GNR-602 PROJECT

Spectral unmixing using K-Means and Fully Constrained Least squares (FCLS):

Group no.: 16

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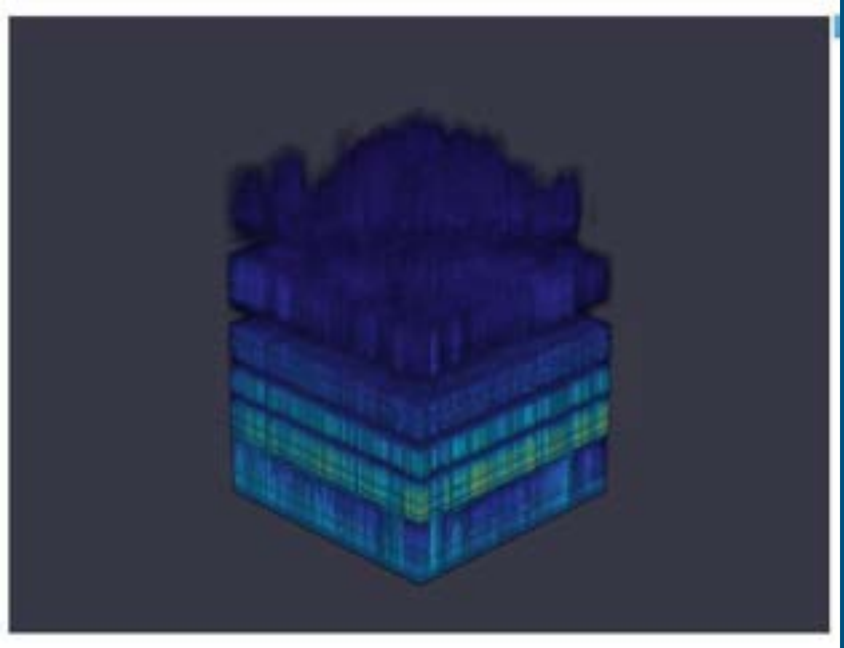
Hyperspectral Imaging

- Hyperspectral imaging (HSI) is a technique that analyzes a wide spectrum of light instead of just assigning primary colors (red, green, blue) to each pixel.
- The narrowness and contiguous nature of measurements makes it hyperspectral.
- We collects many individual images of a scene, each taken within a different narrow wavelength band. The result is a "data cube" of the combined images.



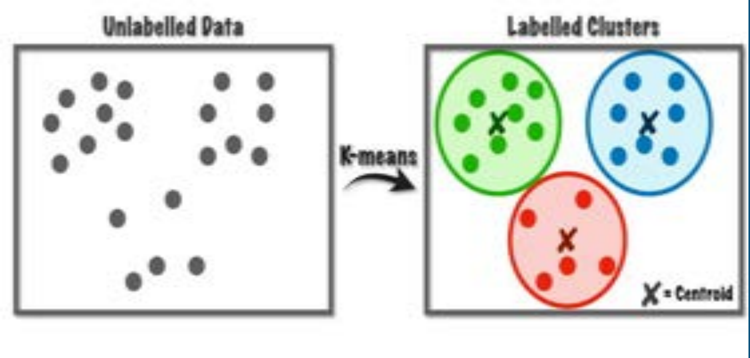
Data Cube

What is Spectral unmixing?

- Decomposition of a pixel spectrum into its constituent spectra
- Spectra of the pure materials, called endmembers, as well as their abundances in each pixel, are considered unknown
- The algorithm performs following tasks:
    1. Endmember extraction :Finding the unknown endmember spectra
    2. Unmixing: Determining the corresponding abundances of each endmember in each pixel

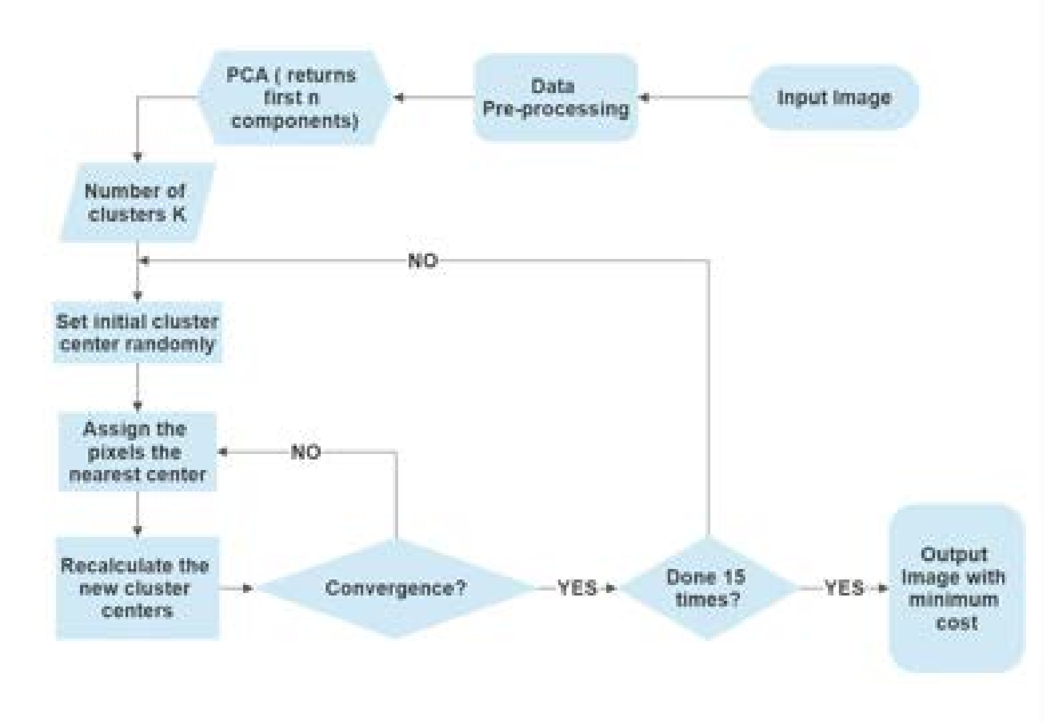
K-MEANS CLUSTERING

- k-Means clustering algorithm is used to detect the homogeneous regions in the image
- We initialize Θ randomly and report the results of the one that minimizes the cost function J of k-Means for different values of m.
- We use Squared Euclidean distance and Canberra distance



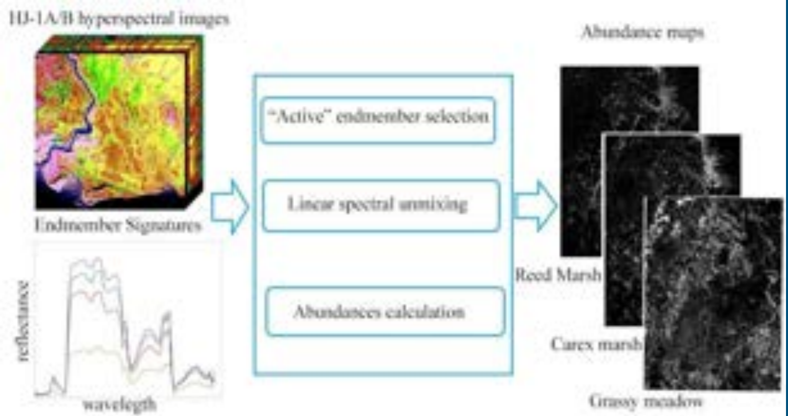
$$J(U,\Theta)=\sum_{i=1}^{N}\sum_{j=1}^{m}u_{ij}\,d(x_i,\theta_j)$$

K-MEANS CLUSTERING



Fully Constrained Least-squares (FCLS) Linear Unmixing

- Fully constrained least squares is least squares with the abundance sum-to-one constraint (ASC) and the abundance nonnegative constraint (ANC).
- Involves iterative computations to generate a nearly optimal solution.
- It requires a maximum of p - 1 iterations and terminates when no more steering is required.



Reference:https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=774644

Fully Constrained Least-squares (FCLS) Linear Unmixing

- Measurement model

$$\mathbf{x}_p = \mathbf{M}\mathbf{s}_p + \mathbf{n}_p$$

  - Observation vector $\mathbf{x}_{l\times 1} = [x_1\, x_2 \cdots x_l]^T$
  - Material signature matrix $\mathbf{M}_{l\times c} = [\mathbf{m}_1\, \mathbf{m}_2 \cdots \mathbf{m}_c]$
  - Abundance fractions $\mathbf{s}_{c\times 1} = [s_1\, s_2 \cdots s_c]^T$

- Nonnegative and sum-to-one constraints

$$s_j \geq 0, \quad \sum_{j=1}^{c} s_j = 1$$

$$J = \frac{1}{2}(\mathbf{r} - \mathbf{M}\alpha)(\mathbf{r} - \mathbf{M}\alpha)^T - \lambda\left(\sum_{j=1}^{p} \alpha_j - 1\right).$$

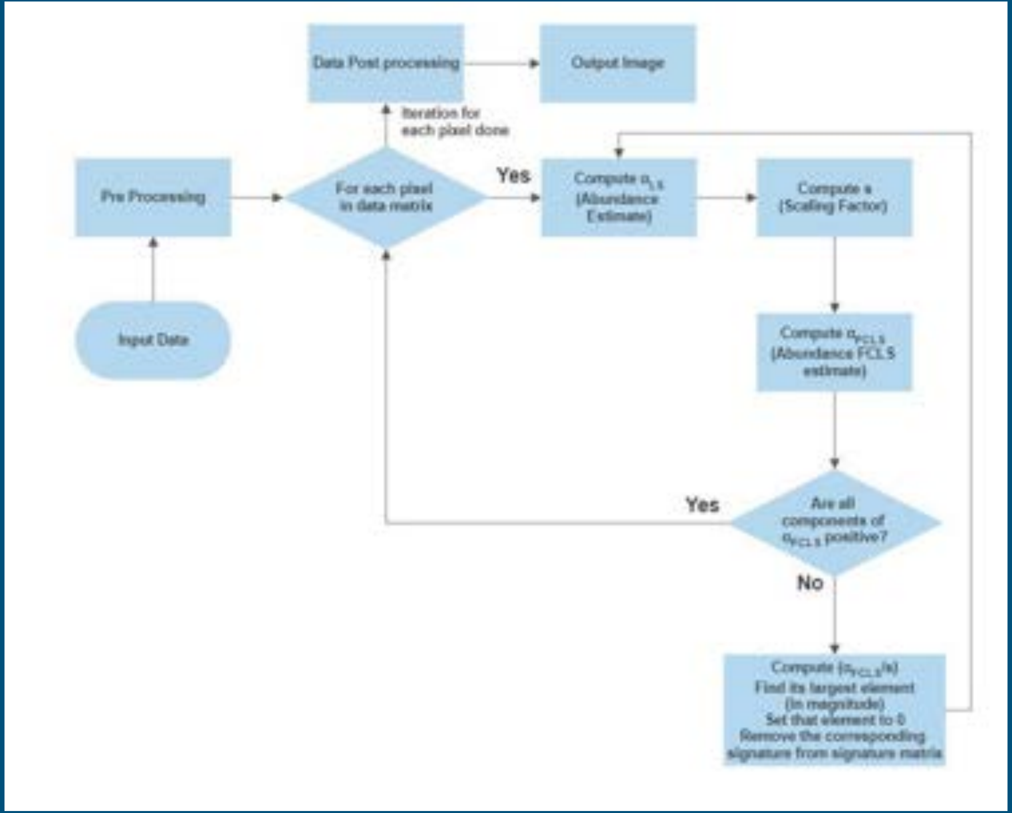
$$\Downarrow$$

$$\left.\frac{\partial J}{\partial \alpha}\right|_{\hat{\alpha}_{FCLS}} = 0 \Rightarrow \hat{\alpha}_{LS} - \lambda \mathbf{s}$$

$$\Downarrow$$

$$\lambda = \left(1 - \mathbf{1}^T \hat{\alpha}_{LS}\right) / \left(\mathbf{1}^T \mathbf{s}\right) \text{ with } \mathbf{s} = \left(\mathbf{M}^T \mathbf{M}\right)^{-1} \mathbf{1}$$

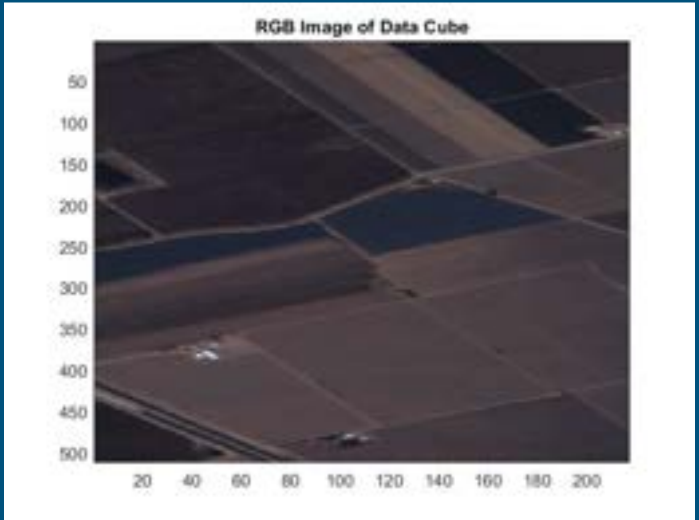
Fully Constrained Least-squares (FCLS) Linear Unmixing

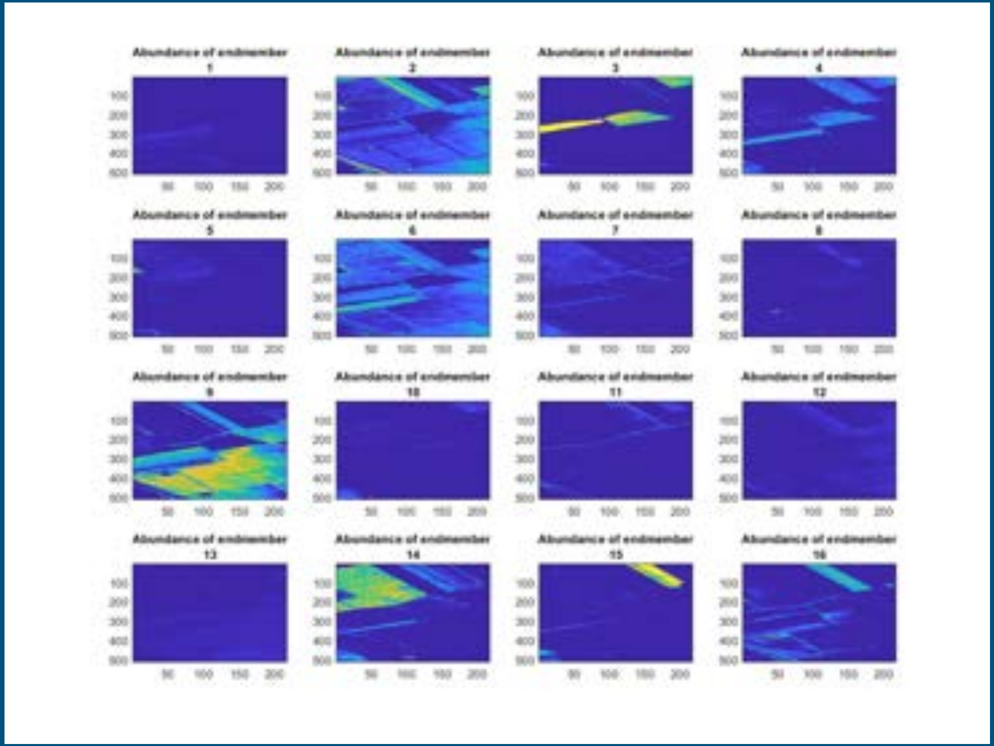


RESULTS (SALINAS)

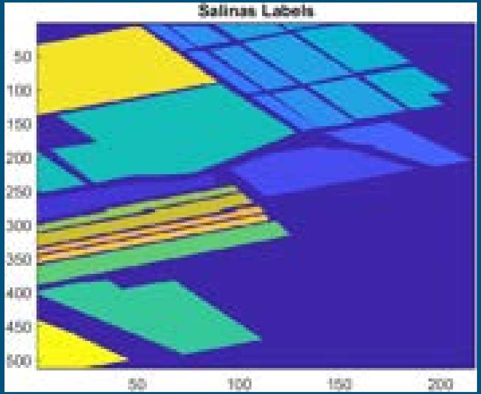
End members

RGB Image

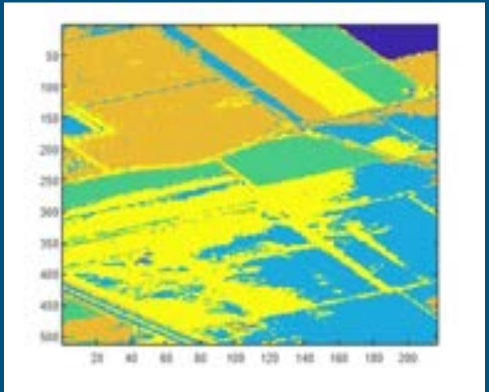




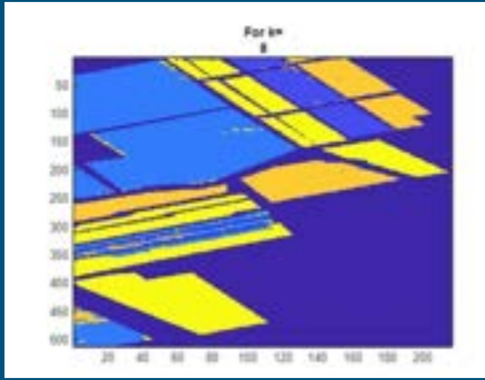
Ground truth



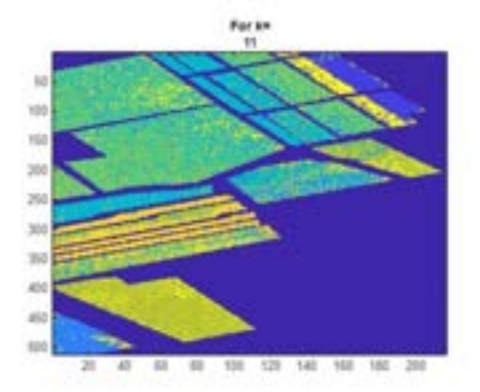
Predicted from FCLS



K-means
(euclidean distance)



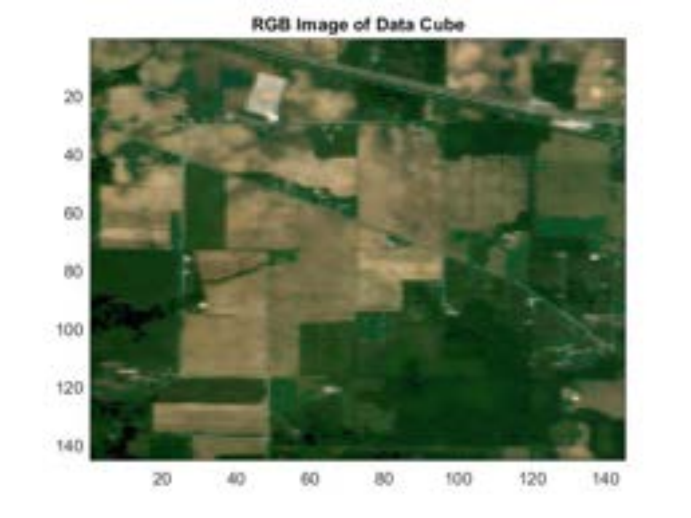
K-means (Canberra distance)

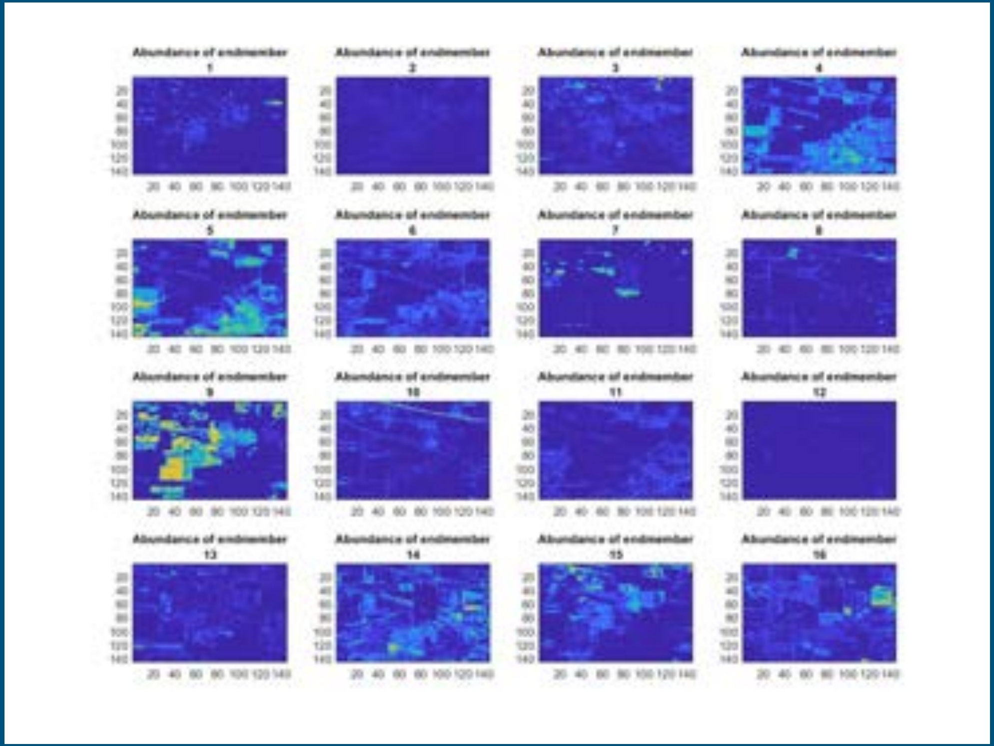


RESULTS (INDIAN PINES)

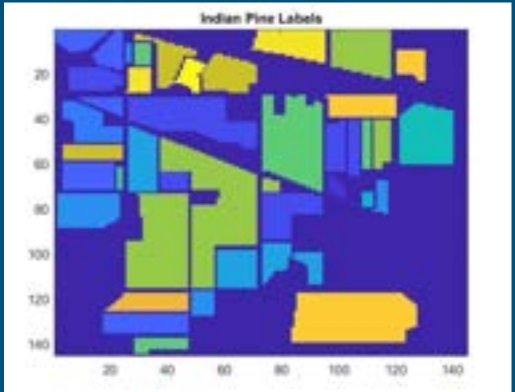
End members

RGB Image

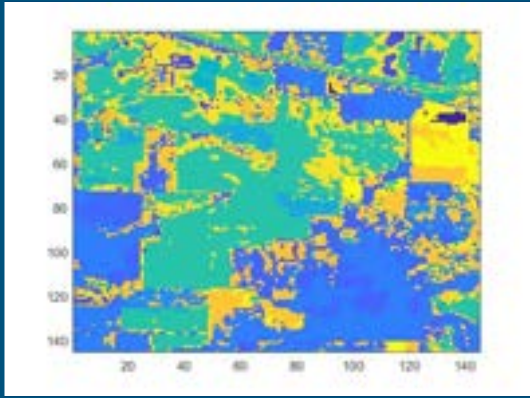




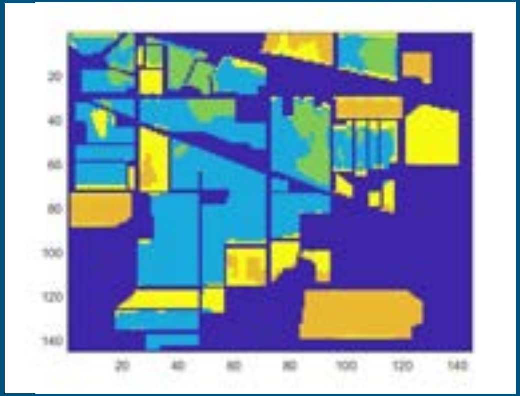
Ground truth



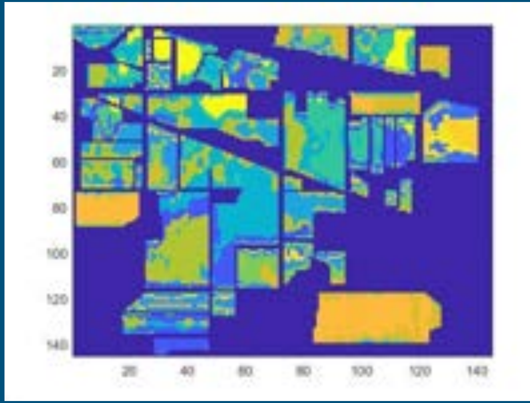
Predicted from FCLS



K-means
(euclidean distance)



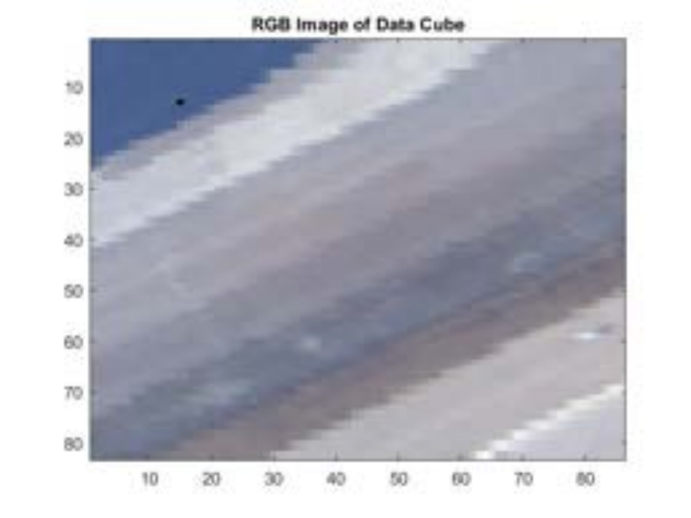
K-means (Canberra distance)

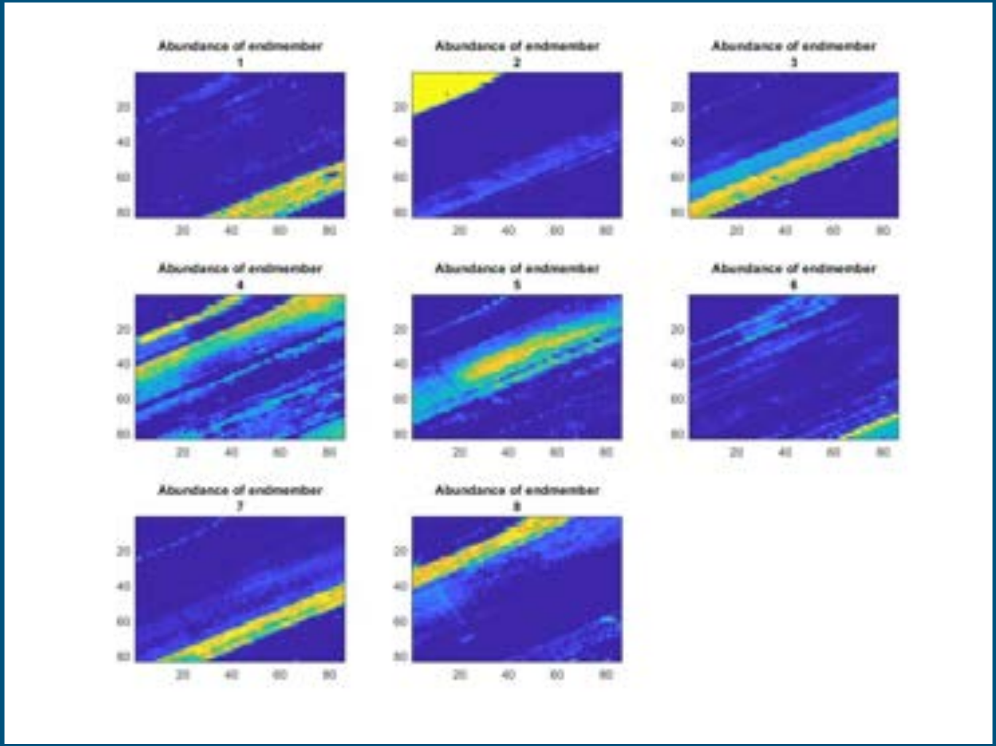


RESULTS (SALINAS-A)

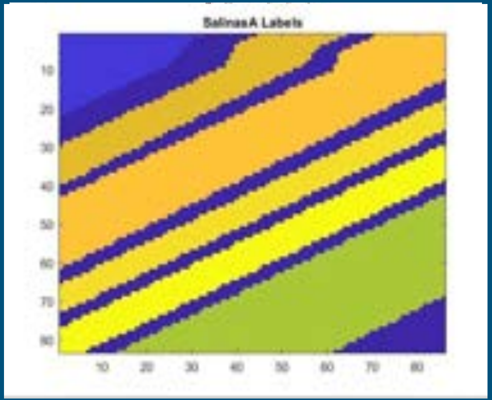
End members

RGB Image

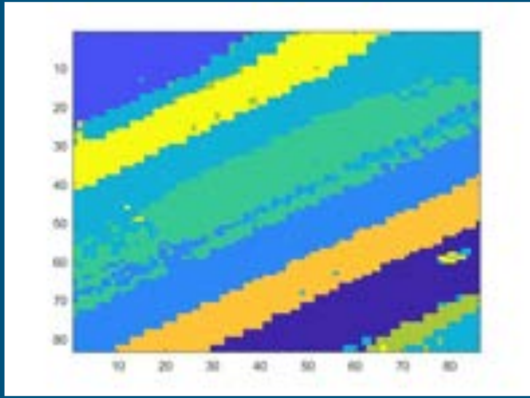




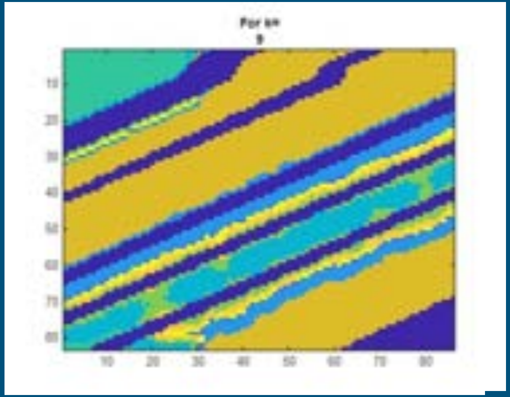
Ground truth



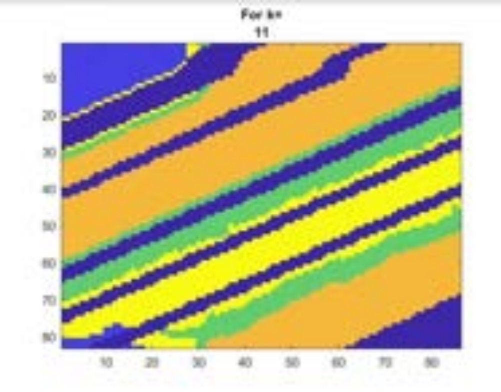
Predicted from FCLS



K-means
(euclidean distance)

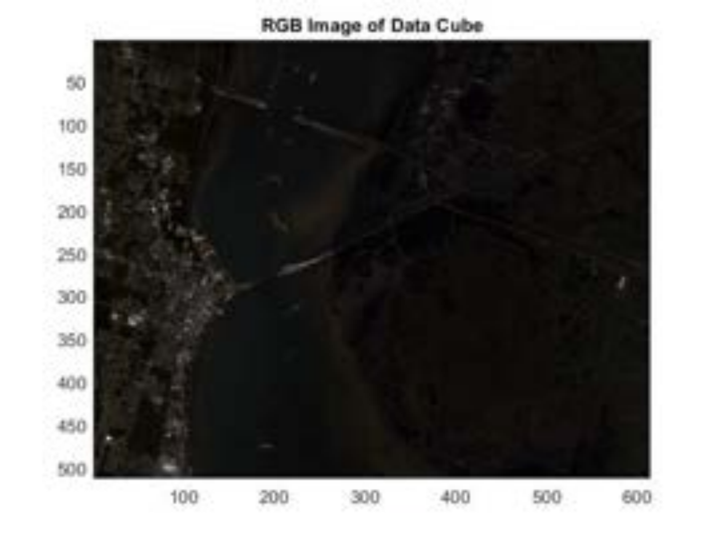


K-means (Canberra distance)

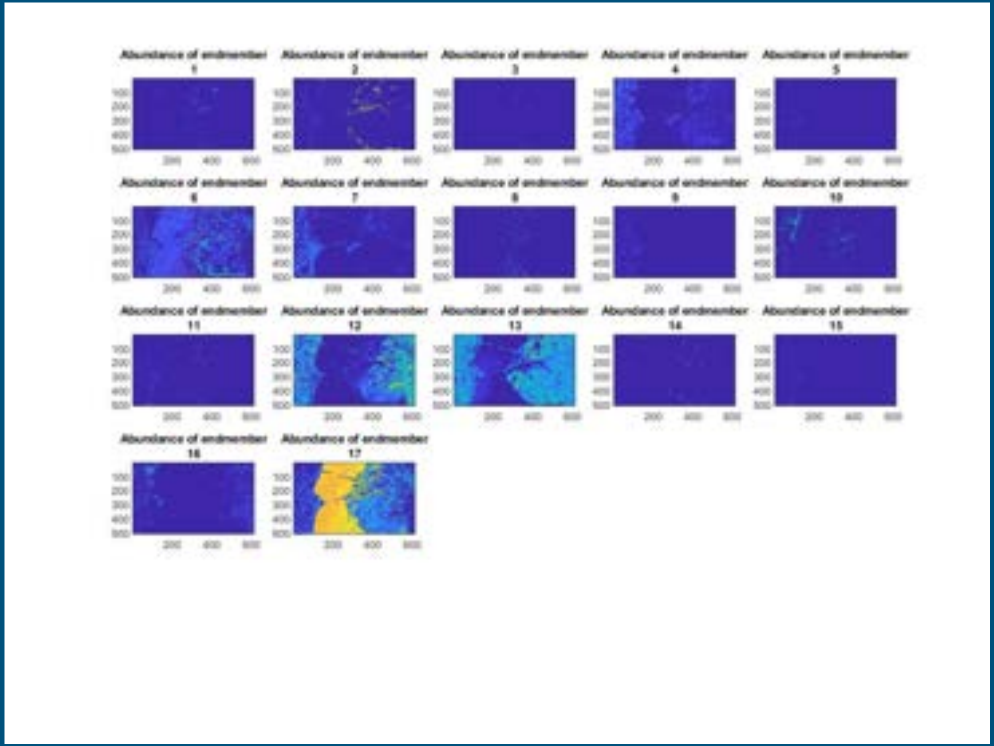


RESULTS (KSC)

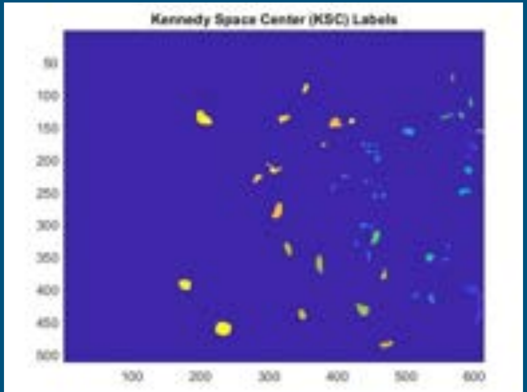
RGB Image



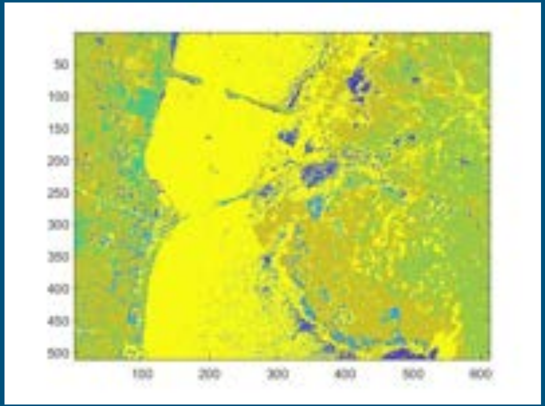
End members



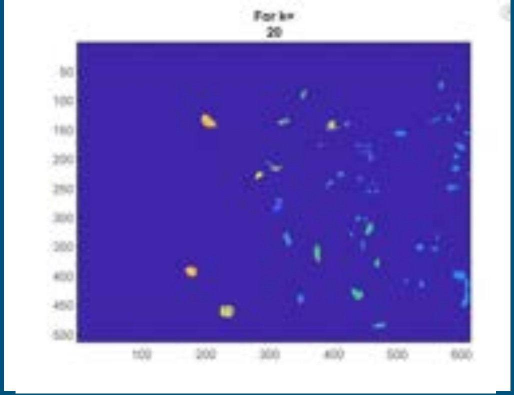
Ground truth



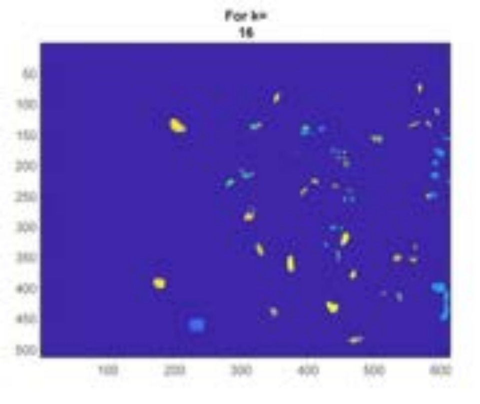
Predicted from FCLS



K-means
(euclidean distance)

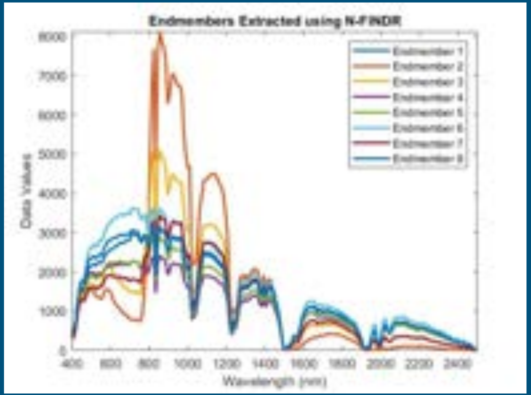


K-means (Canberra distance)

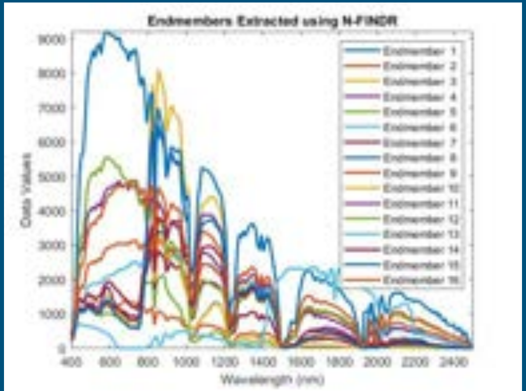


Endmembers extracted from each dataset

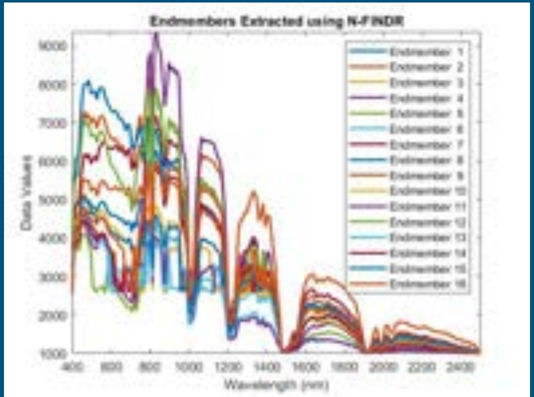
Salinas-A



Salinas



Indian Pines



Kennedy Space Centre