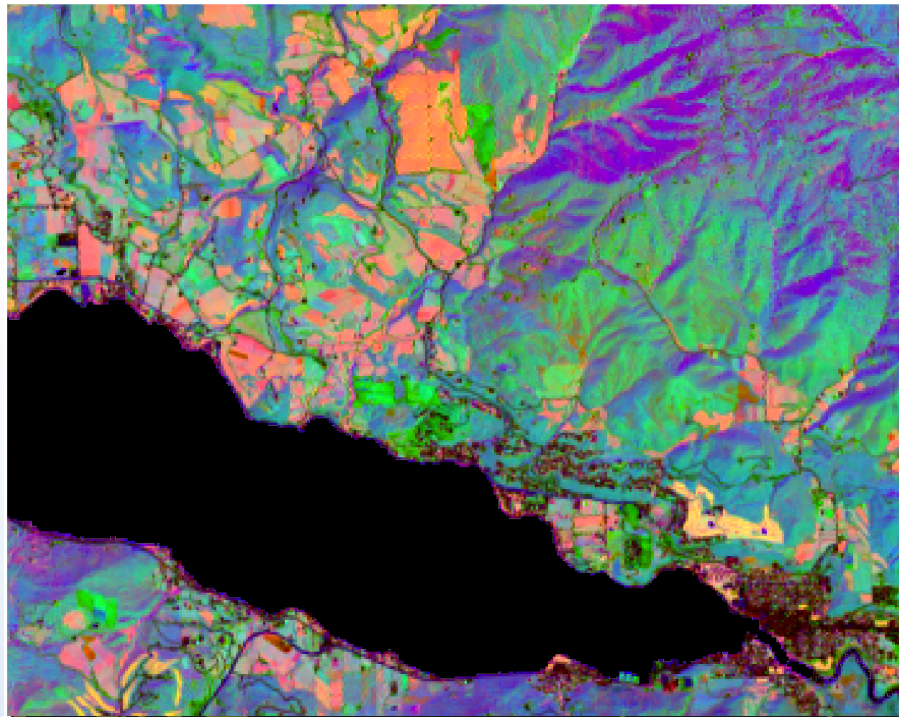
$$\hat{\mathbf{c}}_W = \mathbf{X} \mathbf{W}_c^{-1} \bar{\mathbf{x}}_W \left(\bar{\mathbf{x}}_W^T \mathbf{W}_c^{-1} \bar{\mathbf{x}}_W \right)^{-1}$$

Clutter Suppression

$$\mathbf{W}_c = \frac{1}{M_W - 1} \left(\mathbf{X}_W - \mathbf{1} \bar{\mathbf{x}}_W^T \right)^T \left(\mathbf{X}_W - \mathbf{1} \bar{\mathbf{x}}_W^T \right) + \frac{1}{M_{nW}} \mathbf{X}_{nW}^T \mathbf{X}_{nW}$$

Deweight by intra-class (centered covariance)

... and non-centered “other”.

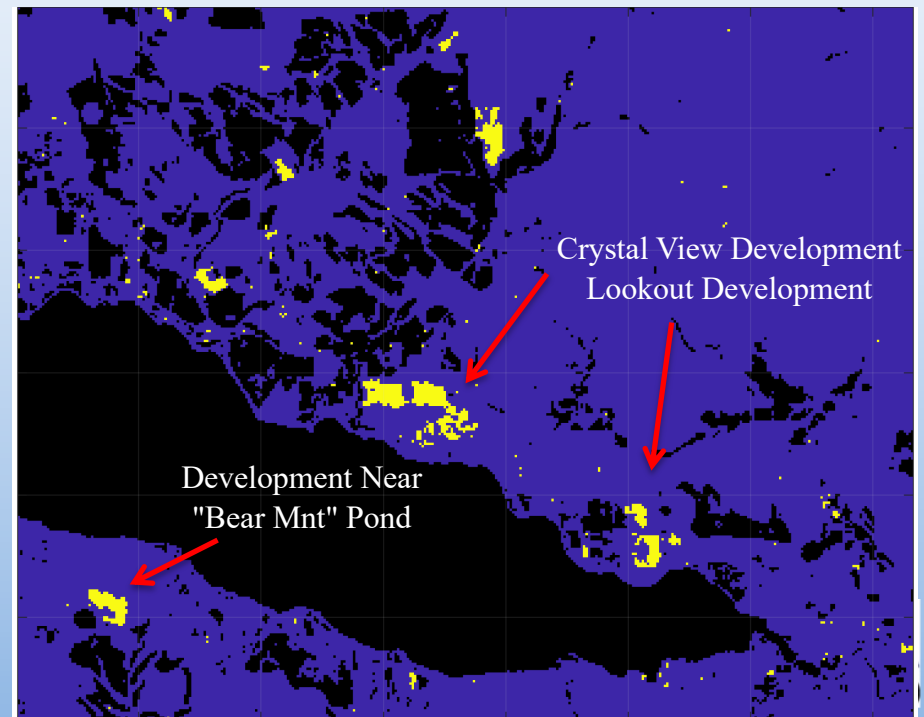
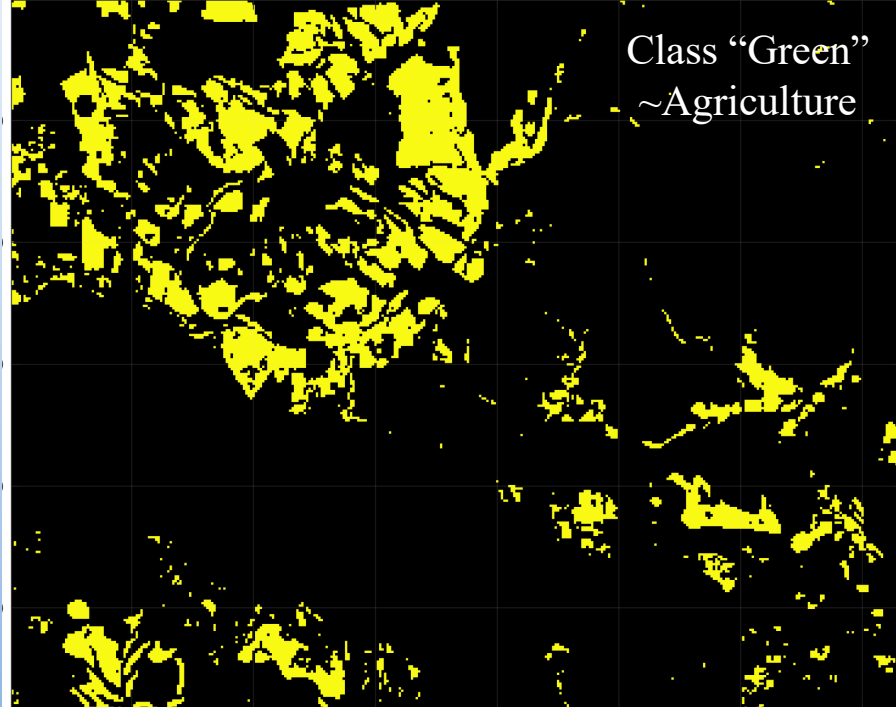


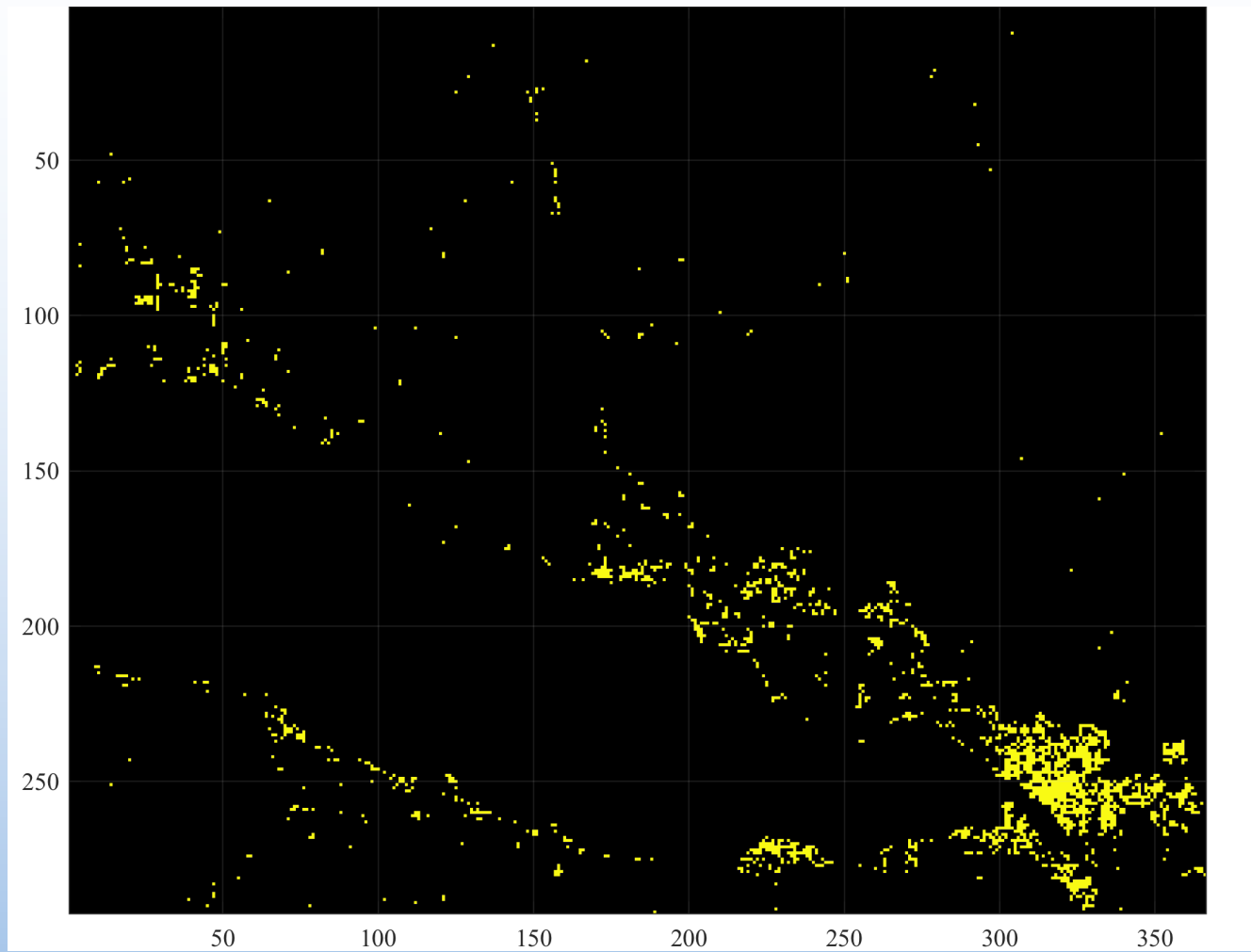
- Remove detected water and continue the process with other classes, one at a time for each of J classes with $j=1, \dots, J$.
- At each step, pixels that have been detected and classified are removed from the analysis.
- This is a “global” hierarchical approach to detection and classification.

Class “Bare Earth”

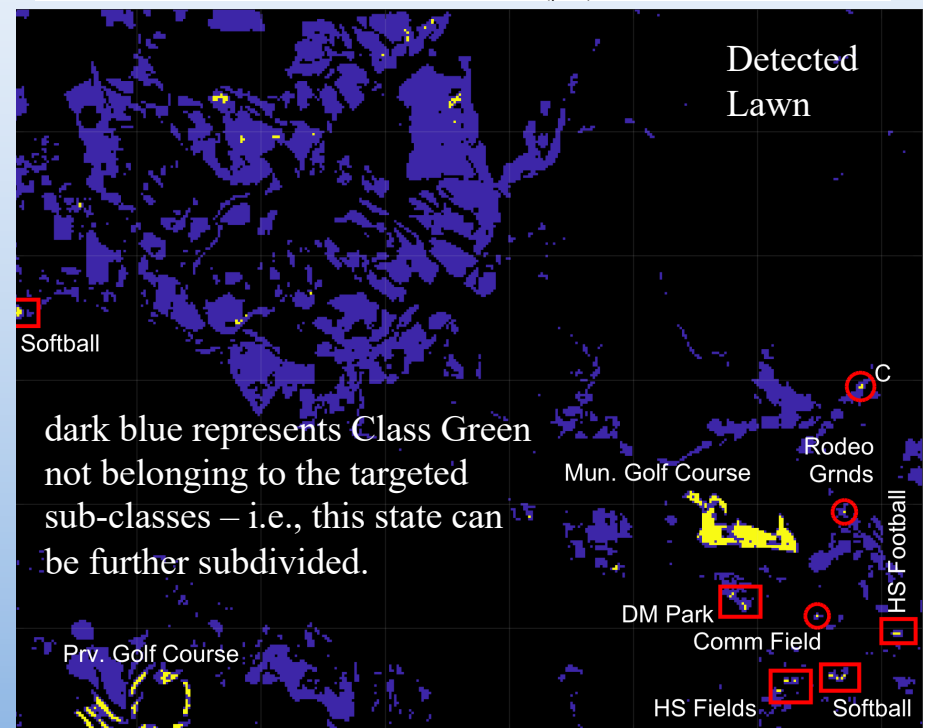
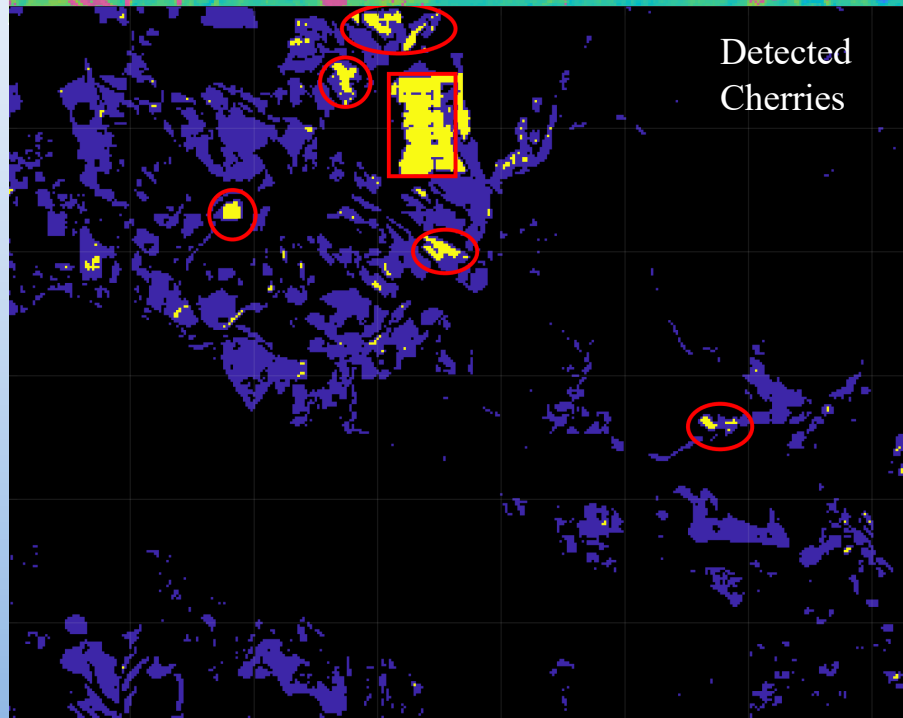
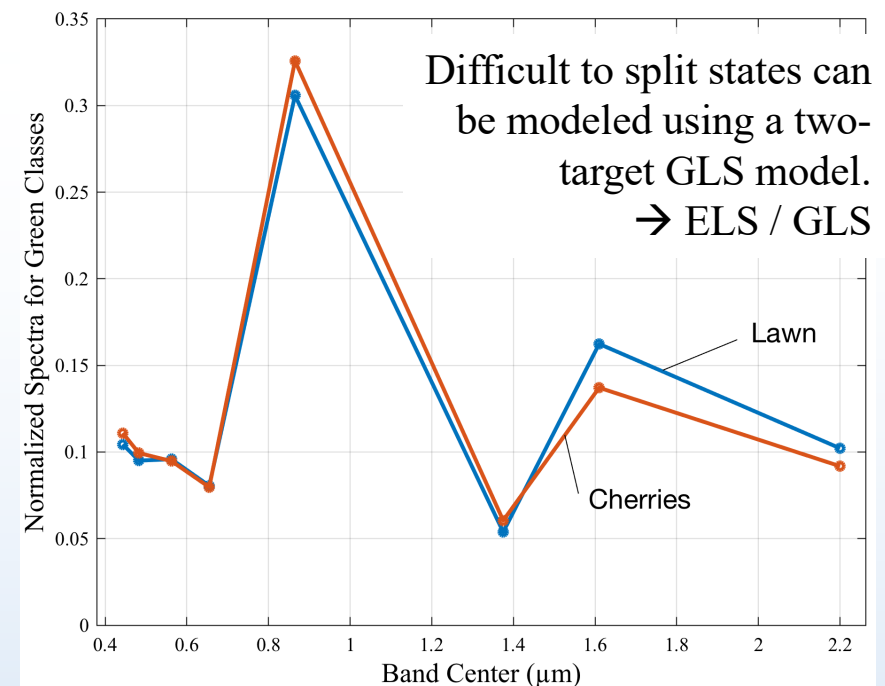
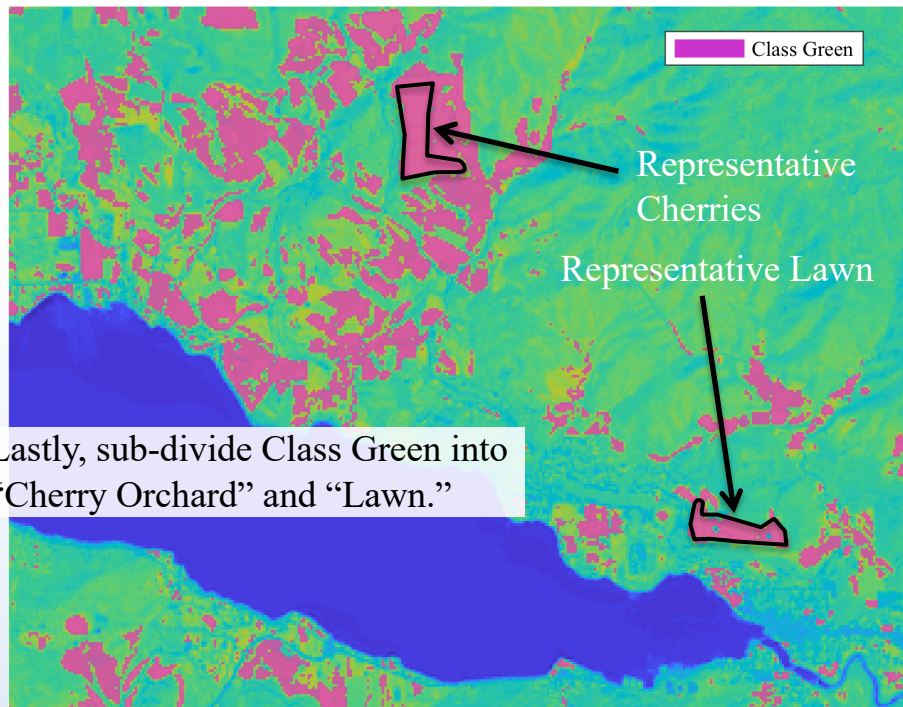
Black = removed pixels

Blue = pixels yet to be classed





Green
Bare Earth
Forest 1
Forest 2
Forest 3
Roads
Buildings



ELS / GLS For Cherries and Lawn

Measured Image for Class Green

Lawn & Cherries Contributions

$$\begin{bmatrix} \hat{\mathbf{c}}_{\text{Lawn}} & \hat{\mathbf{c}}_{\text{Cherry}} \end{bmatrix} = \mathbf{X}_{\text{Green}} \mathbf{W}_c^{-1} \mathbf{Z}^T \left(\mathbf{Z}^T \mathbf{W}_c^{-1} \mathbf{Z} \right)^{-1}$$

$$\mathbf{Z} = \begin{bmatrix} \bar{\mathbf{x}}_{\text{Lawn}} & \bar{\mathbf{x}}_{\text{Cherry}} \end{bmatrix}$$

Lawn & Cherries Targets (from representative pixels).

Deweight by a pooled intra-class covariance

$$\mathbf{W}_c = \frac{1}{M_{\text{Lawn}} - 1} \left(\mathbf{X}_{\text{Lawn}} - \mathbf{1} \bar{\mathbf{x}}_{\text{Lawn}}^T \right)^T \left(\mathbf{X}_{\text{Lawn}} - \mathbf{1} \bar{\mathbf{x}}_{\text{Lawn}}^T \right) + \frac{1}{M_{\text{Cherry}} - 1} \left(\mathbf{X}_{\text{Cherry}} - \mathbf{1} \bar{\mathbf{x}}_{\text{Cherry}}^T \right)^T \left(\mathbf{X}_{\text{Cherry}} - \mathbf{1} \bar{\mathbf{x}}_{\text{Cherry}}^T \right)$$

This is a lot like LDA, however pixels w/ low contributions on either class are not classed (they are a “no call”).

Target Detection for Detection and Classification

- Target detection was based on CLS models.
- GLS was used to provide global classification.
- ELS/GLS provided a sensitive local model for splitting two similar classes (sub-dividing a state).
 - The modeling says, “I know what this is, can I find more like it?”
 - Can identify less significant events.
 - Useful in diagnosis, forensics, fault detection and classification.
 - Development of libraries for process monitoring
 - Process was not optimized but demonstrate the ease of “cobbling together” different approaches (GLS and multi-target GLS) to achieve a detection and classification objective.
- Gallagher, NB, Shaver, JM, Bishop, R, Roginski, RT, Wise, BM, “Decompositions with Maximum Signal Factors,” *J. Chemometr.*, **28**(8), 663-671 (2014), DOI: 10.1002/cem.2634.
- Gallagher, NB, Detection, Classification and Quantification in Hyperspectral Images using Classical Least Squares Models. In *Techniques and Applications of Hyperspectral Image Analysis*; Grahn, HF, Geladi, P, Eds. John Wiley & Sons: West Sussex, England, 2007; 181-201.
- Gallagher, NB, Classical Least Squares for Detection and Classification. In *Hyperspectral Imaging*, Amigo, J.M., Ed. Elsevier., (Feb 2018 submitted)

Principal Components Analysis Model

X-block: Landsat 8 of Lake Chelan 4305385 by 8

4407500x8 total pixels (upper right hand corner was excluded)

2050 by 2150 (subset of pixels)

316,535,170 bytes

Included: [1-8]

Included (in axis units): [n/a] [0.443-2.2]

Preprocessing: Normalize (1-Norm, Area = 1), Mean Center

Num. PCs: 3

Percent Variance Captured by PCA Model

Principal Component Number	Eigenvalue of Cov(X)	% Variance Captured This PC	% Variance Captured Total
1	2.11e-03	58.40	58.40
2	1.23e-03	34.11	92.51
3	2.49e-04	6.87	99.38

```
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MATLAB Version: 9.3.0.713579 (R2017b)
Operating System: Mac OS X Version: 10.11.6 Build: 15G19009
Java Version: Java 1.8.0_121-b13 with Oracle Corporation Java
HotSpot(TM) 64-Bit Server VM mixed mode
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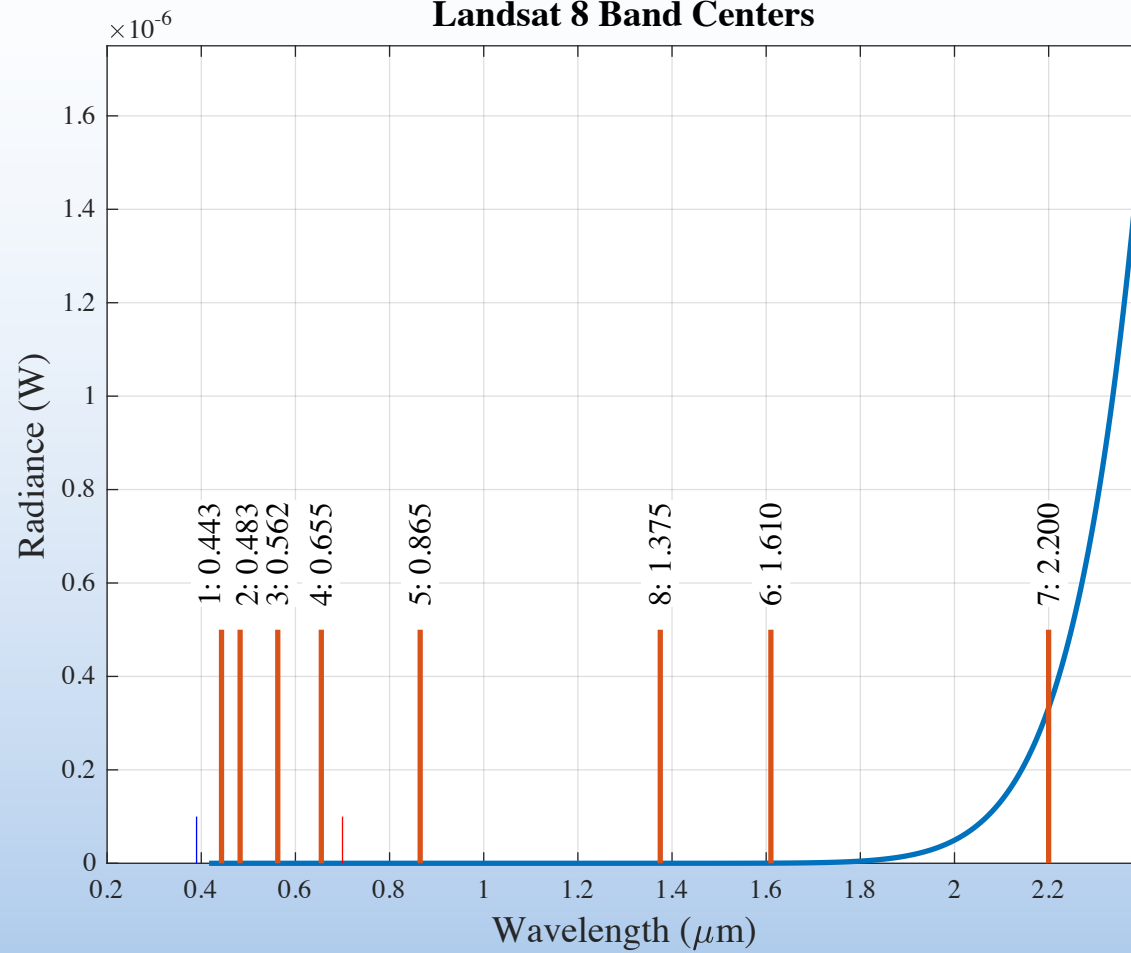
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MATLAB Version 9.3 (R2017b)
MIA_Toolbox Version 3.0.5 (trunk)
PLS_Toolbox Version 8.6 (Trunk)
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Landsat 8 image of Lake Chelan, WA (Image courtesy of the U.S. Geological Survey, FILE_DATE = 2017-06-30T11:25:51Z). The table lists the wavelength bands used for the analysis. The selected image was 2050x2150 with 4,305,385 pixels included in the analysis.

Lake Chelan is in north central Washington state that is 50.5 miles long and 1486 ft deep. The town of Chelan is located on the southeast end, Manson is approximately eight miles up lake on the north shore, and the small, remote community of Stehekin is on the north west end of the lake. The figure shows a scores image (PCs 1,2,3 = RGB) with the image auto-contrasted (the scores were mean-centered and scaled to lie between ± 2 standard deviations). Lake Chelan and other water bodies are shown in blue in the image, green represents surrounding forest land and red tends to be rockier regions. Three lakes near Manson are Roses Lake (~35' deep), Wapato Lake (~70' deep) and Dry Lake (~11' deep).

Band Number	Wavelength Range (μm)	Resolution (m)
1	0.433-0.453	30
2	0.450-0.515	30
3	0.525-0.600	30
4	0.630-0.680	30
5	0.845-0.885	30
6	1.560-1.660	30
7	2.100-2.300	30
8 (not used)	0.500-0.680	15
9	1.360-1.390	30
10 (not used)	10.6-11.2	100
11 (not used)	11.5-12.5	100

Comparison of the Landsat 8 channels with the blackbody radiance curve.



$$\mathbf{W}_c = \frac{1}{M_W - 1} (\mathbf{X}_W - \mathbf{1} \bar{\mathbf{x}}_W^T)^T (\mathbf{X}_W - \mathbf{1} \bar{\mathbf{x}}_W^T) + \frac{1}{M_{nW}} \mathbf{X}_{nW}^T \mathbf{X}_{nW}$$

$$\hat{\mathbf{c}}_W = \mathbf{X} \mathbf{W}_c^{-1} \bar{\mathbf{x}}_W (\bar{\mathbf{x}}_W^T \mathbf{W}_c^{-1} \bar{\mathbf{x}}_W)^{-1}$$

Water model.

Deweight by intra-class (centered covariance) and non-centered clutter.

$$\mathbf{W}_c = \frac{1}{M_j - 1} (\mathbf{X}_j - \mathbf{1} \bar{\mathbf{x}}_j^T)^T (\mathbf{X}_j - \mathbf{1} \bar{\mathbf{x}}_j^T) + \frac{1}{M_{nj}} \mathbf{X}_{nj}^T \mathbf{X}_{nj}$$

$$\hat{\mathbf{c}}_j = \mathbf{X} \mathbf{W}_c^{-1} \bar{\mathbf{x}}_j (\bar{\mathbf{x}}_j^T \mathbf{W}_c^{-1} \bar{\mathbf{x}}_j)^{-1}$$

$$\mathbf{W}_c = \frac{1}{M_{\text{Lawn}} - 1} (\mathbf{X}_{\text{Lawn}} - \mathbf{1} \bar{\mathbf{x}}_{\text{Lawn}}^T)^T (\mathbf{X}_{\text{Lawn}} - \mathbf{1} \bar{\mathbf{x}}_{\text{Lawn}}^T)$$

$$+ \frac{1}{M_{\text{Cherry}} - 1} (\mathbf{X}_{\text{Cherry}} - \mathbf{1} \bar{\mathbf{x}}_{\text{Cherry}}^T)^T (\mathbf{X}_{\text{Cherry}} - \mathbf{1} \bar{\mathbf{x}}_{\text{Cherry}}^T)$$

$$\begin{bmatrix} \hat{\mathbf{c}}_{\text{Lawn}} & \hat{\mathbf{c}}_{\text{Cherry}} \end{bmatrix} = \mathbf{X}_{\text{Green}} \mathbf{W}_c^{-1} \mathbf{Z}^T (\mathbf{Z}^T \mathbf{W}_c^{-1} \mathbf{Z})^{-1}$$

$$\mathbf{Z} = \begin{bmatrix} \bar{\mathbf{x}}_{\text{Lawn}} & \bar{\mathbf{x}}_{\text{Cherry}} \end{bmatrix}$$