Iterative Target Detection for Detection and Classification with an Example Application in Hyperspectral Imaging

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SciX, Oct 12-15, 2020

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"Iterative Target Detection for Detection and Classification with an Example Application in Hyperspectral Imaging."

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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 and the Aitken estimator.) An iterative target detection approach exhibits synergy between GLS and the extended mixture model (extended least squares, ELS) to further improve discrimination. To enhance visualization of the methodology an example is shown for a Landsat 8 image of Lake Chelan, WA USA. However, the concepts demonstrated are applicable to a wide range of applications including fault detection and classification in the process environment. The distinct advantages over approaches like principal components analysis and partial least squares include interpretability and ease of model updating (adaptability) relevant for time-series application. The example shown utilizes GLS iteratively in a hierarchical approach to classification, followed by a combined GLS / ELS model was used to further split a single class that was otherwise difficult to classify. Both objectives were complicated by the presence of significant interference signal but showed good results verified using ground truth.

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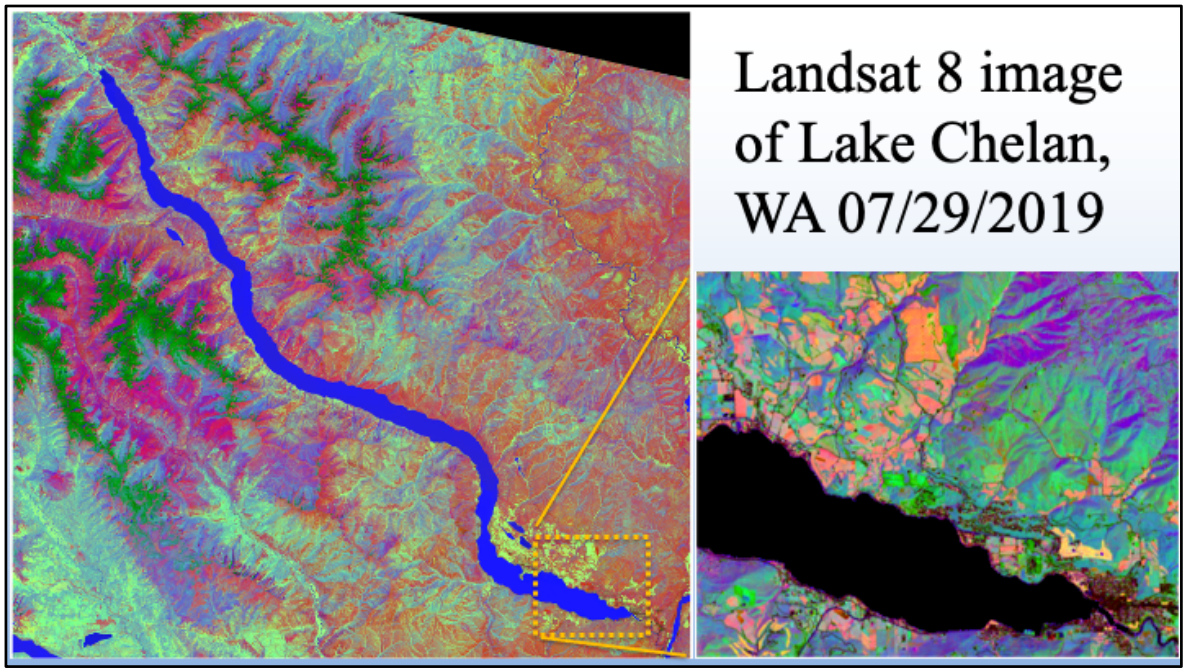

Landsat image with region of interest highlighted. This is a rural community dominated by fruit production. The example is described in detail in Gallagher, N.B., "Classical Least Squares for Detection and Classification," in Hyperspectral Imaging, Vol 32 (Data Handling in Science and Technology) 1st Ed, J. Manuel Amigo editor, Elsevier, Oct 1 (2019) ISBN: 9780444639776; https://doi.org/10.1016/B978-0-444-63977-6.00011-0.

Analysis Objective

- Use targeted anomaly detection iteratively to detect and classify regions in the image
- Discriminate signals with only very minor differences

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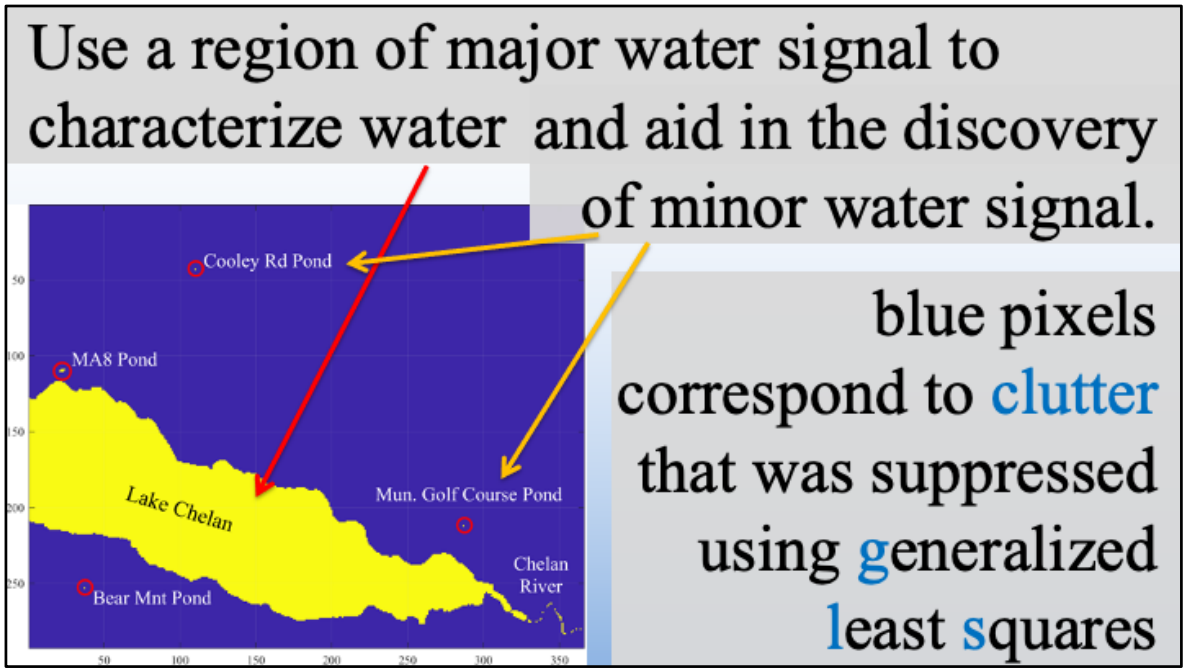
Targeted anomaly detection is a manual approach to exploring a hyperspectral image (could be applied to process data also). The weighting strategies are based on the classical least squares model and is related to using whitened principal components analysis, e.g. see Gallagher, NB, Shaver, JM, Bishop, R, Roginski, RT, Wise, BM, "Decompositions with Maximum Signal Factors," *J. Chemometr.*, **28**(8), 663-671 (2014), DOI: 10.1002/cem.2634 and 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.



The lake was used as signal to characterize the water signal. All other pixels were used as clutter that was suppressed using a generalized least squares de-weighting strategy. Signal identified as water can be removed from the clutter signal and the process is iterated to identify water pixels in the image. This is “iterative targeted anomaly detection.”

Iterate Through Additional Classes

- Exclude water signal from subsequent analysis
- Continue identifying additional regions.

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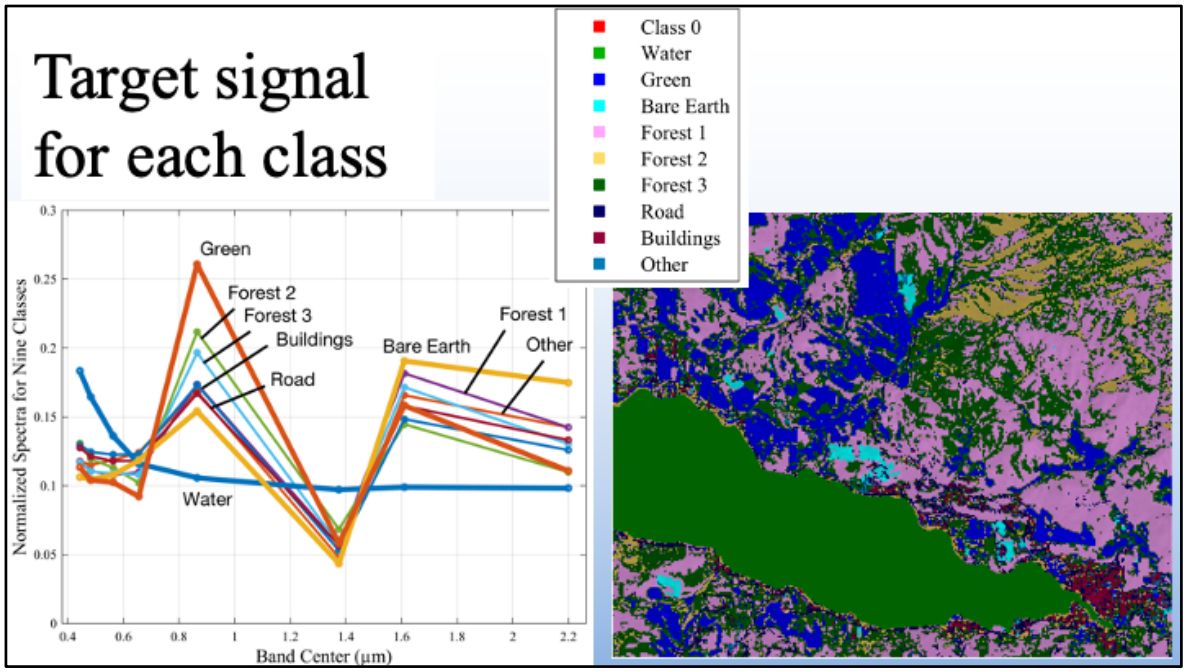
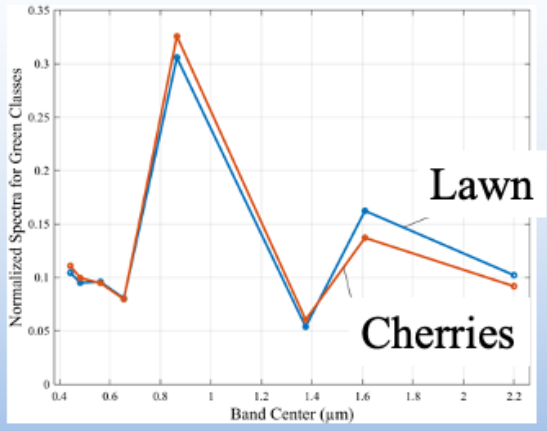
The naming and the total number of additional classes is a bit arbitrary and is also image specific. In fact, being image specific can be seen as a distinct advantage for the methodology.


Target signal for each class
Class 0
Water
Green
Bare Earth
Forest 1
Forest 2
Forest 3
Road
Buildings
Other
Green
Forest 2
Forest 3
Buildings
Road
Bare Earth
Forest 1
Other
Water
Normalized Spectra for Nine Classes
Band Center (μm)
0
0.05
0.1
0.15
0.2
0.25
0.3
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
2.2

Split a Class into Two Similar Sub-Classes

- "Lawn" and "Cherries" have a similar signal
- GLS → ELS/GLS
- multiple target GLS



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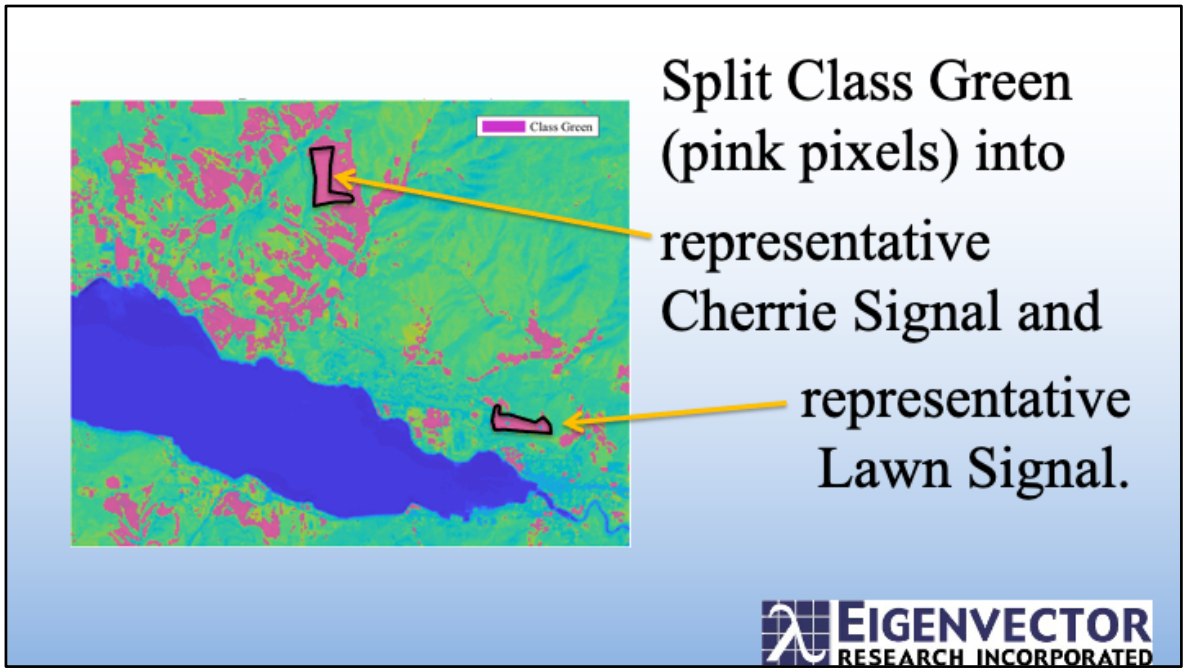
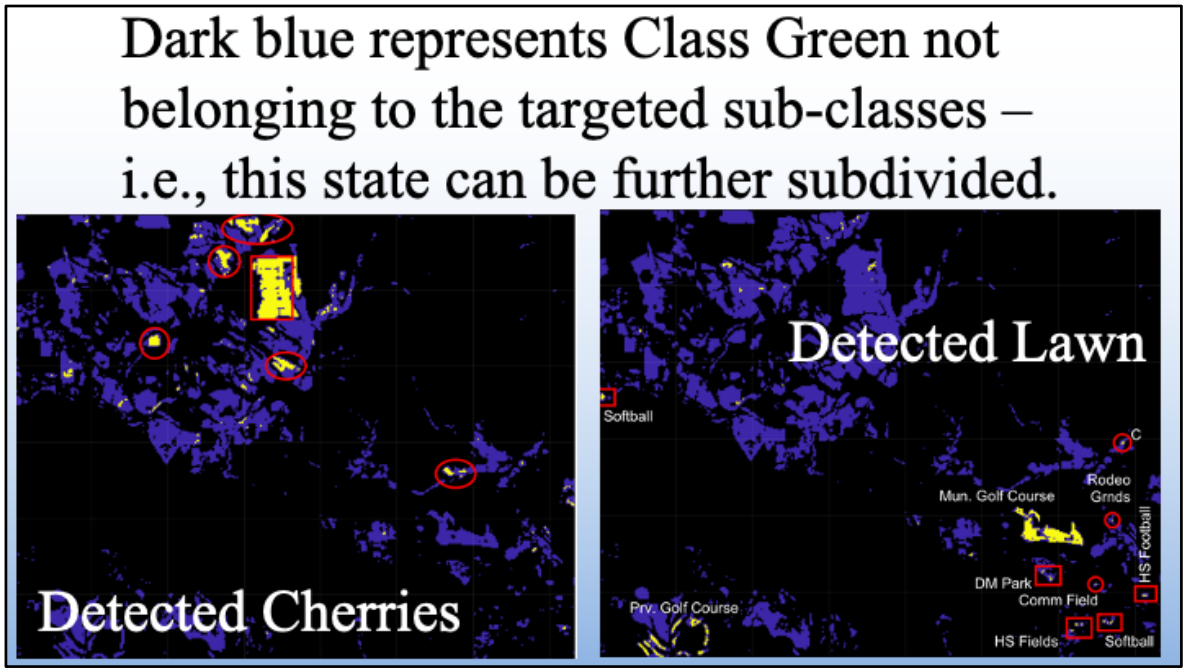
Extended Least Squares is based on the linear mixture model call the extended mixture model.



Class “Green” are the only pixels being used in the ELS/GLS model i.e., Class Green is being sub-divided.



Yellow highlighted regions correspond to detections. Ground truth was determined using other satellite imagery and with help from M. Cochran of Manson Growers, Manson, WA.

- Iterative target anomaly detection:
- GLS was used to provide global classification, and
- ELS/GLS provided a sensitive local model for splitting two similar classes (sub-dividing a class).
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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?"
    - Major process upsets can be used to model and 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, N.B., "Classical Least Squares for Detection and Classification," in Hyperspectral Imaging, Vol 32 (Data Handling in Science and Technology) 1st Ed, J. Manuel Amigo editor, Elsevier, Oct 1 (2019) ISBN: 9780444639776; https://doi.org/10.1016/B978-0-444-63977-6.00011-0.

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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

```
-----------------------------------------------------
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
-----------------------------------------------------
MATLAB       Version 9.3          (R2017b)
MIA_Toolbox Version 3.0.5        (trunk)
PLS_Toolbox Version 8.6          (Trunk)
```

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

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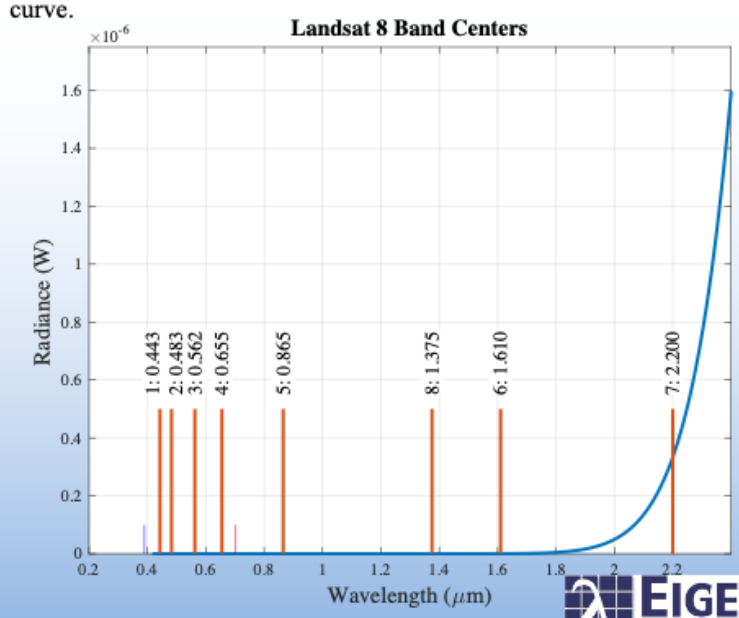
curve.



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

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

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

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

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

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

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

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

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