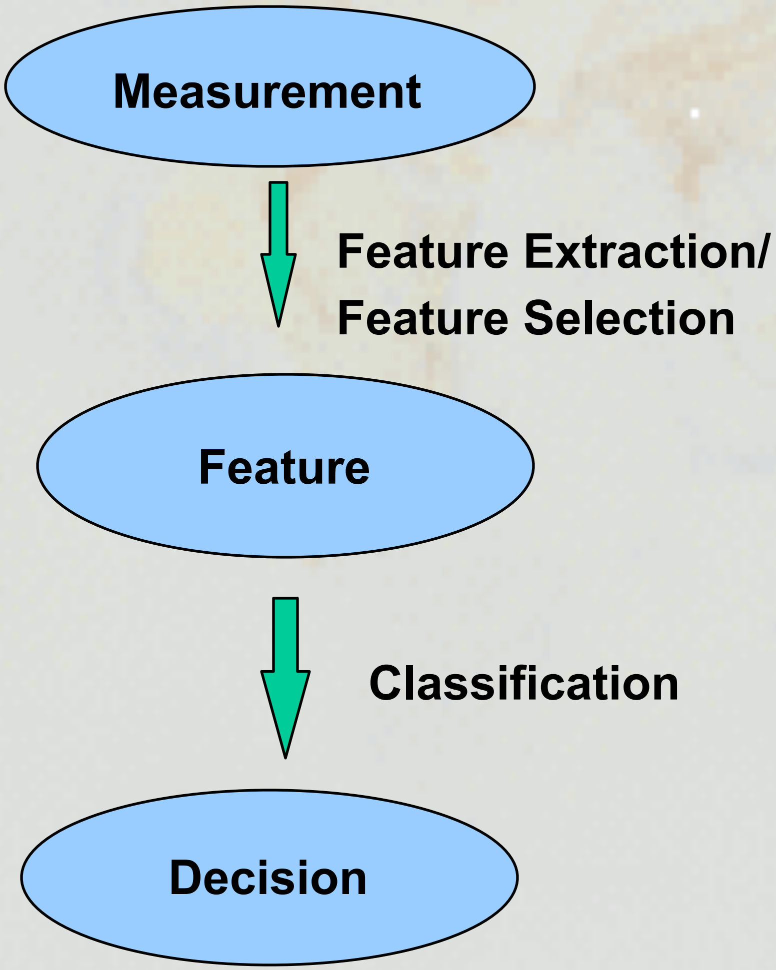
# Image processing

## Part I – theory

Thomas Gumbricht,
www.mapjourney.com

To understand is to perceive patterns – Isaiah Berlin

# Image processing = pattern recognition



# Image processing = pattern recognition

- Raster image = grid of pixels
- Pixels part of patterns

– Spectral patterns (1, 10, 45, 235)

– Spatial patterns (contextual information)

– Temporal patterns (agriculture)

- Classification:

– recognition of patterns and their assignment to (landcover) classes

– Process of assigning pixels to classes

– Pixels within classes are spectrally more similar to one another than they are to pixels in other classes

# Image processing = pattern recognition

- science—and art—of finding meaningful patterns in data
- the human brain automatically sorts certain textures and colors into categories; skills to recognize shape, shade, pattern, shadow, tone/color, texture and site
- In a computer system, spectral pattern recognition can be more scientific. Pixels are sorted based on mathematical criteria/decision rules (e.g. statistically derived or mapping functions(ANN))

# Image processing – Input data

- Multispectral data (MSS, SPOT etc)
- Visualisation of data

– Image, spatial patterns: landscapes, roads, houses, forests, agriculture

– Bands as histograms

– Bands plotted in feature space (FS) / scatterdiagram

# Image processing

- Image rectification
- Image enhancement
- Image classification

# Image processing

## Image radiometric rectification

# Geometrical radiometric correction

- Sun elevation correction
- Earth-Sun distance correction

# Atmosphere effects

•Radiation – top of atmosphere
– Incident energy
– Target reflectance
– Atmospheric effects

• Pixel values
– do not accurately represent spatial distribution of ground surface reflectance (dark / bright objects!) (autocorrelation)
– Their magnitude is influenced by other factors than the physical, chemical or biological properties of the ground surface

$L_{app}=\rho TE/\Pi+L_p$
$L_{app}$=apparent radiance at sensor
$\rho$ = target reflectance
T = atmospheric transmittance
E = incident solar irradiance
$L_p$ = path radiance/haze

# Why radiometric corrections

- Objectives!
- Single scene analysis
  - Differences within image?
- Multi scene analysis
  - Comparability
- Sensors
- Time of year/day
- atmosphere
  - Magnitude of change you are looking for
- Units?
  - Ground measurements in reflectance/radiance – conversion!
  - Necessity in itself!

# Radiometric corrections

- Absolute correction
  - Units
  - Modelling
  - Regression; ground truth
- Relative correction/normalisation
  - Reference image

# Radiometric corrections

- If atmospheric optical depth and sensor calibration data are available for the reference image, then an atmospheric correction algorithm may be used to correct all the rectified images to absolute surface reflectance.

# Absolute radiometric corrections

- Three step process

1. Convert DN to radiance, Lapp

- Sensor dependent
- Lapp=Ai*DN+Bi (landsat)
- Lapp=DN/Ai (spot)
- Ai calibration gain, Bi calibration offset
- Which values to use? And what is done at ground
station? Old datasets!
- MSS 8-12% difference ; sensor + ground
processing (Markham and Barker, 1987)

Pixel DN

Apparent radiance, Lapp

Apparent Reflectance, ρ*

Ground target Reflectance, ρs

# Absolute radiometric corrections

2. Convert to reflectance, $\rho^*$

• In case of 100 % reflectance, radiance measured is result of:

1. solar radiance (tables)
2. Cosine of solar zenith angle (header file) and
3. Earth – sun distance, d, (formula)

• $\rho^* = (d^*L_{app})/(\cos(\theta_s)E/\pi)$

– Why d

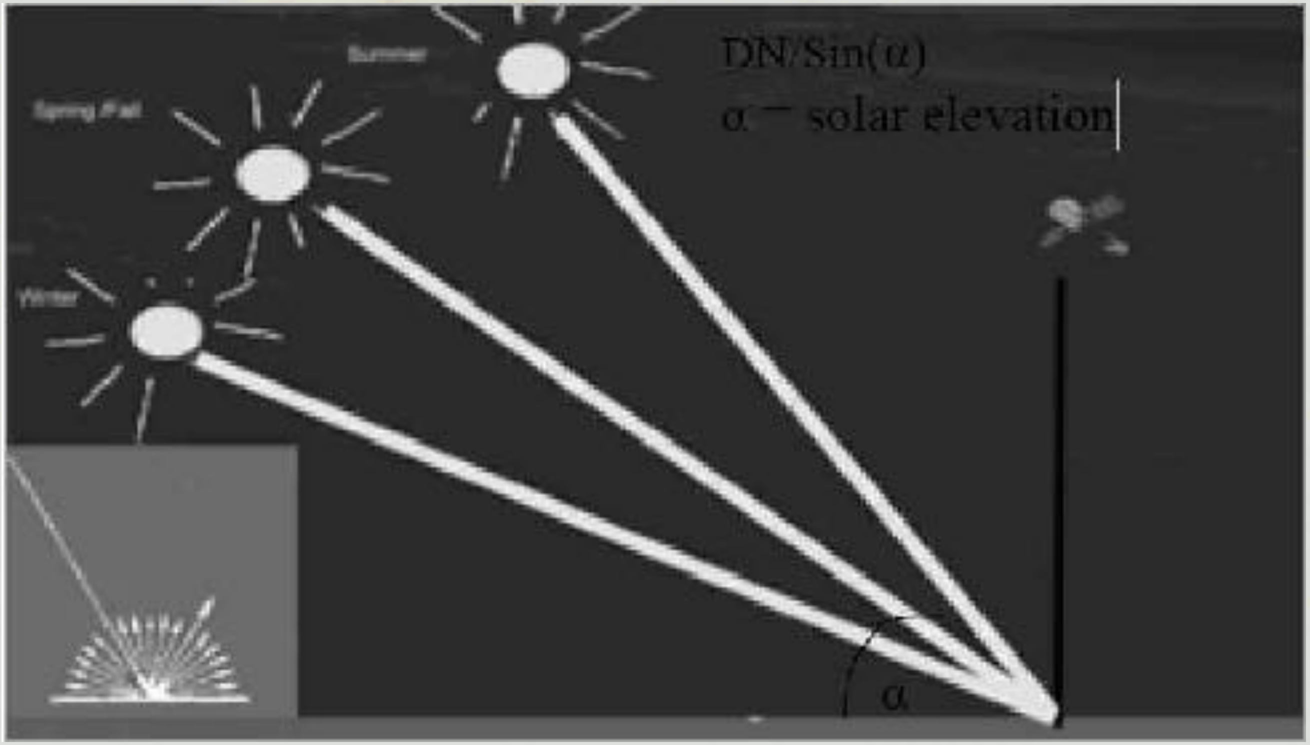
• Seasonal changes in earth – sun distance

• Irradiance decreases as the square of the E-S distance

• Solar irradiance at Aphelion < perihelion

# Absolute radiometric corrections

Sun elevation
– Seasonal(day) position of sun relative to earth
– Correction - assuming sun was at zenith at each date of sensing
– Dividing each pixel value by the sine of the solar elevation angle
– solar elevation angle: Time- and location dependent



# Image processing

## Image enhancement

# Image enhancement

Local
Focal
Regional
multispectral

# Local Image enhancement

Local = per pixel
contrast stretching
level slicing
thresholding

# Local Image enhancement

contrast stretching

# Local Image enhancement

level slicing

# Local Image enhancement

thresholding

# Focal Image enhancement

Focal (neighbor) Image enhancement

# Focal Image enhancement

## Filtering

## Focal Image enhancement

## Edge enhancement

# Image enhancement – spectral rationing

## Vegetation indexes

# Image enhancement – spectral rationing

Tasseled cap

# Tasseled Cap

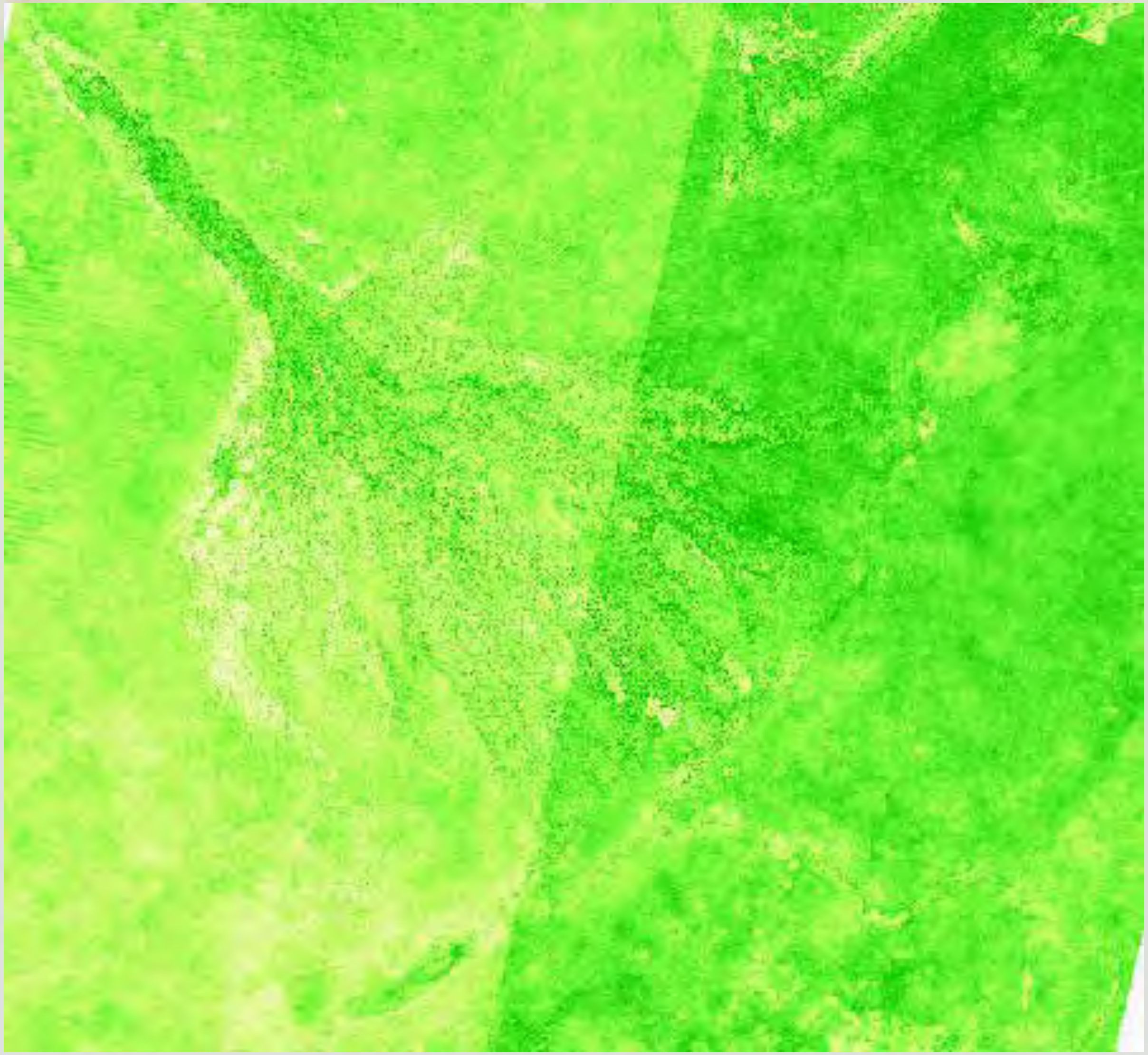
| sensor | axis name | $W_{TC}$ | | | | | |
|---|---|---|---|---|---|---|---|
| | MSS band | 1 | 2 | 3 | 4 | | |
| L-1 MSS | soil brightness | +0.433 | +0.632 | +0.586 | +0.264 | | |
| | greenness | −0.290 | −0.562 | +0.600 | +0.491 | | |
| | yellow stuff | 0.829 | +0.522 | 0.039 | +0.194 | | |
| | non-such | +0.223 | +0.120 | −0.543 | +0.810 | | |
| L-2 MSS | soil brightness | +0.332 | +0.603 | +0.676 | +0.263 | | |
| | greenness | +0.283 | −0.660 | +0.577 | +0.388 | | |
| | yellow stuff | +0.900 | +0.428 | +0.0759 | −0.041 | | |
| | non-such | +0.016 | +0.428 | −0.452 | +0.882 | | |
| | TM band | 1 | 2 | 3 | 4 | 5 | 7 |
| L-4 TM | soil brightness | +0.3037 | +0.2793 | +0.4743 | +0.5585 | +0.5082 | +0.1863 |
| | greenness | 0.2848 | 0.2435 | 0.5436 | +0.7243 | +0.0840 | 0.1800 |
| | wetness | +0.1509 | +0.1973 | +0.3279 | +0.3406 | −0.7112 | −0.4572 |
| | haze | −0.8242 | +0.0849 | +0.4392 | −0.0580 | +0.2012 | −0.2768 |
| | TC5 | 0.3280 | +0.0549 | +0.1075 | +0.1855 | 0.4357 | +0.8085 |
| | TC6 | +0.1084 | −0.9022 | +0.4120 | +0.0573 | −0.0251 | +0.0238 |
| L-5 TM | soil brightness | +0.2909 | +0.2493 | +0.4806 | +0.5568 | +0.4438 | +0.1706 |
| | greenness | −0.2728 | −0.2174 | −0.5508 | +0.7221 | +0.0733 | −0.1648 |
| | wetness | +0.1446 | +0.1761 | +0.3322 | +0.3396 | −0.6210 | −0.4186 |
| | haze | +0.8461 | +0.0731 | +0.4640 | 0.0032 | 0.0492 | +0.0119 |
| | TC5 | +0.0549 | −0.0232 | +0.0339 | −0.1937 | +0.4162 | −0.7825 |
| | TC6 | +0.1186 | −0.8069 | +0.4094 | +0.0571 | −0.0228 | +0.0220 |
| | soil brightness | additive terms: | −10.3695 | | | | |
| | greenness | | −0.7310 | | | | |
| | wetness | | −3.3828 | | | | |
| | haze | | +0.7879 | | | | |
| | TC5 | | −2.4750 | | | | |
| | TC6 | | −0.0336 | | | | |

Tasseled Cap transformation was developed by Crist and Cicone (1984) for Landsat MSS. It is a way to get more “physical” intelligible information from satellite data.

## Tasseled Cap - Brightness

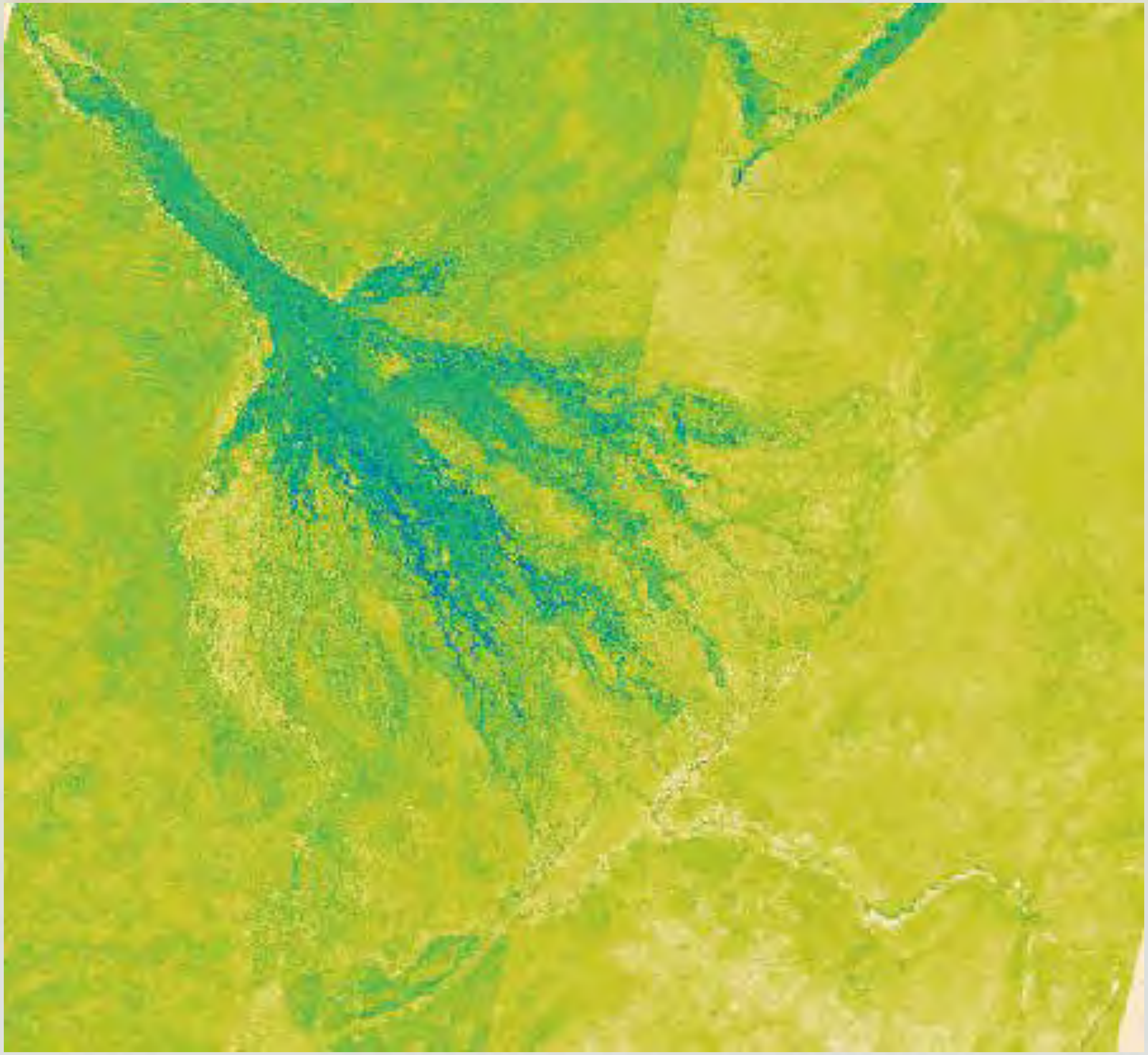
Tasseled Cap Brightness represent a pancromatic (black and white) photograph.

# Tasseled Cap - Greenness



Tasseled Cap Greenness represent the amount of green stuff.
It has advantages over Vegetation indices when recognizing  e.g. under-water vegetation.

# Tasseled Cap - Wetness



Tasseled Cap Wetness represent the amount of water at the soil surface or in the topsoil layer. It is useful for e.g. flooding mapping and for soil water modelling.

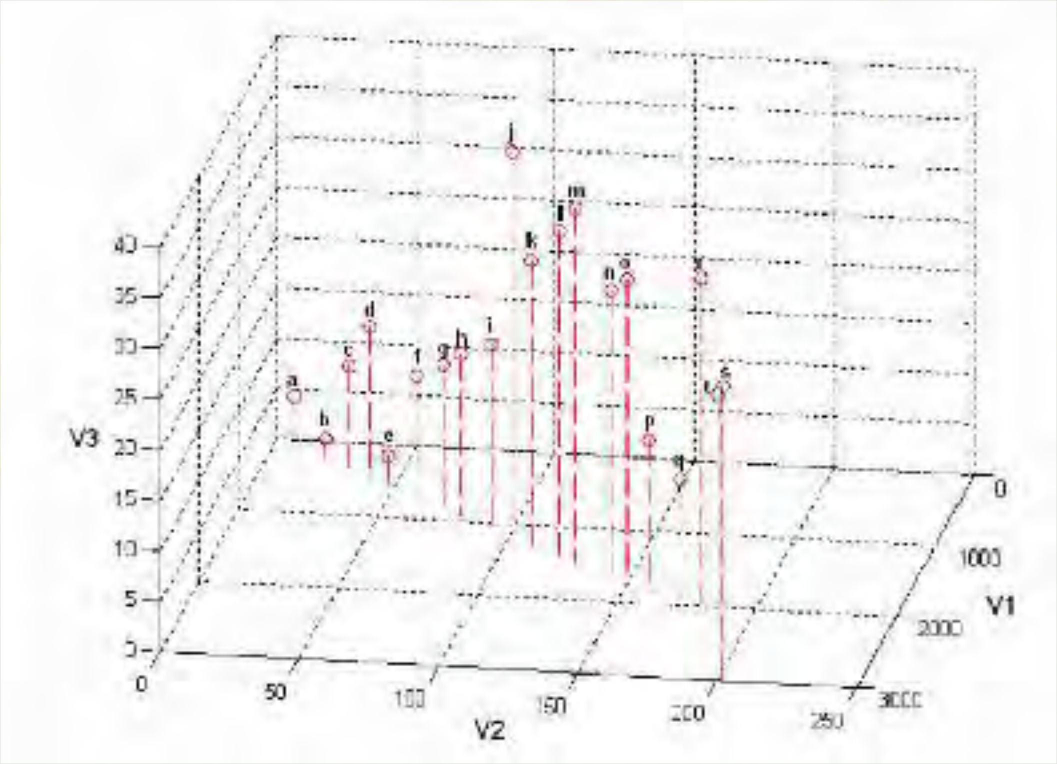
# Tasseled Cap - Development

The development in sensors and especially their internal calibration capacity has led to a renewed interest in Tasseled Cap. Detailed algorithms are hence being developed for many of the recent sensors, including for those with very high resolution.

# Principal Component Analysis

Principal components analysis (PCA) is used for two objectives:

1. Reducing the number of variables comprising a dataset while retaining the variability in the data.
2. Identifying hidden patterns in the data, and classifying them according to how much of the information, stored in the data, they account for.



# Image processing – Feature space

- The pattern recognition process involves subdivision of feature space into homogenous regions by decision boundaries
- We are looking for clusters in the FS
- Assuming the variation to be mapped is separable

– Spatially vs. Problem of mixed pixels

– Spectrally vs. Problem of overlap in FS

Separability can improve with additional input data, postclassification etc.

# Image processing – Feature space

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# Image processing – Feature space

• Distance – concept that the brain use in seeing patterns

• FS is a Euclidean space

• Euclidean distance/theorem of Pythagoras

– *e.g.* distance between point to be classified and the center of the cluster

• 2-dimensional space $$d_{ab} = \sqrt{((a_x - b_x)^2 + (a_y - b_y)^2))}$$

• p-dimensional space $$d_{ab} = \sqrt{\sum_{i=1}^{p} (x_{ia} - x_{ib})^2}$$

# Classification process

• The classification process breaks down into two parts:

– training

• the computer system must be trained to recognize patterns in the data. Training is the process of defining the criteria by which these patterns are recognized. Training can be performed with either a supervised or an unsupervised method.

– classifying (using a decision rule)

# Classification process

- Depending on the type of information you want to extract from the original data, classes
  - may simply represent areas that look different to the computer, i.e. spectral classes (resulting from unsupervised methods)
  - may be associated with known features on the ground according to a classification scheme; i.e. information classes
- information classes requires training!

# From spectral fields to objects

- Spectral classes related to brightness
- Information classes

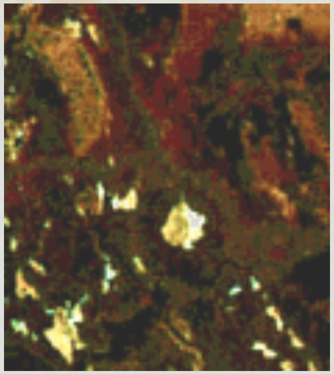
– Categories of interest for the user (forest, roads, urban, agriculture etc.)

– Not directly recorded in an image

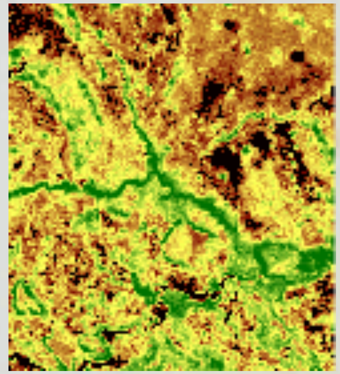
– May consist of several spectral subclasses

- Is there a correspondence?

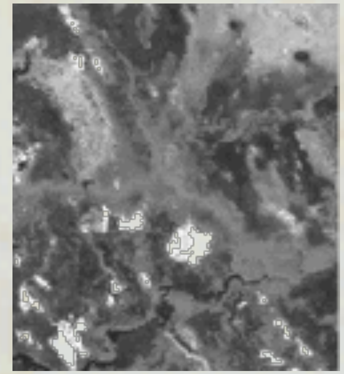
# Field and Object data models



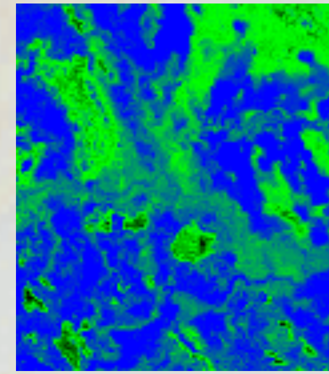
Landsat image (field)



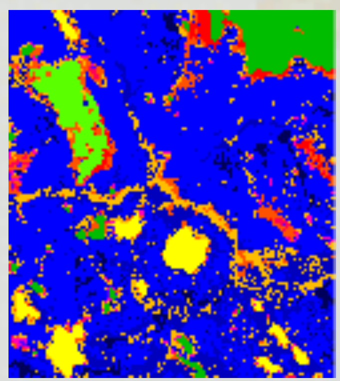
NDVI (field)



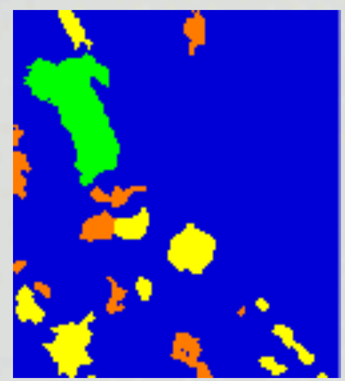
Brightness (field)



Wetness (field)



Classes (objects)



Islands (objects)

# Classification scheme

- is a set of target (information) classes you have in mind (classification system)
- provides a framework for organizing and categorizing the information that can be extracted from the data.
- the proper classification scheme includes classes that are both
  - important to the study and
  - discernible from the data on hand.
- has hierarchical structure, which can describe a study area in several levels of detail.

# Object classes and ground truth

• A good classification scheme consists of representative classes

– Requires knowledge of the area in question and ground truth data

• ground truth also known as reference or ancillary data

• various categories: maps and databases, test sites, field and laboratory measurements, and most importantly actual onsite visits to the areas being studied by remote sensing

# Ground truth and training data

- In supervised classification processes ground truth data are required both for
  - Training
  - Accuracy assessment
- Important considerations of such data
  - Sample size
  - Sample scheme

# Image classification methods

Forward (data driven)
Backward (goal driven)

# Forward driven image classification

**Statistical**
- Unsupervised (clustering)
- Supervised (statistical)
- Fuzzy classifications
- Artificial Neural Networks (ANN)

**Deterministic**
- Knowledge inferred rules
- Fuzzy logic
- Ancillary

**Hybrid**

# Goal driven image classification

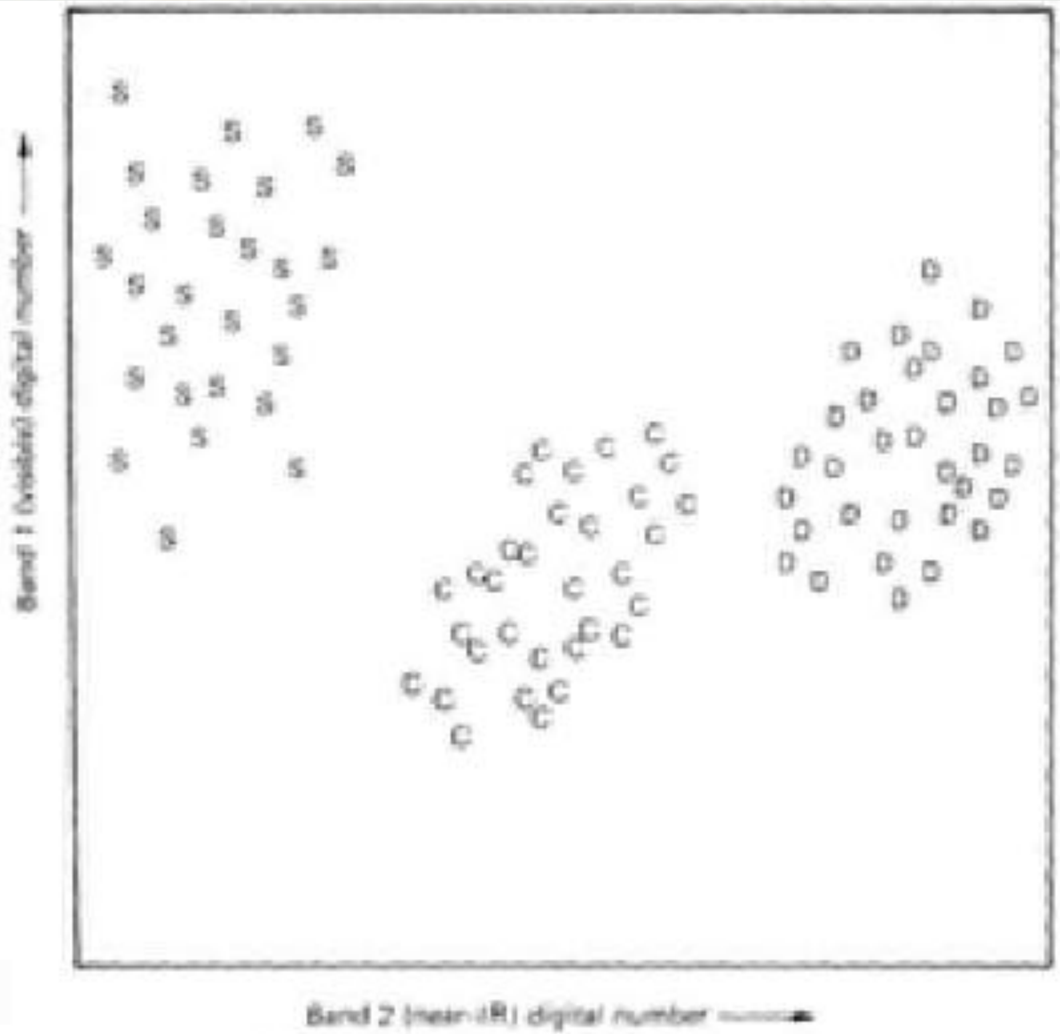
- Multi Criteria Evaluation
- Multi Objective Land Allocation

# Unsupervised classification

- No apriori knowledge required
- Unknown, but distinct, spectral classes are generated
- Exploratory method
  - Are classes you have in mind discriminable?
  - Are classes pure or mixed?
- Different algorithms
  - RGB clustering
  - Migrating mean clustering algorithm/ISODATA
  - Fuzzy clustering
  - Vacuum shell detection
  - AMOEBA

# Unsupervised classification

After comparing classified image data with ground truth, clusters are assigned to classes




Spectral classes in two-channel image data.

# Unsupervised RGB classification

- Input - three bands
- 3D FS partitioned into clusters on a grid.
- Simple version: each clusters becomes a class in the output thematic raster layer.
- Advanced version: minimum threshold on the clusters
- Unclassified: city-block distance is calculated as the sum of the distances in the red,green, and blue directions in 3-dimensional space.

# Unsupervised ISOCLASS classification

Iterative Self-Organising Data Analysis Technique
• Steps in the algorithm
– Initial state selected; i.e. no. and center of clusters
– Each point in FS labelled to closest center (decision rule of closest distance to center)
– Mean calculated for cluster center
– Relabel points using new means
– Iterate until acceptable percentage of pixels don't change between clusters

# Unsupervised ISOCLASS classification

- Iterative process
- User defined variables

– Number of Classes this number specifies the exact number of thematic categories (classes) that will be produced

– Number Iterations this number will determine the maximum number of times the ISODATA process will be performed on a given data set.

– Convergence Threshold this setting will determine the percentage of pixels that must remain in a cluster from one iteration to the next in order to stop the ISODATA process.

– Classify Zeros this option specifies whether the classification will include pixels with a value of zero.

– Skip Factor this option will have the process skip the number of pixels for the 'X' and 'Y' set by the user. The higher the skip factors, the faster the process, but the lower the overall accuracy and the smaller the output thematic image.

– Initialize options; principal versus diagonal axis

# Unsupervised AMOEBA classification

- Bryant 1978
– Location + spectral properties
– Greater diversity allowed for adjacent pixels
– Included in class if within tolerance limit
– Work well for areas with large homogenous areas

# Unsupervised classification

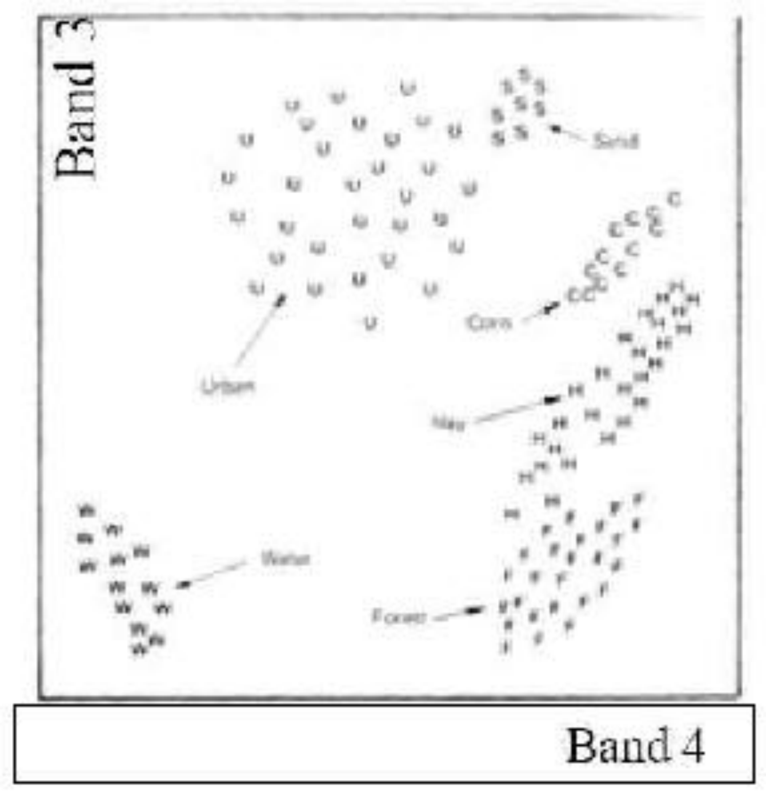
- Advantages
  - No extensive prior knowledge required
  - Opportunities of human error minimalised
  - Unique classes recognised as distinct units
- Disadvantages/limitations
  - Spectral classes vs. Information classes
  - Limited control over classes and identities
- Comparison of data; spatially and temporally

# Supervised classification

- Informally: process of using samples of known ID to classify pixels of unknown ID
- Requires training data
  - Typical
  - Homogeneous
- Methods/Decision rules
  - Parallelepiped
  - Feature space
  - Minimum/Mahalanobis Distance
  - Isodata (hybrid)
  - Maximum likelihood

# Supervised classification

• Pixel observations from selected training sites are basis for the classification process



# Training Data

• No of pixels
– 100 pr. category, 10n – 100n (n = no. Of bands), 30 pr. band pr. class
– Omittance vs. redundance
– Dimensionality/
• How many parameters must be estimated?
• Disproportionate increse (ML): 6b - 27, 12b – 90
• Efficient estimation of statistical parameters – representativeness and size of sample!
• Stable sample size and increase in dimensionality ?
• Decreasing effectiveness of classifier Hughes phenomena

# Training Data

- Located throughout image
- No. Of areas
– 5-10 areas/category
– Representativeness
– Many small > few large, autocorrelation
- Placement – within region, avoid mixed pixels
- Uniformity – homogeneity/ unimodal frequency
distribution – parametric methods

# Training Data

- Idealised sequence (Campbell, 2002)
  - Assemble information
  - Conduct field studies
  - Carefully plan selection of field observations
  - Conduct preliminary examination of digital scene
  - Identify prospective training areas (TA)
  - Locate TA on image
  - Inspect signatures/statistics
  - Refine TA
  - Final TD

# Training Data Signature Evaluation

- Important and timeconsuming step
- Objective: set of signatures that describe the spectral response pattern of classes
- If signatures overlap the spectral information of the data itself cannot support classes -Separability!
- Non-parametric signatures/ boundaries in FS (statistics for ellipsoids possible)
- Parametric signatures/ statistical parameters - normality!

# Supervised classification decision rules

- reliable signatures has been created
- pixels analyzed independently
- measurement vectors for each pixel compared to each signature, according to a decision rule, or algorithm
- Pixels that pass the criteria that are established by the decision rule are then assigned to the class for that signature.
- Decision rules

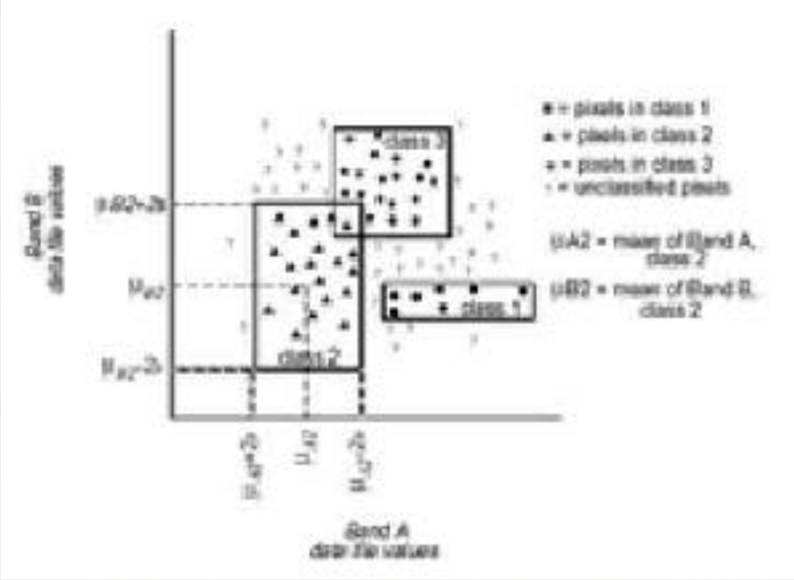
– Non-parametric
– Parametric

# Decision rules

• Non-parametric decision rule
– is independent of the properties/statistics of the data
– determines whether or not the pixel is located inside of nonparametric signature boundary.
• parametric decision rule
– trained by the parametric signatures
– defined by the mean vector and covariance matrix for the data file values of the pixels in the signatures
– every pixel is assigned to a class since the parametric decision space is continuous.

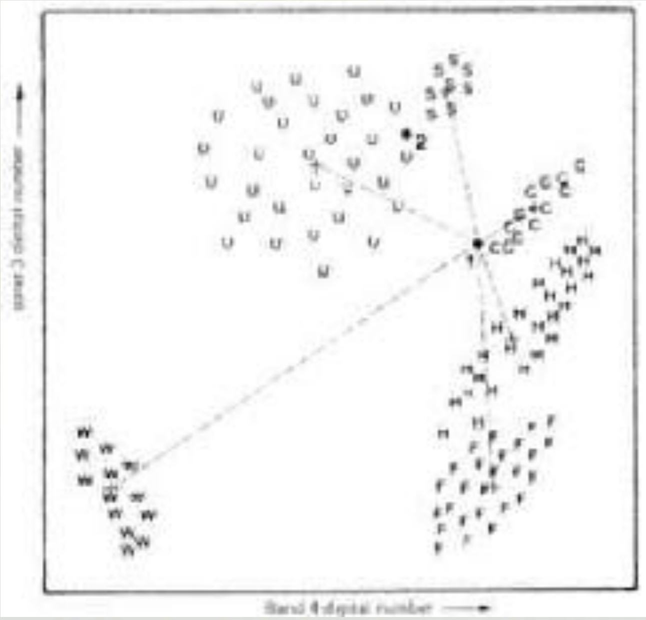
# Parallelepiped classification

- Is a pixel within a set of limits in FS?
  – Boxes (constants)
  – Mean + std. Dev
- \+ fast and simple, first pass classification, no distributions assumed
- \- covariance



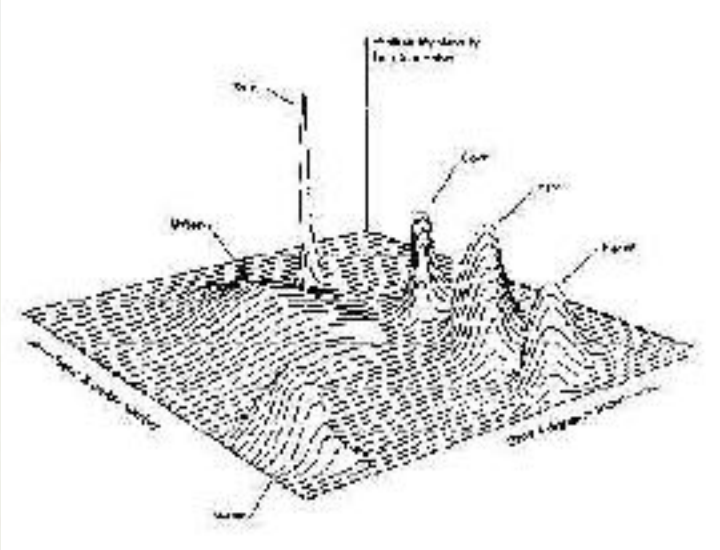
# Minimum Distance to Mean

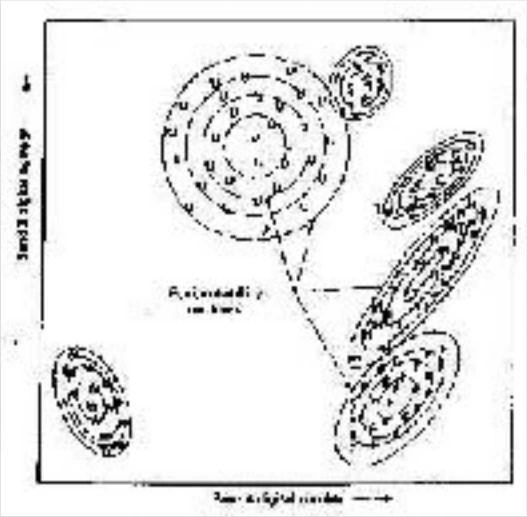
- Parametric
- Euclidean distance
- Mean – candidate pixel
- + fast
- +/- all pixels classified
- - variability of classes



# Maximum Likelihood/Bayes

• Strategy: maximize the probability of correct classification
• Equal probabilities
• normal distribution
• Known probabilities = Bayes
– Bayes theorem: state probability of one occurence given that another has already occured; conditional pr.
– Good performance requires good TDs
• Independence, autocorrelation!





# Segmentation

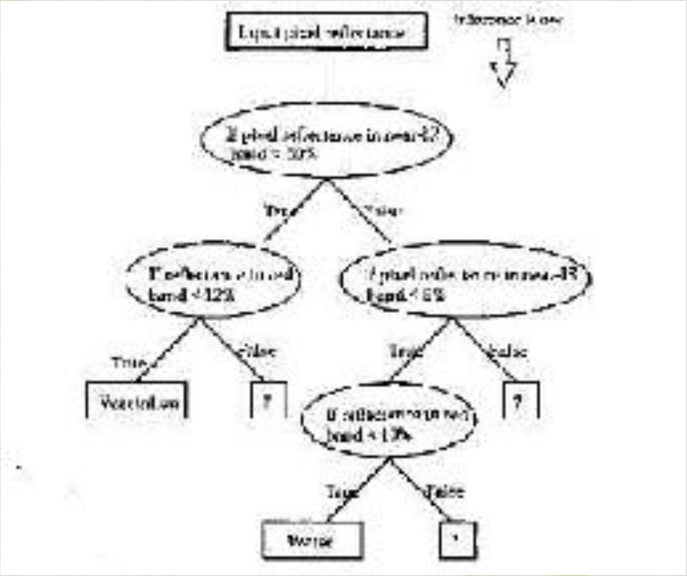
• What are you classifying?
– Pixels vs. Regions
• Segmentation – pathces delimited and merged according to various growingalgorithms
• Features of the regions used in classification
– Mean, variance, perimeter, area, holes
– ECHO
• Adv. in homogeneous landscapes; forestry, agriculture

# Textural classification

• Landscapes regions – diverse!
– Low-density residential land (buildings, lawns, trees, streets) – overall pattern of interest
• Texture – distinctive spatial and spectral pattern between neighboring pixels

# Rule based classification/decision tree

- If … then … else …
- Nonparametric
- Not needed extensive training
- Separability of classes!

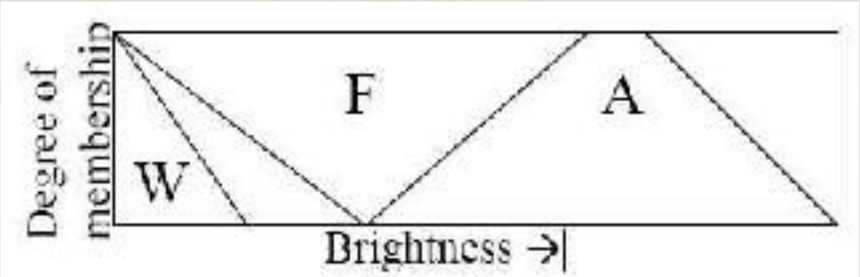


# Ancillary data

• Other data used to assist classification
• Compatibility!
• Strategies
– Stratification
• Layered classification (veg – non-veg)
• Slope/elvation
– Additional channel
– Modifying prior probabilities
– postclassification

# Fuzzy classifications

• Problem of one-to-one matches between pixels and classes
• Partial membership (mixed pixels!), one
pixel can belong to several classes
• Membership function
– General relationship
– Definitional rules
– Experimental data
• Apply to both statistical and deterministic classifications



# Contextual classifications

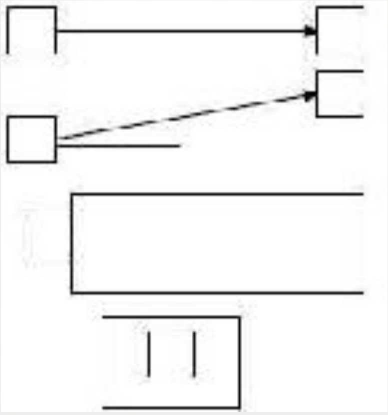
• Context – positional relationship between
pixels, classified or unclassified
• Preliminary classes

– Distance

– Direction

– Contiguity

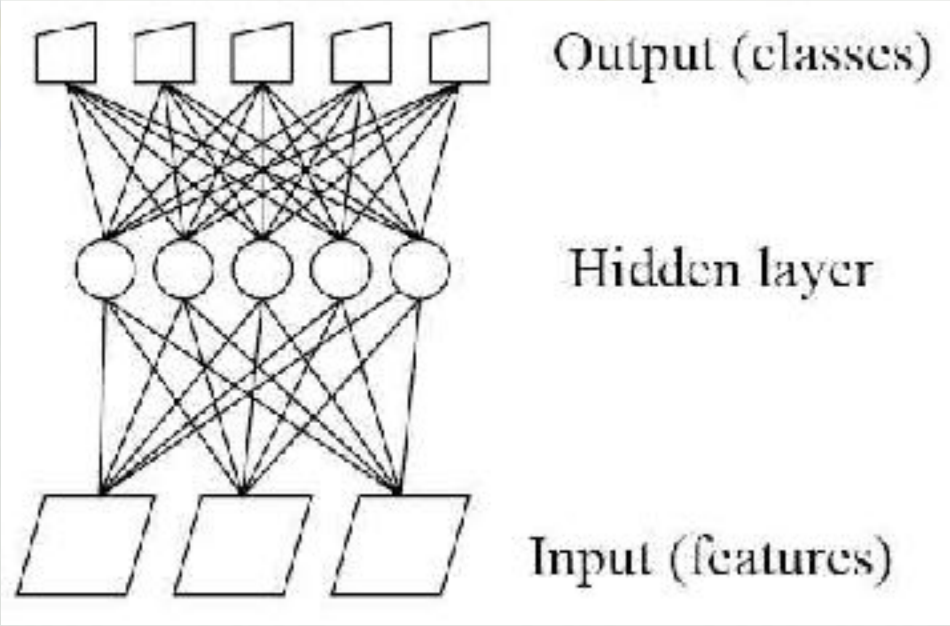
– Inclusion



• Used in post-classification or in rule based classifications

# Artificial Neural Networks

- Speech and handwriting recognition
- Complex mathematical function that converts input data to a desired output
- Function determined by learning (training samples)
- Applied for crisp and fuzzy classifications
- Non-normal distribution!



# Artificial Neural Networks

- Improved accuracy in image analysis!
- Processing units – neurones
- Various structures and learning algorithms developed – back propagation
- Difficult to apply successfully – parameters!

# The future

Statistical
Or
Determinsitic?