# CONTENTS

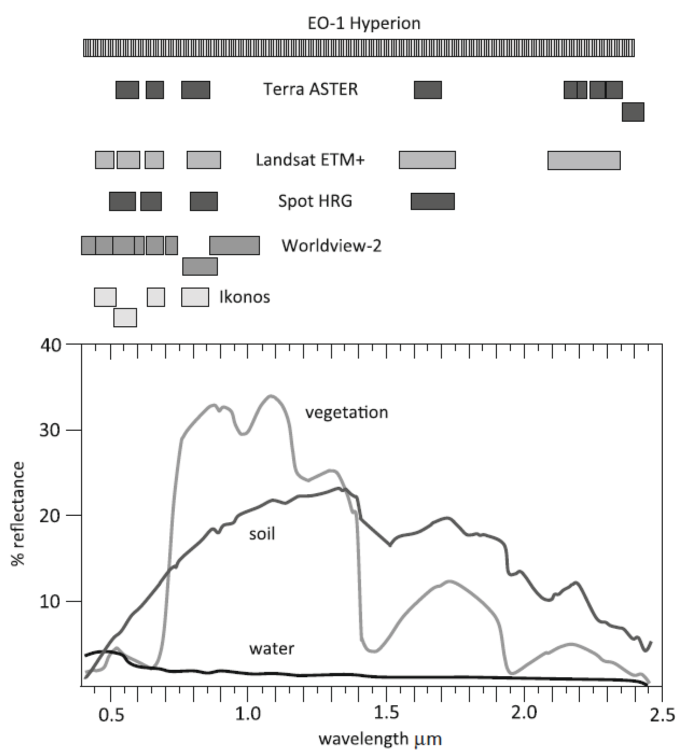




# Hyperspectral Imagery



- Simultaneous acquisition of hundreds of spectral wavelengths for each image pixel.
- Bands are continuous, regularly spaced.
- Spectral resolution ~10nm.

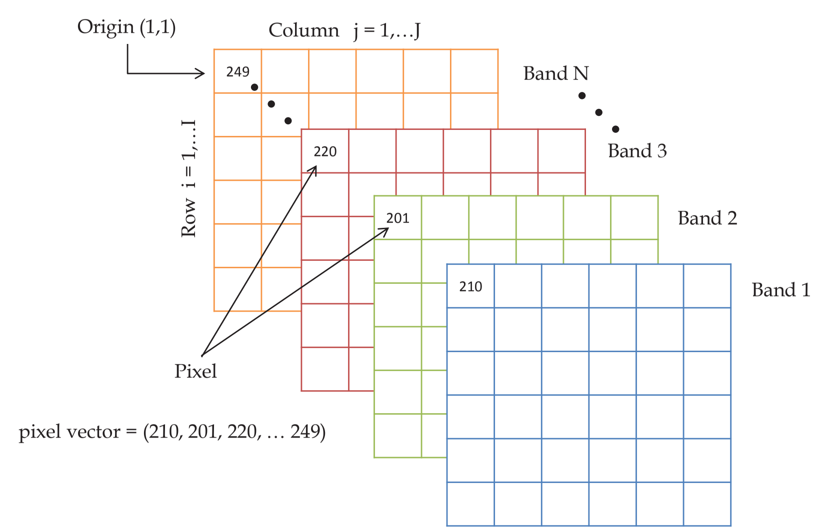



Richards (2013)



# Hyperspectral Image



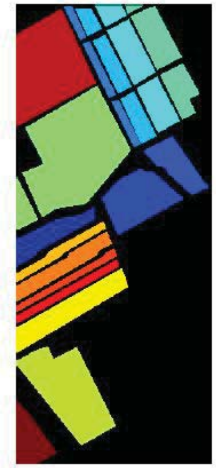


191 Band HYDICE image of Washington DC Mall area

220 Band AVIRIS image Indian Pine Test Site

https://engineering.purdue.edu/~biehl/MultiSpec/hyperspectral.html

Salinas



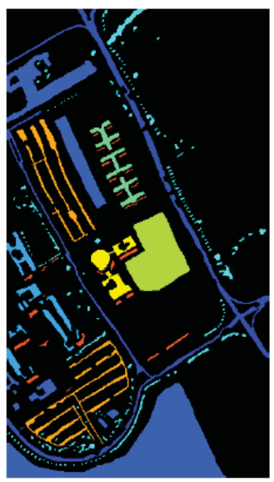
Reference

AVIRIS: 512 × 217, 204 Bands (0.4–2.5 µm), 3.7 m per pixel, 16-bit

| | | | | |
|---|---|---|---|---|
| Broccoli green weeds 1 | Broccoli green weeds 2 | Fallow | Fallow rough plow | Fallow smooth |
| Stubble | Celery | Grapes untrained | Soil vineyard develop | Corn senesced green weeds |
| Lettuce romaine 4 weeks | Lettuce romaine 5 weeks | Lettuce romaine 6 weeks | | |
| Lettuce romaine 7 weeks | Vineyard untrained | Vineyard vertical trellis | Unlabeled | |



PaviaU



Reference

ROSIS: 610 × 340, 103 Bands (0.43–0.86 µm), 1.3 m per pixel, 14-bit

| | | | | |
|---|---|---|---|---|
| Asphalt | Meadows | Gravel | Trees | Painted metal sheets |
| Bare Soil | Bitumen | Self-blocking bricks | Shadow | Unlabeled |

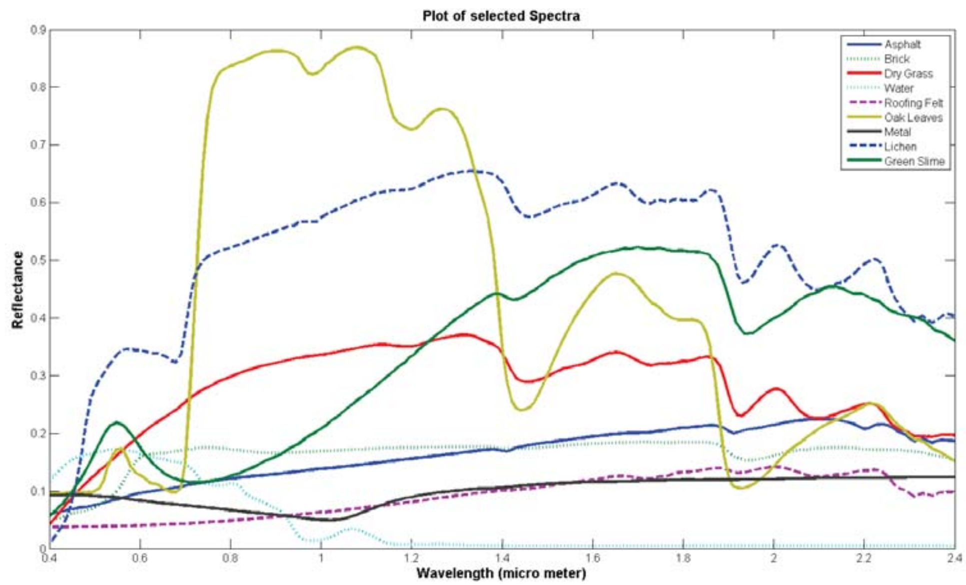


PaviaC

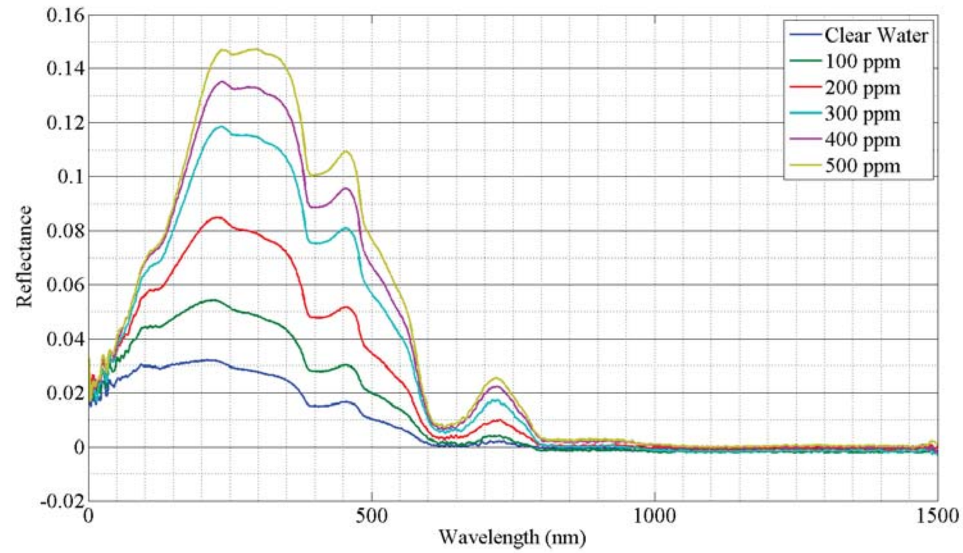
Reference

ROSIS: 400 × 400, 102 Bands (0.43–0.86 µm), 1.3 m per pixel, 14-bit

| | | | | |
|---|---|---|---|---|
| Water | Trees | Meadows | Self-blocking bricks | |
| Bare Soil | Asphalt | Bitumen | Shadow | Unlabeled |





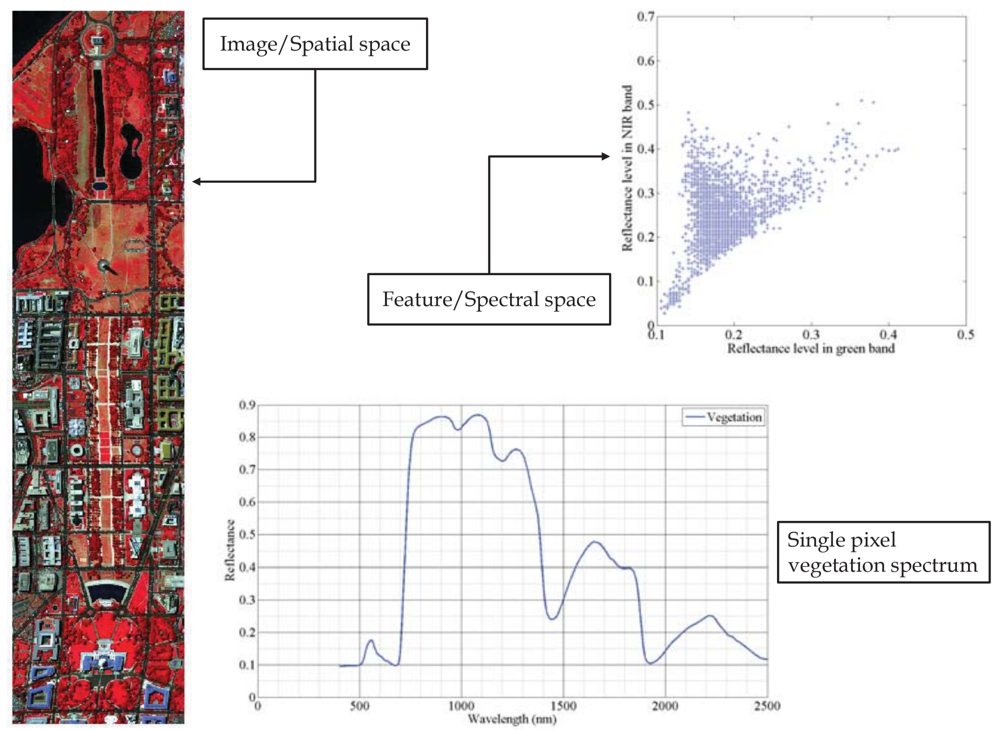






# Why Hyperspectral Imagery



- Possibility of more accurate discrimination among materials of interest.
- Higher spectral resolution, thus giving the opportunity to push further the information extraction capability.
- Inter class and intra class delineation.
- Lots of application in diverse fields.



# Issues

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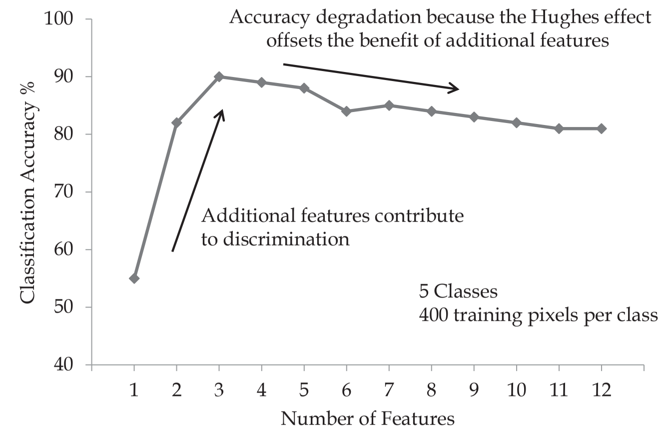
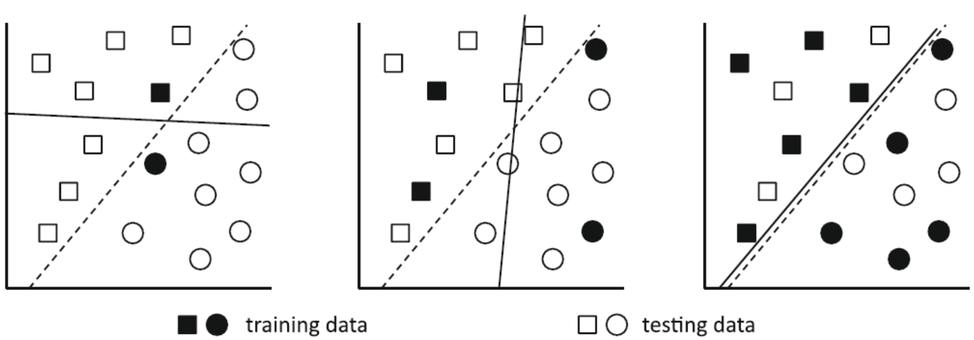
- Huge quantity of data to store.
- Computationally intensive.
- Exhibit redundant information.
- Hughes phenomenon: classifiers achieve better performances at some reduced data dimensionality for a given sample pattern size.
- Curse of dimensionality: the representation space becomes very sparse as the dimensionality of the data increases.




Fu *et al.* (1969); Richards (2013)








Richards (2013)

# Issues

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- Problem 1: Visualization and tabularization of data becomes extremely difficult.

Kriegel *et al.* (2009)

# Issues

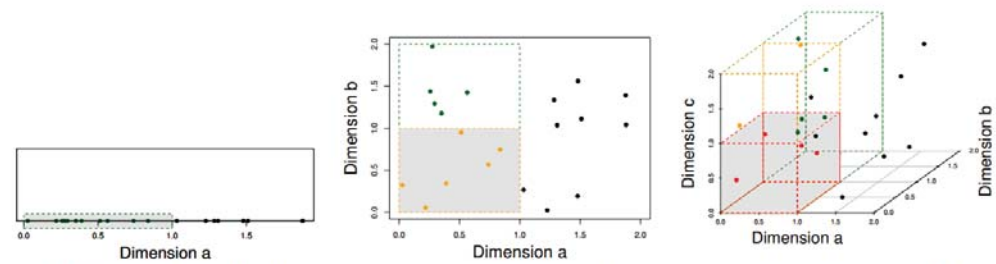


- Problem 1: Visualization and tabularization of data becomes extremely difficult.
- Problem 2: Discrimination between nearest and farthest point in high dimension becomes poor (Beyer *et al.* 1999).

Kriegel *et al.* (2009)

# Curse of Dimensionality






(a) 11 Objects in One Unit Bin (b) 6 Objects in One Unit Bin (c) 4 Objects in One Unit Bin

Parsons, Haque and Liu (2004)

# Issues

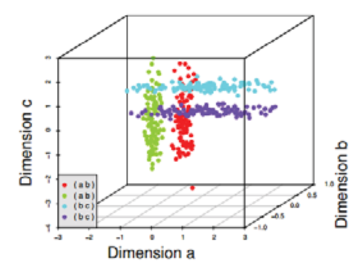


- Problem 1: Visualization and tabularization of data becomes extremely difficult.
- Problem 2: Discrimination between nearest and farthest point in high dimension becomes poor (Beyer *et al.* 1999).
- Problem 3: Subset of some bands may be relevant to one cluster and subset of some other bands may be relevant to other cluster, and so on.

Kriegel *et al.* (2009)

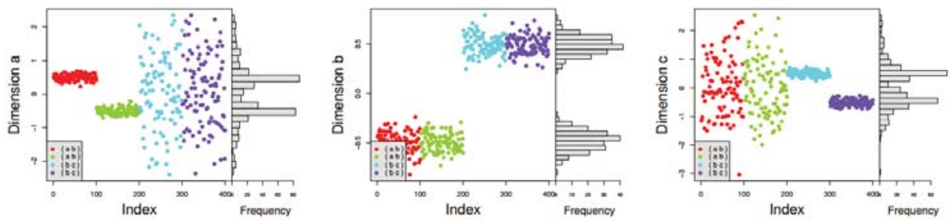
# Example






Parsons, Haque and Liu (2004)

*400* data points
*4* clusters of *100* data points each
Normally distributed, $\mu$ = *0.5* and *-0.5* in dim *a* and 0.5 in dim *b*, and σ = *0.2*, dim *c* $\mu$ = *0* and σ = *1*
Other two clusters in dim *b* and *c* (same manner)




(a) Dimension $a$ (b) Dimension $b$ (c) Dimension $c$

(a) Dims $a$ & $b$ (b) Dims $b$ & $c$ (c) Dims $a$ & $c$

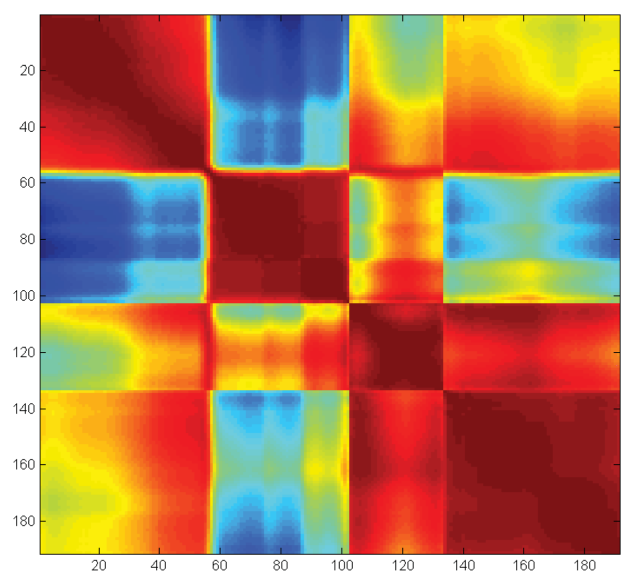
Parsons, Haque and Liu (2004)

# Issues



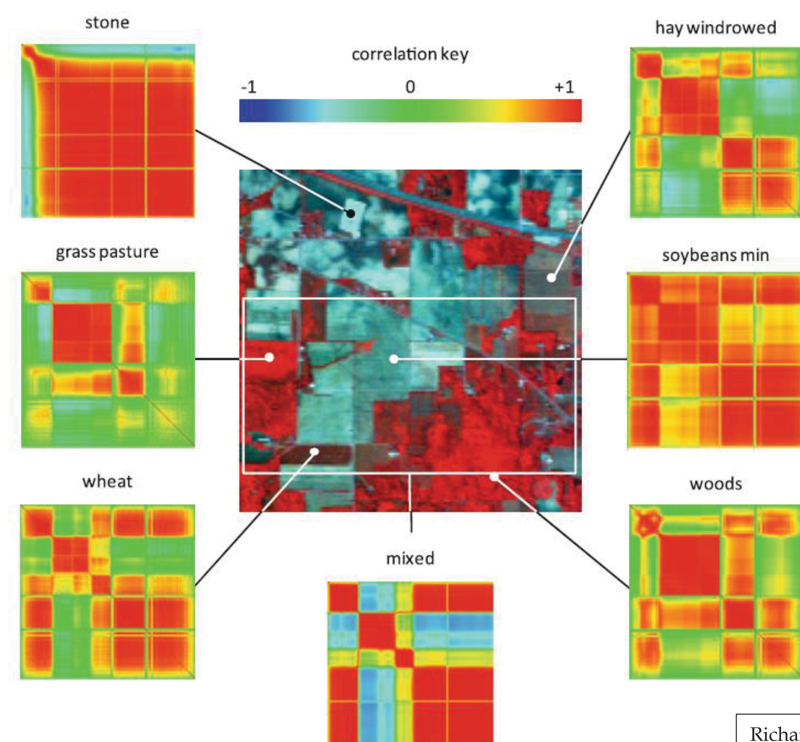
- Problem 1: Visualization and tabularization of data becomes extremely difficult.
- Problem 2: Discrimination between nearest and farthest point in high dimension becomes poor (Beyer *et al.* 1999).
- Problem 3: Subset of some bands may be relevant to one cluster and subset of some other bands may be relevant to other cluster, and so on.
- Problem 4: Large number of bands are correlated.

Kriegel *et al.* (2009)




Color coded visualization of correlation matrix. Red color indicates high correlation and blue color indicates low correlation.

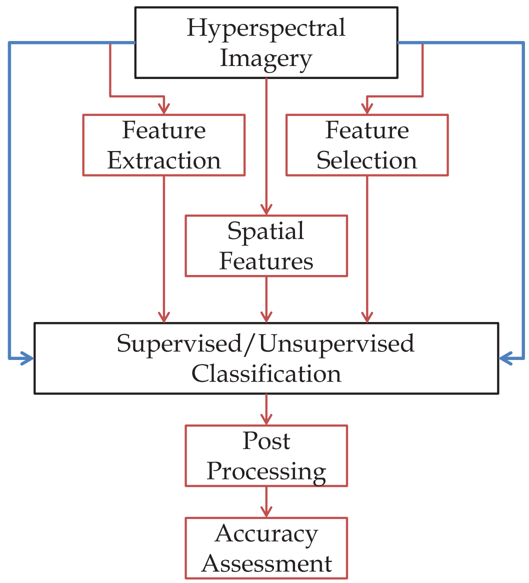





Richards (2013)

# General Framework





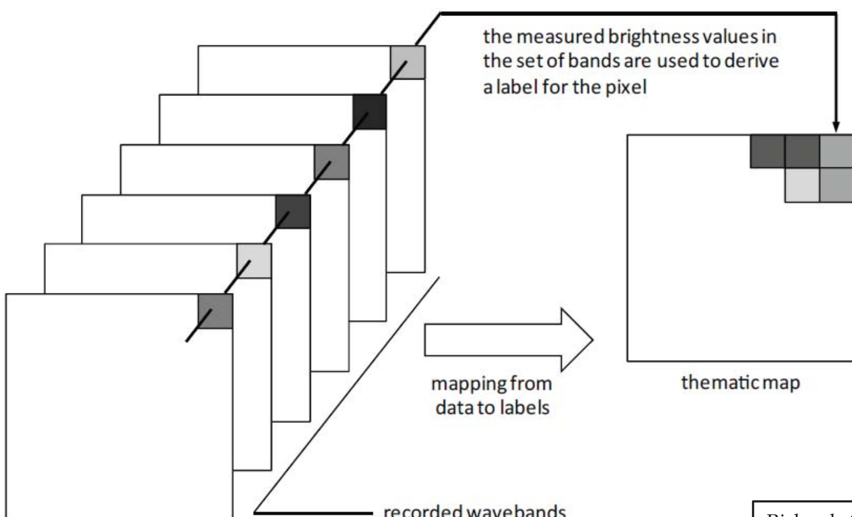



# Classification

Examples

# Thematic Map

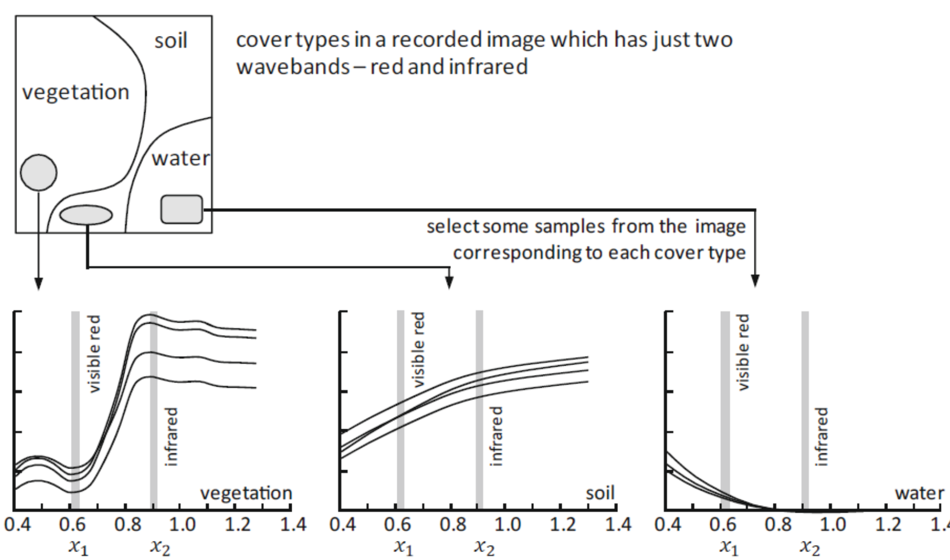




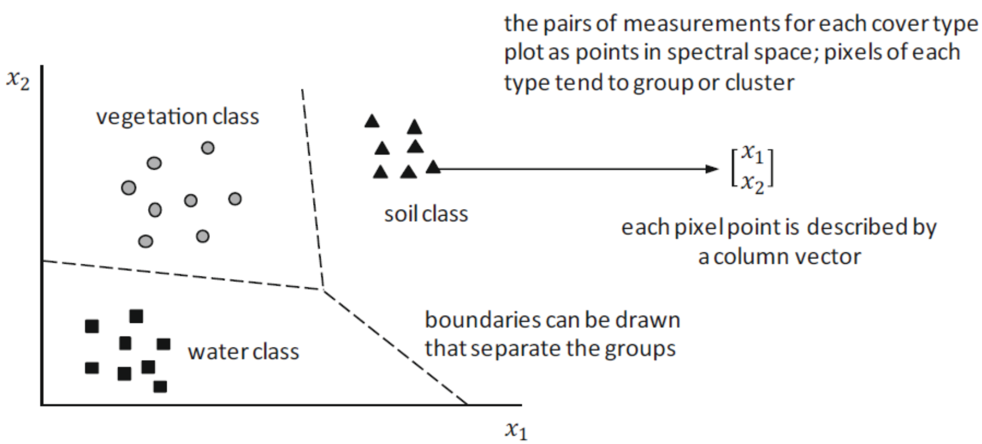

Richards (2013)

# Supervised Classification





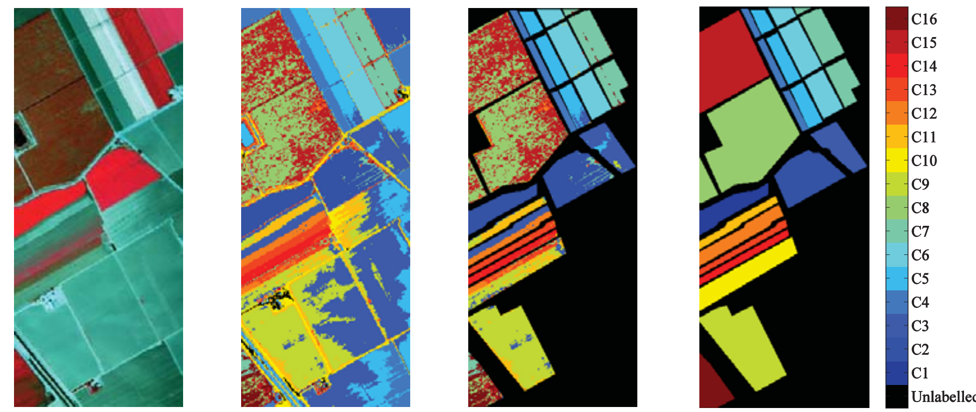
# Supervised Classification




Richards (2013)



# Clustering

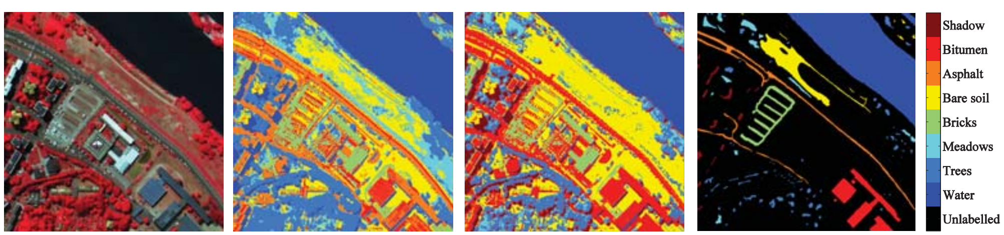



Salinas | *k*-means | Masked | Reference Image

| | Purity | NMI |
|---|---|---|
| *k*-means | 0.6963 | 0.7453 |



# Clustering




Pavia City | *k*-means | *k*-means + PCA | Reference Image

| | Purity | NMI |
|---|---|---|
| *k*-means | 0.8268 | 0.7598 |
| *k*-means + PCA | 0.8484 | 0.7677 |



# Clustering Evaluation

**Purity[1]**

$$purity(\Omega,\mathbb{C}) = \frac{1}{N}\sum_k \max_j \left|\omega_k \cap c_j\right|$$

**Normalized Mutual Information[1,2] (NMI)**

$$NMI(\Omega,\mathbb{C}) = \frac{MI(\Omega,\mathbb{C})}{\max(H(\Omega),H(\mathbb{C}))}$$

$$MI(\Omega,\mathbb{C}) = \sum_k \sum_j p(\omega_k \cap c_j)\log_2 \frac{p(\omega_k \cap c_j)}{p(\omega_k)p(c_j)}$$

$$H(\Omega) = -\sum_k p(\omega_k)\log_2 p(\omega_k)$$

$\Omega = \{\omega_1, \omega_2, \ldots, \omega_k\}$ is the set of clusters

$\mathbb{C} = \{c_1, c_2, \ldots, c_j\}$ is the set of classes obtained from reference image

$N$ is total number of pixel samples

[1] http://nlp.stanford.edu/IR-book/html/htmledition/evaluation-of-clustering-1.html
[2] Cai, D., X. He, and J. Han. 2005. "Document Clustering Using Locality Preserving Indexing." *IEEE Transactions on Knowledge and Data Engineering*, 17 (12): 1624-1637.

$$\Omega = \begin{bmatrix} 1 & 1 & 1 & 2 \\ 2 & 2 & 2 & 1 \end{bmatrix}; \mathbb{C} = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 2 & 2 & 2 & 2 \end{bmatrix}$$

$purity = 0.7500$
$NMI = 0.1888$



**Purity**

$$purity(\Omega, \mathbb{C}) = \frac{1}{N} \sum_k \max_j |\omega_k \cap c_j|$$

**Normalized Mutual Information (NMI)**

$$NMI(\Omega, \mathbb{C}) = \frac{MI(\Omega, \mathbb{C})}{\max(H(\Omega), H(\mathbb{C}))}$$

$$MI(\Omega, \mathbb{C}) = \sum_k \sum_j p(\omega_k \cap c_j) \log_2 \frac{p(\omega_k \cap c_j)}{p(\omega_k) p(c_j)}$$

$$H(\Omega) = -\sum_k p(\omega_k) \log_2 p(\omega_k)$$

$\Omega = \{\omega_1, \omega_2, ..., \omega_k\}$ is the set of clusters

$\mathbb{C} = \{c_1, c_2, ..., c_j\}$ is the set of classes obtained from reference image

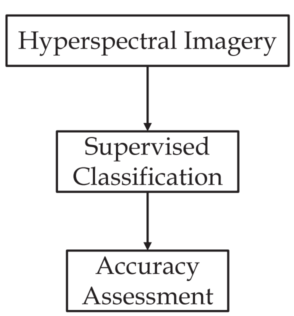
$N$ is total number of pixel samples



# Application of clustering in Supervised Classification

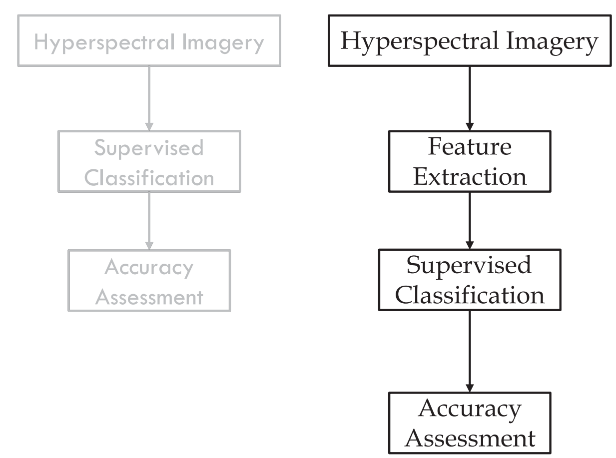
# Classification Strategy I



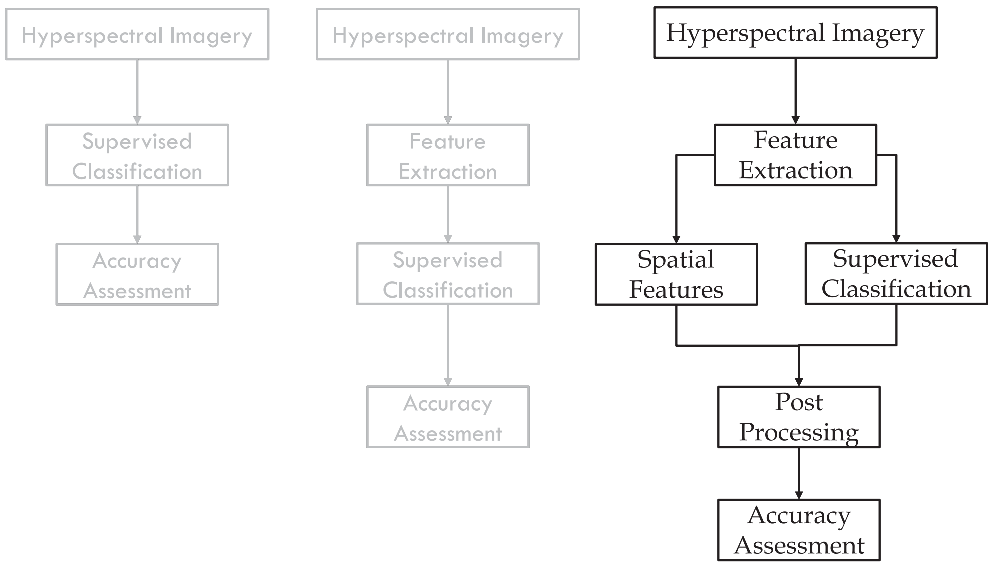



# Classification Strategy II

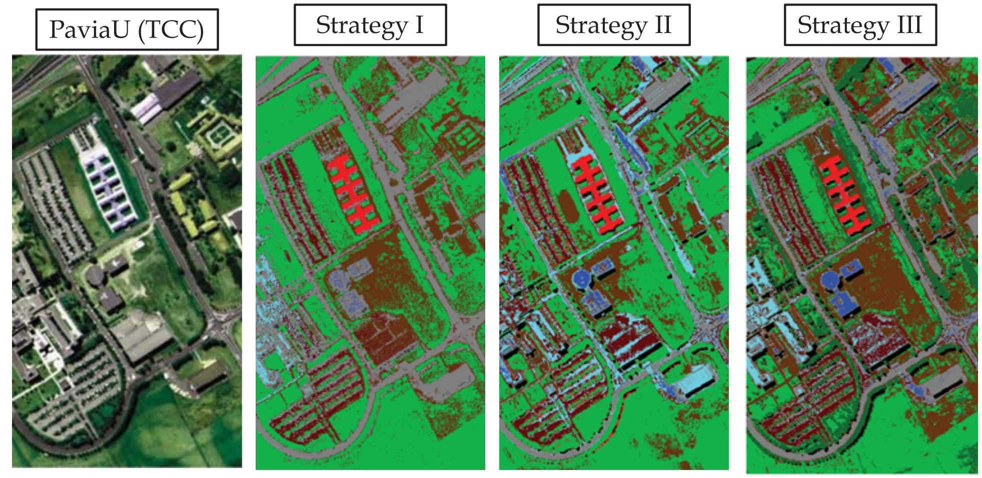




# Classification Strategy III




# Thank You





| | Strategy I | Strategy II | Strategy III |
|---|---|---|---|
| Overall Kappa (%) | 57.98 | 73.67 | 82.80 |