Unsupervised Classification

Feature Space and Geometrical Basis of Classification

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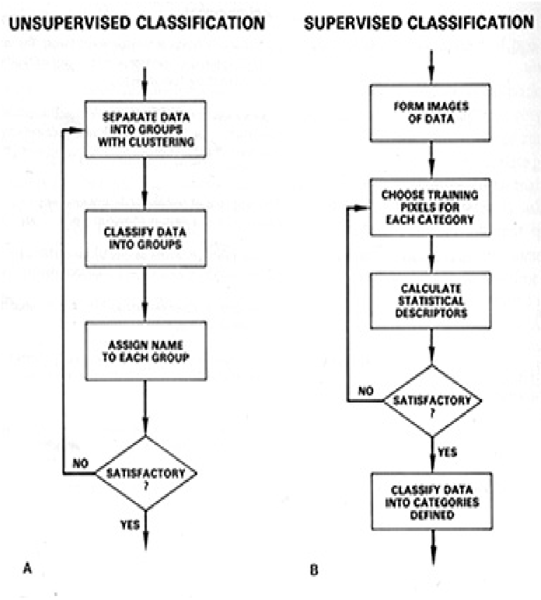
Classification

1. Selecting categories of real world objects or land covers. Examples: water, forest, bare soil, etc.
2. Labeling the pixels to be classified on the basis of their properties using classification rules. For a digital image, the labels are numeric (1 = water, 2 = forest, 3 = bare soil, etc.) and the significance of the number supplied by the user.

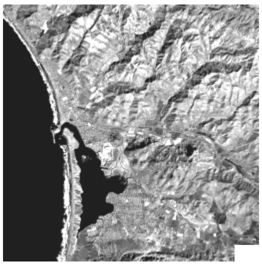


Features are properties of a pixel that may include the DN values in each band of an image,context, texture, land surface elevation, soil type, or other data georeferenced to the raster image dataset.

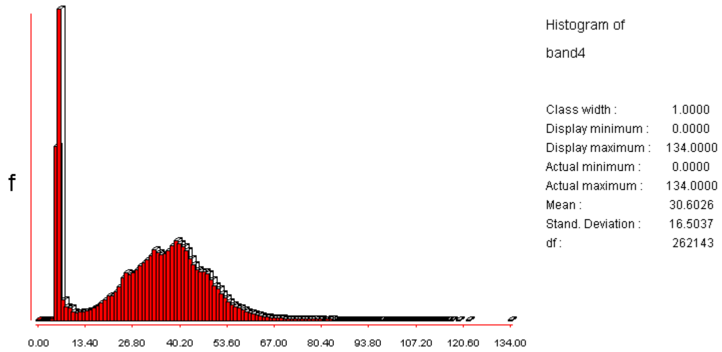
Feature space is the representation of features in Euclidean space, each feature plotted on an axis perpendicular to each other axis.

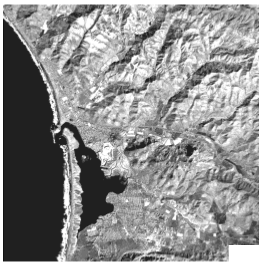
Feature space may be algebraically expressed for 2, 3, 4, or more dimensions.

Pixels located near each other in feature space are clustered together on the basis of their geometrically similar location that may be described algebraically using Pythagorean theorem

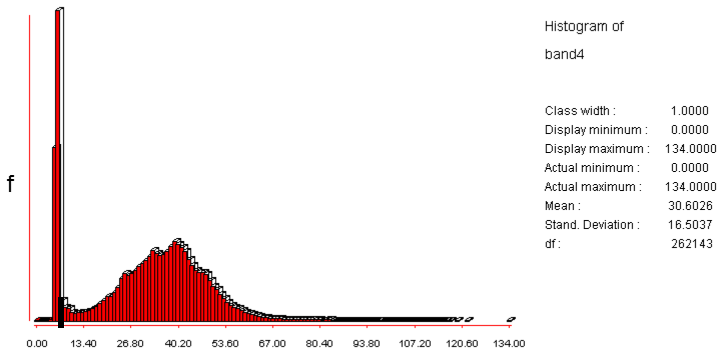


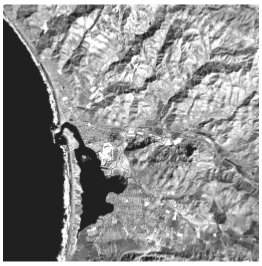
TM4 of Morro Bay, CA





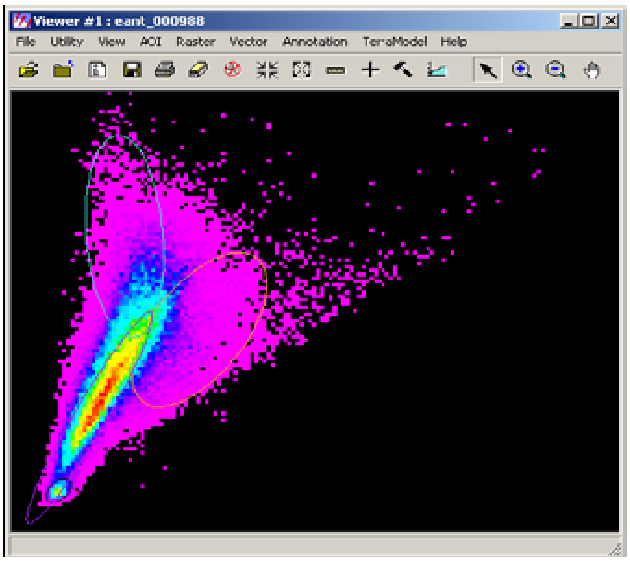
TM4 of Morro Bay, CA





TM4 of Morro Bay, CA

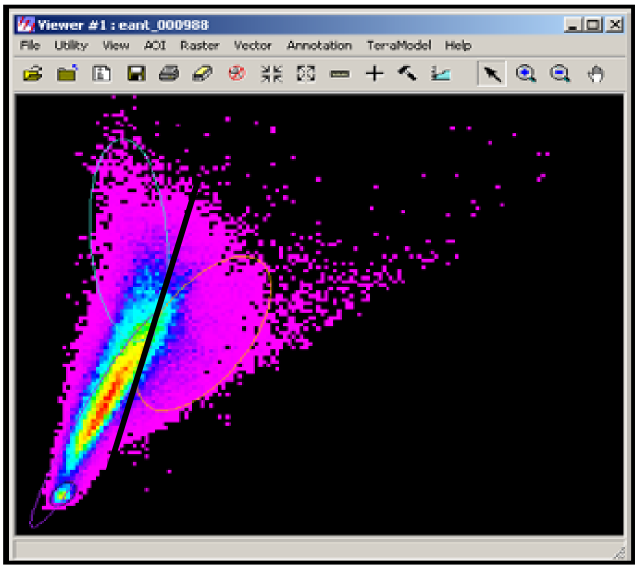
TM3 of Morro Bay, CA



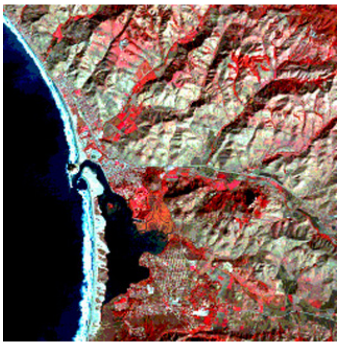
Bands 3 & 4 (different image)

TM4 of Morro Bay, CA

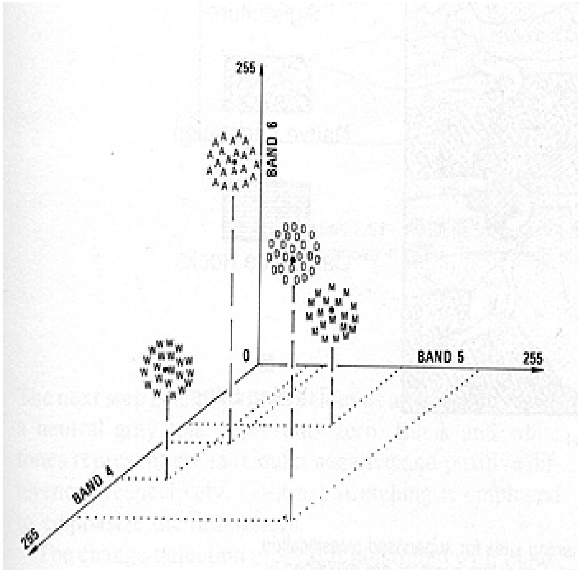
TM3 of Morro Bay, CA



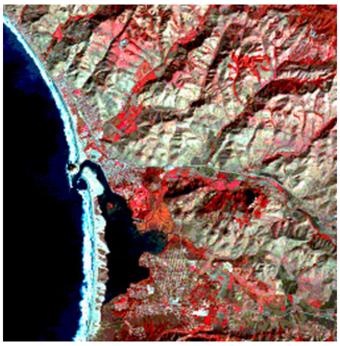
Bands 3 & 4 (different image)



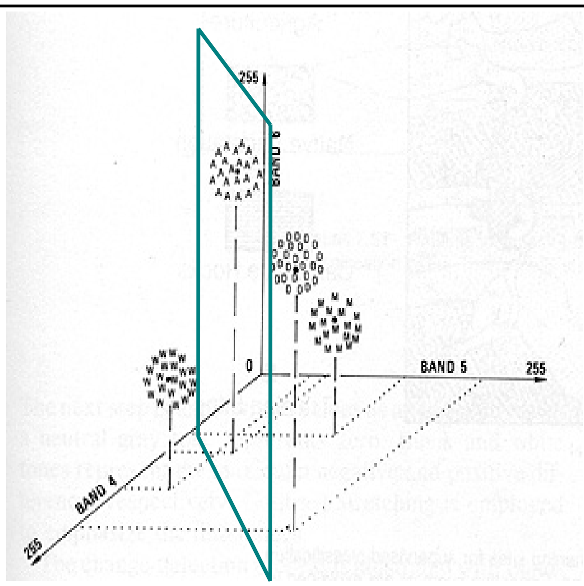
Bands 2,3,4 false color image
of Morro Bay, CA



Hypothetical 3 band plot of feature space and pixel clusters



Bands 2,3,4 false color image
of Morro Bay, CA



Hypothetical 3 band plot of feature space and pixel clusters

Unsupervised....hands off

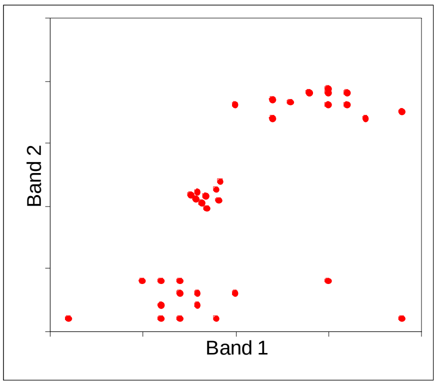
User options in unsupervised classification are limited:

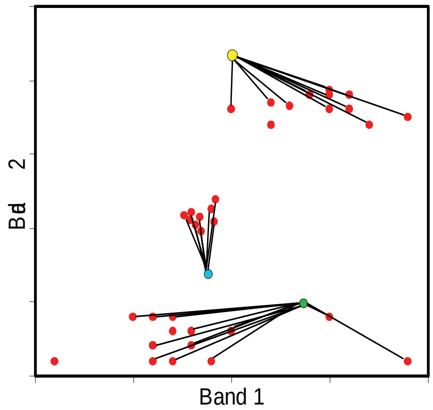
1. to control compute time, limit number of iterations
2. to select number of clusters desired
3. to select minimum or maximum number of clusters in process

The user does not direct choices about where clusters should be or what the features of a cluster should be—see supervised.

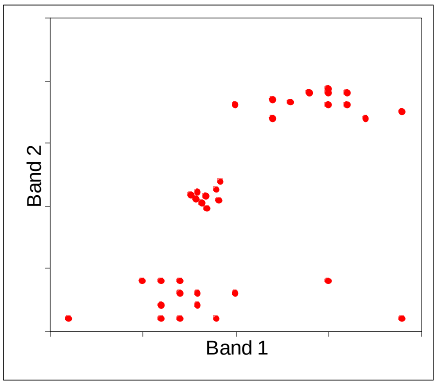
Assumptions

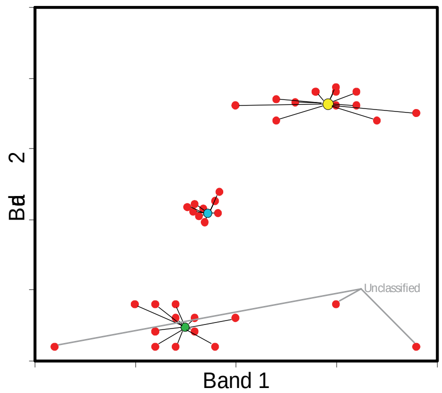
1. Clusters are spheroidal, ideally spheres.
2. Clusters are separate and do not overlap.



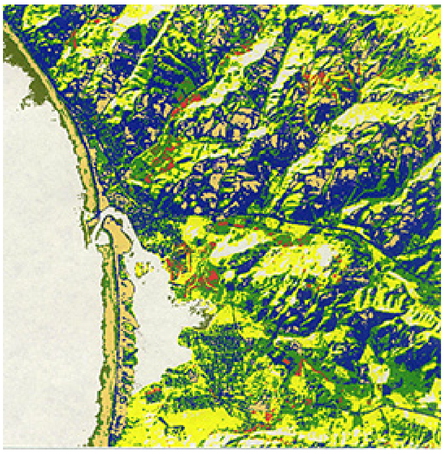


First iteration of identifying clusters with random starting points.





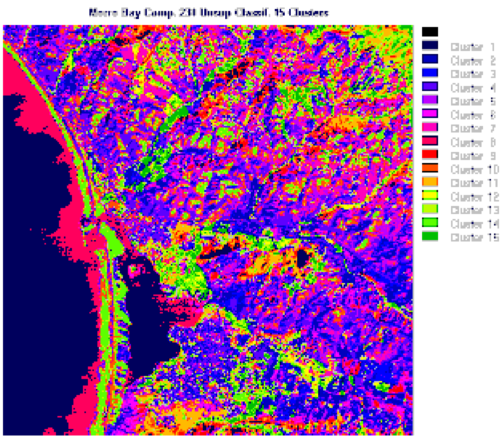
Each cluster is based on the least sum of the distances of the pixels to the centroid of the cluster.



Band 2, 3, 4 unsupervised classification with 6 classes Morro Bay, CA

The classes are a mixed bag of land covers.
The buff occurs in ocean & shadowed hillsides
Aspect appears to have best correlation.
Red was found where there was heavy vegetation.
Three classes are very mixed less discrete association to land cover.

This attempt may have too few classes or need additional data from DEM or other sources.



Bands 2, 3, 4, unsupervised classification into 15 classes Morro Bay, CA

The classes are difficult to interpret.

Aspect is significant with small variations in aspect effecting reflectance.

Classes still mixed or effected by mixels.

Why use unsupervised classification?

Exploration of the image dataset...getting a sense of the clustering in the data in feature space. Which land covers are identifiable? which are occurring in mixed clusters? The results are often too general or too mixed for a thematic map.

Sometimes a lack of other observational data exists for the image leaves unsupervised classification as a best option.

From F.F. Sabins, Jr., "Remote Sensing: Principles and Interpretation." 2nd Ed., © 1987. Reproduced by permission of W.H. Freeman & Co., New York City.

http://www.eng.auburn.edu/users/doughmp/Webfiles/Classification_report.pd
f

http://rst.gsfc.nasa.gov/Sect1/Sect1_3.htm
l

http://www.biaoqiang.org/default.aspx?event=vd&docid=257#277,23,Example spectral plot