CLASSIFICATION ACCURACY ASSESEMENT and Change detection

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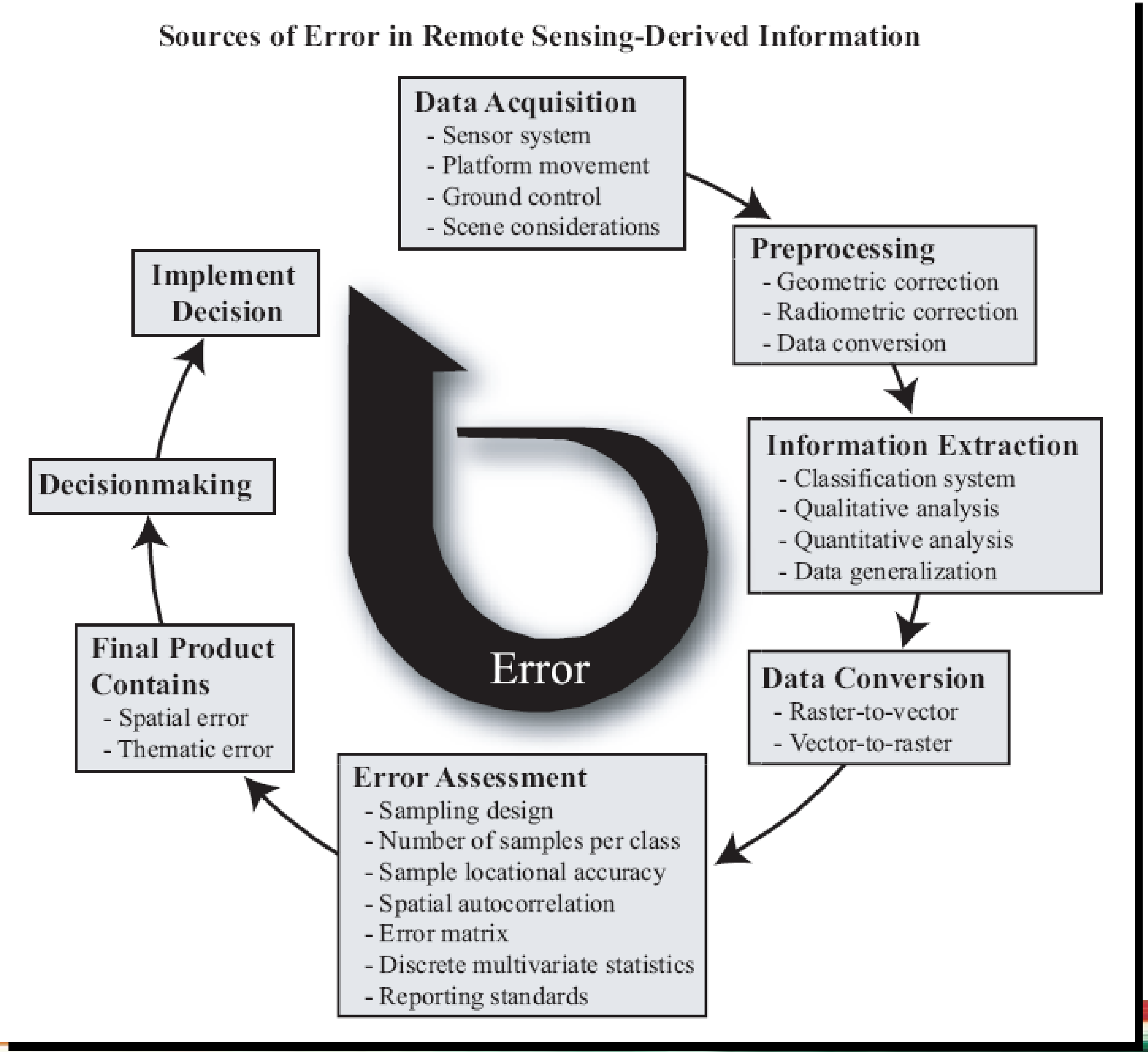
Accuracy Assessment……

Accuracy assessment is a general term for comparing the classification to geographical data that are assumed to be true, in order to determine the accuracy of the classification process. Usually, the assumed-true data are derived from ground truth data.

Accuracy Assessment

Because it is not practical to test every pixel in the classification image, a representative sample of reference points in the image with known class values is used

Sources of Errors



Ground Reference Test pixels

Locate *ground reference test pixels* (or polygons if the classification is based on human visual interpretation) in the study area.

- These sites are *not* used to train the classification algorithm and therefore represent unbiased reference information.
- It is possible to collect some ground reference test information prior to the classification, perhaps at the same time as the training data.
- Most often collected after the classification using a random sample to collect the appropriate number of unbiased observations per class.

Accuracy assessment "best practices"

- 30-50 reference points per class is ideal
- Reference points should be derived from imagery or data acquired at or near the same time as the classified image
- If no other option is available, use the original image to visually evaluate the reference points (effective for generalized classification schemes)

Sample Size

Sample size *N* to be used to assess the accuracy of a land-use classification map for the binomial probability theory:

$$N = \frac{Z^2(p)(q)}{E^2}$$

P **- expected percent accuracy,**

$q = 100 - p$,

E **- allowable error,**

Z **= 2 (from the standard normal deviate of 1.96 for the 95% two-sided confidence level).**

Sample Size

For a sample for which the expected accuracy is 85% at an allowable error of 5% (i.e., it is 95% accurate), the number of points necessary for reliable results is:

$$N = \frac{2^2(85)(15)}{5^2} = \text{a minimum of } 203 \text{ points.}$$

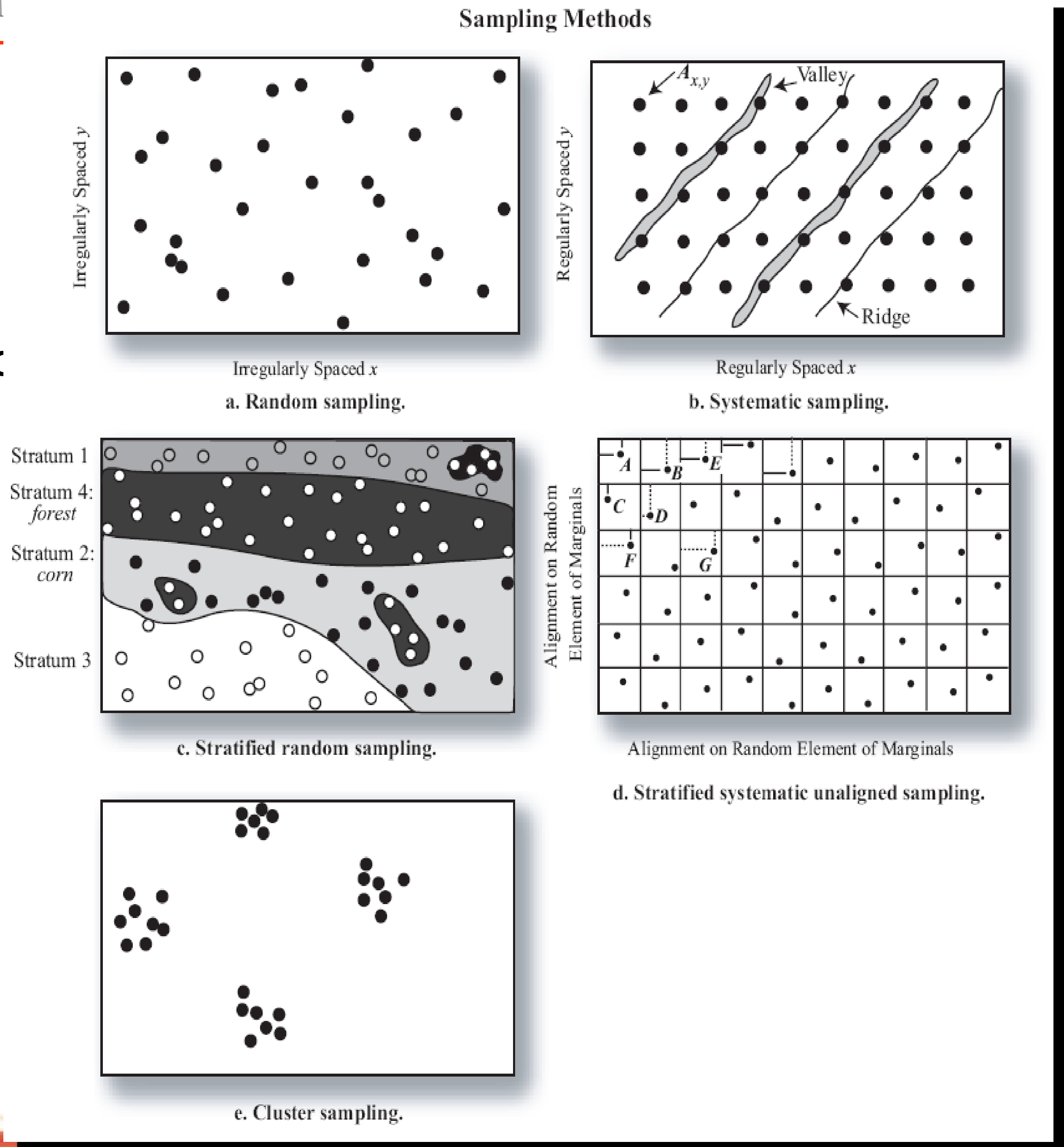
With expected map accuracies of 85% and an acceptable error of 10%, the sample size for a map would be 51:

$$N = \frac{2^2(85)(15)}{10^2} = 51 \text{ points}$$

Sample Design

There are basically five common samplin designs used to collect ground reference data for assessing the accuracy of a remo sensing-derived thematic map:

1. random sampling,
2. systematic sampling,
3. stratified random sampling,
4. stratified systematic unaligned sampling, and
5. cluster sampling.



a. Random sampling.

b. Systematic sampling.

c. Stratified random sampling.

d. Stratified systematic unaligned sampling.

e. Cluster sampling.

Commonly Used Methods of Generating Reference Points

- *Random*: no rules are used; created using a completely random process
- *Stratified random*: points are generated proportionate to the distribution of classes in the image
- *Equalized random*: each class has an equal number of random points

Commonly Used Methods of Generating Reference Points

- With a "stratified random" sample, a minimum number of reference points in each class is usually specified (i.e., 30)
- For example, a 3 class image (80% forest, 10% urban, 10% water) & 30 reference points:
- completely random: 30 forest, 0 urban, 1 water
- stratified random: 24 forest, 3 urban, 3 water
- equalized random: 10 forest, 10 urban, 10 water

ERROR MATRIX

Once a classification has been sampled a contingency table (also referred to as an error matrix or confusion matrix) is developed.

- This table is used to properly analyze the validity of each class as well as the classification as a whole.
- In this way the we can evaluate in more detail the efficacy of the classification.

One way to assess accuracy is to go out in the field and observe the actual land class at a sample of locations, and compare to the land classification it was assigned on the thematic map.

- There are a number of ways to quantitatively express the amount of agreement between the *ground truth* classes and the remote sensing classes.
- One way is to construct a confusion error matrix, alternatively called a ***error matrix***
- This is a row by column table, with as many rows as columns.
- Each row of the table is reserved for one of the information, or remote sensing classes used by the classification algorithm.
- Each column displays the corresponding ground truth classes in an identical order.

		Ground truth classes			No. classified
		A	B	C	pixels
Thematic map classes	A	**35**	2	2	39
	B	10	**37**	3	50
	C	5	1	**41**	47
No. ground truth pixels		50	40	46	136

OVERALL ACCURACY

- The diagonal elements tally the number of pixels classified correctly in each class.

An overall measure of classification accuracy is

$$\frac{total\ number\ of\ correct\ classifications}{total\ number\ of\ classifications}$$

which in this example amounts to $\frac{35+37+41}{136}$, or 83%.

- But just because 83% classifications were accurate overall, does not mean that each category was successfully classified at that rate.

USERS ACCURACY

- A user of the imagery who is particularly interested in class A, say, might wish to know what proportion of pixels assigned to class A were correctly assigned.
- In this example 35 of the 39 pixels were correctly assigned to class A, and the *user accuracy* in this category of 35/39 = 90%

		Ground truth classes			No. classified pixels
		A	B	C	
Thematic map classes	A	**35**	2	2	39
	B	10	**37**	3	50
	C	5	1	**41**	47
No. ground truth pixels		50	40	46	136

$$\frac{number\ of\ correct\ classifications}{total\ number\ of\ classifications\ in\ the\ category}$$

$$\frac{number\ in\ diagonal\ cell\ of\ error\ matrix}{number\ in\ row\ total}.$$

PRODUCERS ACCURACY

- Contrasted to user accuracy is producer accuracy, which has a slightly different interpretation.
- Producers accuracy is a measure of how much of the land in each category was classified correctly.
- It is found, for each class or category, as

$$\frac{number\ in\ diagonal\ cell\ of\ error\ matrix}{number\ in\ column\ \ total}$$

		Ground truth classes			No. classified
		A	B	C	pixels
Thematic	A	**35**	2	2	39
map	B	10	**37**	3	50
classes	C	5	1	**41**	47
No. ground truth pixels		50	40	46	136

The Producer's accuracy for class A is 35/50 = 70%

Kappa Analysis

K_{hat} Coefficient of Agreement:

- Kappa analysis yields a statistic, $\hat{K}$, which is an estimate of Kappa.
- It is a measure of agreement or accuracy between the remote sensing–derived classification map and the reference data as indicated by a) the major diagonal, and b) the chance agreement, which is indicated by the row and column totals (referred to as *marginals*).

Kappa Coefficient

- Expresses the proportionate reduction in error generated by the classification in comparison with a completely random process.
- A value of 0.82 implies that 82% of the errors of a random classification are being avoided

Kappa Coefficient

The Kappa coefficient is not as sensitive to differences in sample sizes between classes and is therefore considered a more reliable measure of accuracy; Kappa should always be reported

A Kappa of 0.8 or above is considered a good classification; 0.4 or below is considered poor

$$\hat{K} = \frac{M \sum_{i=j=1}^{r} n_{ij} - \sum_{i=j=1}^{r} n_i n_j}{M^2 - \sum_{i=j=1}^{r} n_i n_j}$$

Where:

r = number of rows in error matrix
n_{ij} = number of observations in row i, column j
n_i = total number of observations in row i
n_j = total number of observations in column j
M = total number of observations in matrix

Kappa Coefficient

classified image

reference data

	forest	shrubland	grassland	urban	*totals*
forest	150	5	15	10	*180*
shrubland	15	55	5	5	*80*
grassland	10	20	105	5	*140*
urban	25	20	5	50	*100*
totals	*200*	*100*	*130*	*70*	*500*

$$\hat{K} = \frac{M\sum_{i=j=1}^{r} n_{ij} - \sum_{i=j=1}^{r} n_i n_j}{M^2 - \sum_{i=j=1}^{r} n_i n_j}$$

$$= \frac{(500\times 360) - [(180\times 200) + (80\times 100) + (140\times 130) + (100\times 70)]}{500^2 - [(180\times 200) + (80\times 100) + (140\times 130) + (100\times 70)]}$$

$$= \frac{180{,}000 - 69{,}200}{250{,}000 - 69{,}200} = \frac{110{,}800}{180{,}800}$$

$$= 0.613$$

KAPPA COEFFICENT

For an error matrix with **r** rows, and hence the same number of columns, let – A = the sum of **r** diagonal elements, which is the numerator in the computation of overall accuracy. Let B = sum of the r products (row total x column total).Then

$$\hat{\kappa} = \frac{NA - B}{N^2 - B}$$

where N is the number of pixels in the error matrix (the sum of all r individual cell values).

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For the above error matrix,
– A = 35 + 37 + 41 = 113
– B = (39 * 50) + (50 * 40) + (47 * 46) = 6112
– N = 136

Change Detection

Methods and Procedures

CHANGE DETECTION

- The process of identifying differences in the state of an object or phenomenon by observing it at different times.
- Usually applied to Earth surface changes at two or more times.
- Land-use/land-cover change - a major component of global change with an impact perhaps greater than that of climate change.
- It provides the foundation for better understanding relationships and interactions between human and natural phenomena to better manage and use resources.
- It involves the application of multi-temporal datasets for quantitative analysis of the temporal effects of the phenomenon.

Applications of change detection techniques

- Land-use and land-cover (LULC) change
- Forest or vegetation change
- Forest mortality, defoliation and damage assessment
- Deforestation, regeneration and selective logging
- Wetland change
- Forest fire and fire-affected area detection
- Landscape change
- Urban change
- Environmental change, drought monitoring, flood monitoring, monitoring coastal marine environments, desertification, and detection of landslide areas
- Other applications such as crop monitoring, shifting cultivation monitoring, road segments, and change in glacier mass balance.

Considerations before implementing change detection

The following conditions must be satisfied:

1. Precise registration of multi-temporal images.

2. Precise radiometric and atmospheric calibration or normalization between multi-temporal images.

3. Selection of the same spatial and spectral resolution images if possible.

Note:

Digital change detection is affected by spatial, spectral, radiometric and temporal constraints.

Change detection techniques :

1. Algebra Based Approach
- Image differencing
- image regression
- image ratioing
- Vegetation index differencing
- change vector analysis

2. Classification Based
- Post-Classification Comparison
- Spectral-Temporal Combined Analysis
- EM Transformation
- Unsupervised Change Detection
- Hybrid Change Detection
- Artificial Neural Networks (ANN)

3. Transformation
- PCA
- Tasseled Cap (KT)
- Gramm-Schmidt (GS)
- Chi-Square

4. Advanced Models
- Li-Strahler Reflectance Model
- Spectral Mixture Model
- Biophysical Parameter Method

5. GIS based
- Integrated GIS and RS Method
- GIS Approach

6. Visual Analysis
- Visual Interpretation

7. Other Change Detection Techniques
- Measures of spatial dependence
- Knowledge-based vision system
- Area production method
- Combination of three indicators: vegetation indices, land surface temperature, and spatial structure
- Change curves
- Generalized linear models
- Curve-theorem-based approach
- Structure-based approach
- Spatial statistics-based method

Category I: Algebra based Approach

- These algorithms have a common characteristic, i.e. selecting thresholds to determine the changed areas.

- The algebra category includes-

1. Image differencing
2. Image regression
3. Image rationing
4. Vegetation index differencing
5. Change vector analysis (CVA)
6. Background subtraction

- These methods (excluding CVA) are relatively simple, straightforward, easy to implement and interpret, but these cannot provide complete matrices of change information.

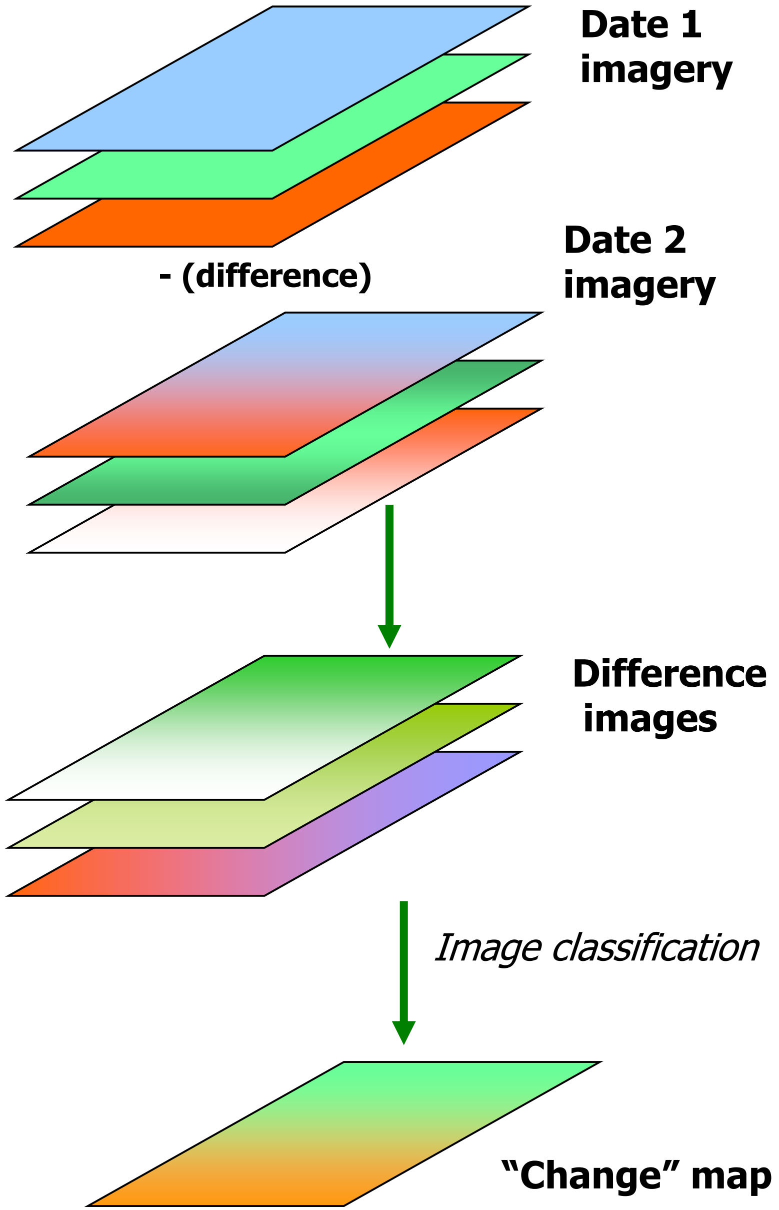
- In this category, two aspects are critical for the change detection results: selecting suitable image bands, selecting suitable thresholds.

Image differencing

- **Characteristics:** Subtracts the first date image from a second-date image, pixel by pixel.

- **Advantages:**
  - Simple and straightforward, easy to interpret results.
  - Efficient way to detect change
  - Requires only one classification

- **Disadvantages:**
  - Cannot provide a detailed change matrix ("From-to" change information is not available)
  - Requires careful definition of "change - no change" threshold (differences in DN values due to other factors such as phenology, sun angle, atmosphere or sensors differences are not "real" changes)
  - Requires acquisition of comparable imagery and careful radiometric calibration such that where there are no changes in land cover the images are near identical (i.e., difference equals zero)



- **Key factors:** Identifies suitable image bands and thresholds.

Image differencing

8	10	8	11
240	11	10	22
205	210	205	54
220	98	88	46

Image Date 1

5	9	7	10
97	9	8	22
98	100	205	222
103	98	254	210

Image Date 2

3	1	1	1
143	2	2	0
107	110	0	-168
117	0	-166	-164

Difference Image =
Image 1 - Image 2

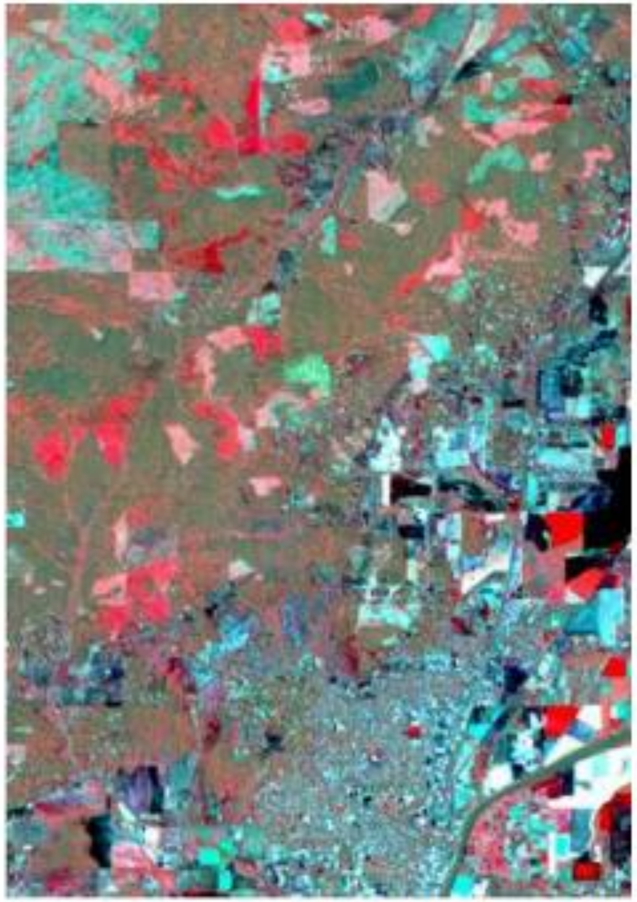


Image Difference (TM99 – TM88)

Image regression

- Characteristics: Establishes relationships between bi-temporal images, then estimates pixel values of the second-date image by use of a regression function, subtracts the regressed image from the first-date image.

- Advantages: Reduces impacts of the atmospheric, sensor and environmental differences between two-date images.

- Disadvantages: Requires to develop accurate regression functions for the selected bands before implementing change detection.

- Examples: Tropical forest change (Singh 1986) and forest conversion (Jha and Unni 1994).

- Key factors: Develops the regression function; identifies suitable bands and thresholds

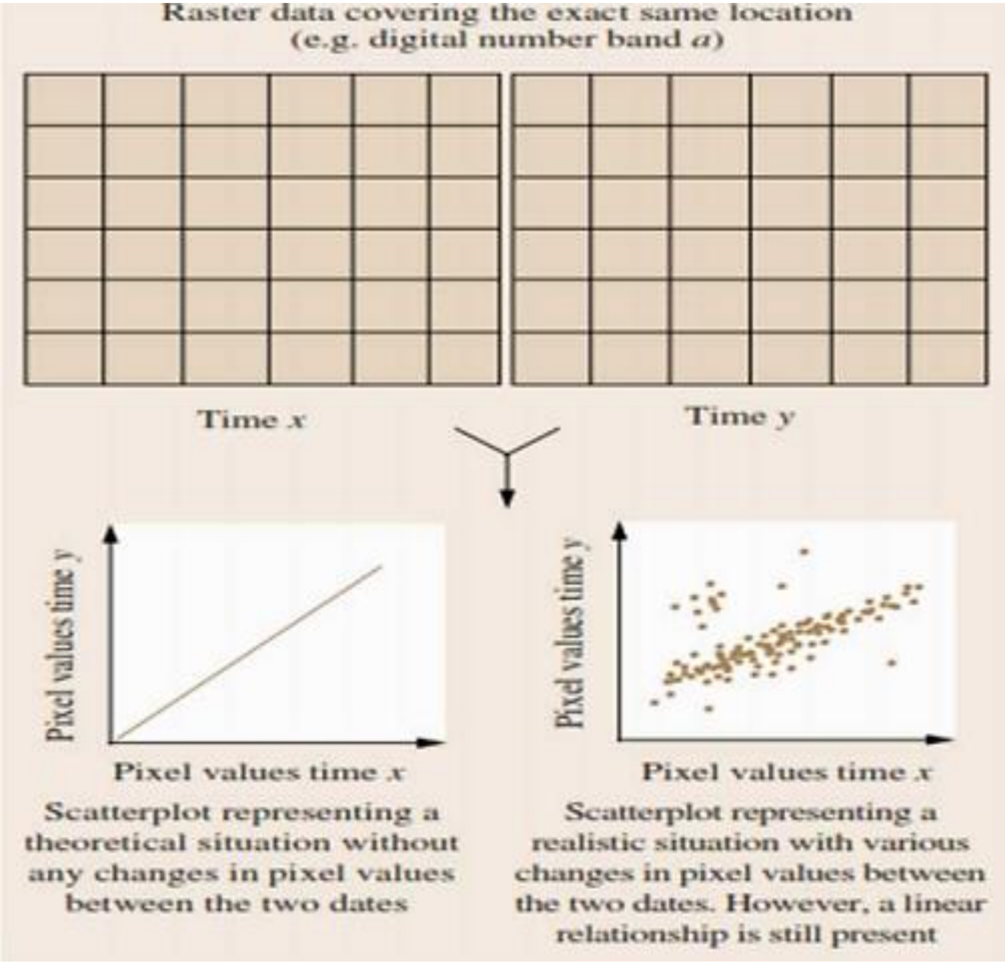


Image ratioing

- Characteristics: Calculates the ratio of registered images of two dates, band by band.
- Advantages: Reduces impacts of Sun angle, shadow and topography.
- Disadvantages: Non-normal distribution of the result is often criticized.
- Examples: Land-use mapping and change detection (Prakash and Gupta 1998).
- Key factors: Identifies the image bands and thresholds.

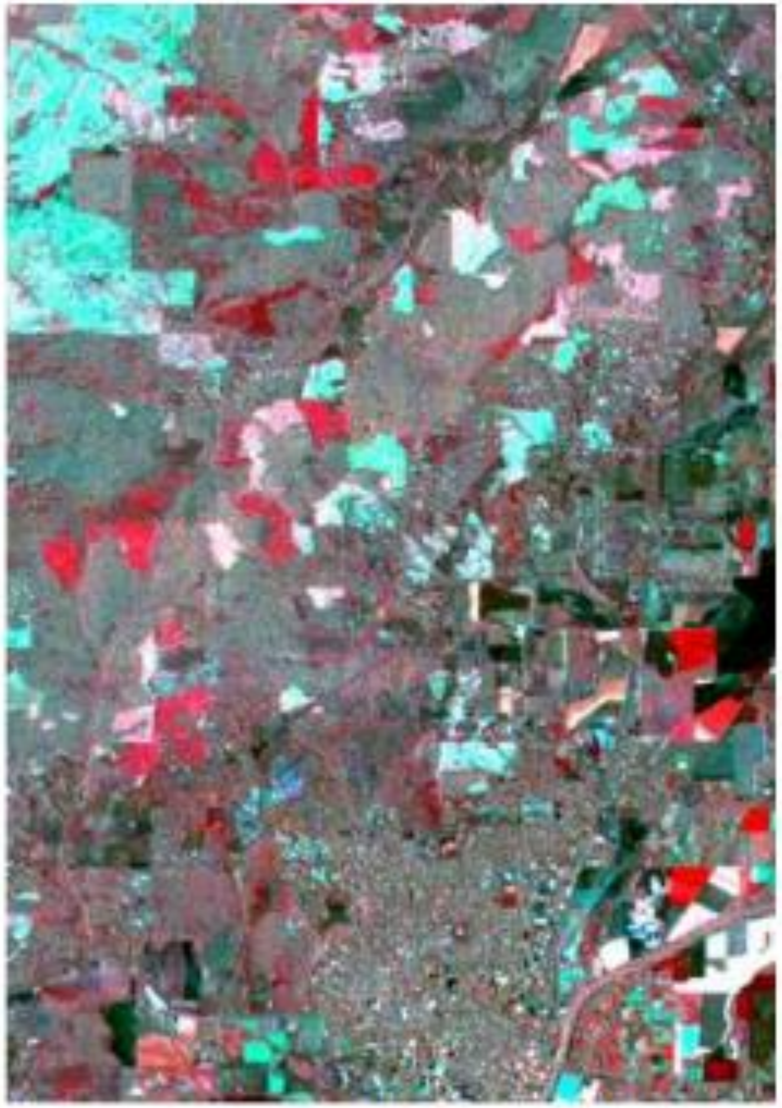


Image Ratio (TM99 / TM88)

Vegetation index differencing

- Characteristics: Produces vegetation index separately, then subtracts the second-date vegetation index from the first-date vegetation index.
- Advantages: Emphasizes differences in the spectral response of different features and reduces impacts of topographic effects and illumination.
- Disadvantages: Enhances random noise or coherence noise.
- Key factors: Identifies suitable vegetation index and thresholds.

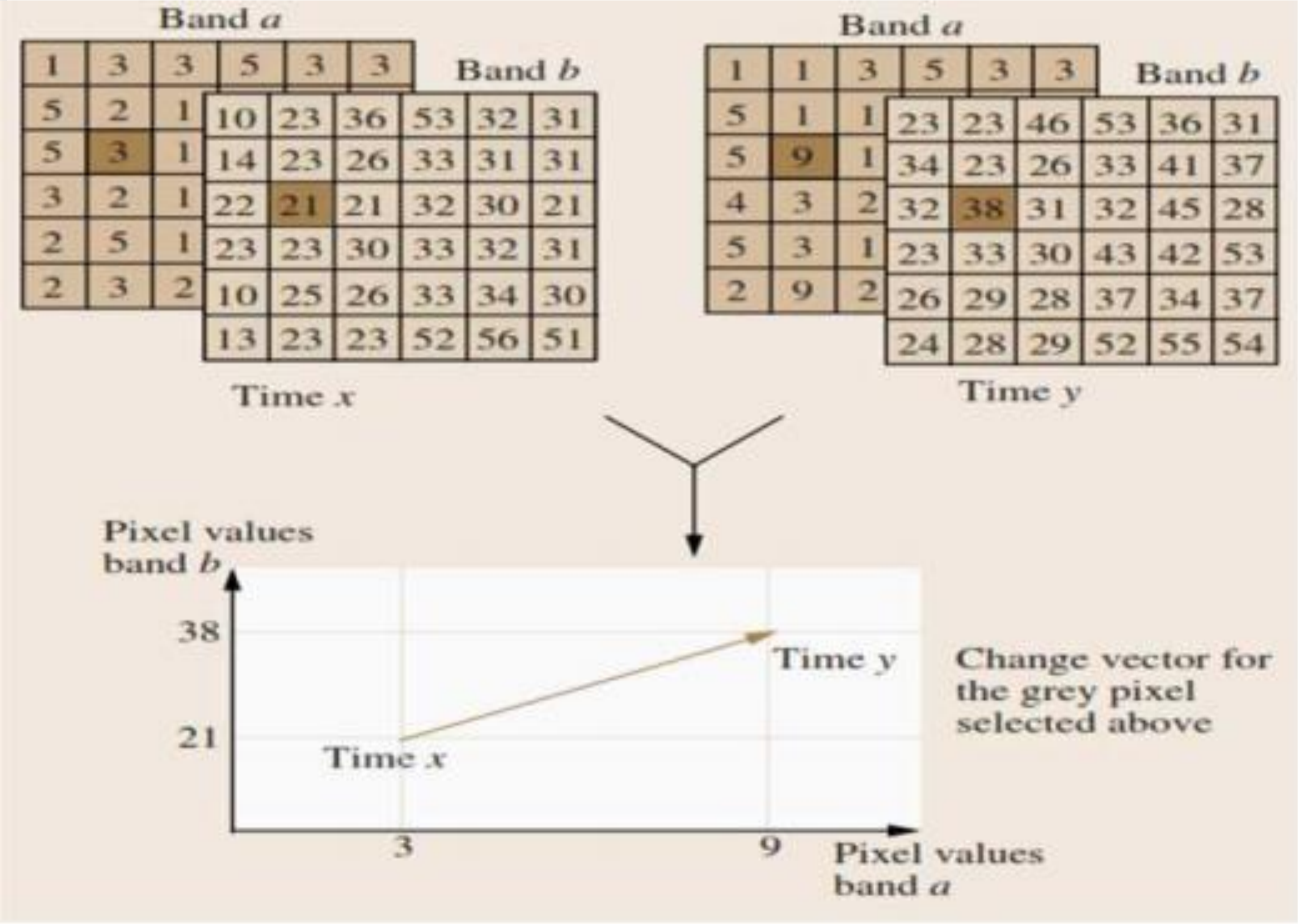
Background subtraction

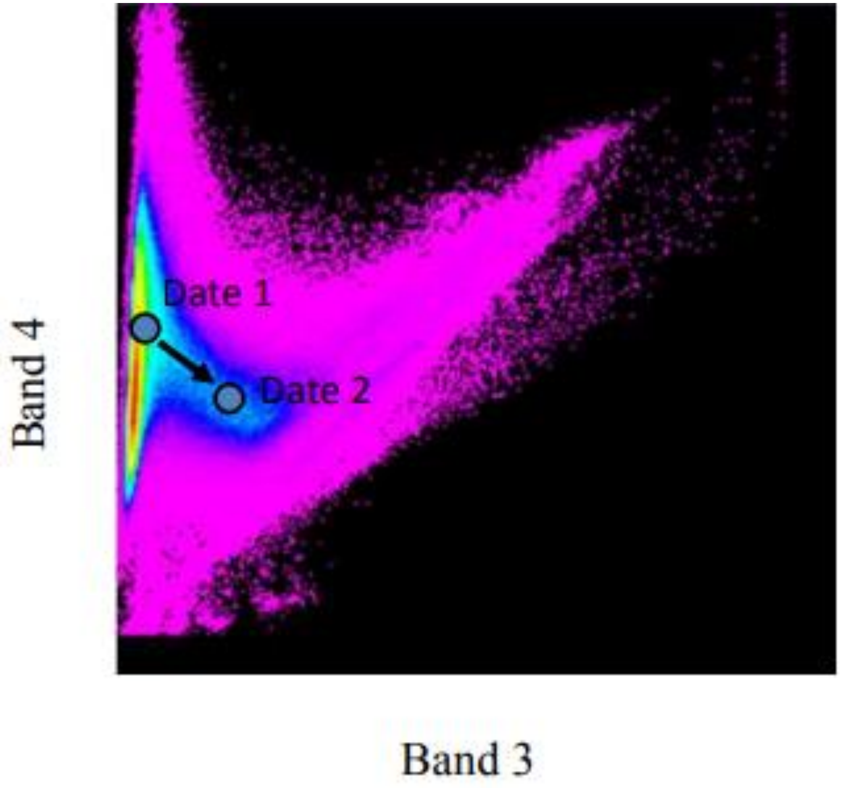
- Characteristics:
  - Non-change areas have slowly varying background grey levels.
  - A low-pass filtered variant of the original image is used to approximate the variations to the background image.
  - A new image is produced through subtracting the background image from the original image.
- Advantages: Easy to implement.
- Disadvantages: Low accuracy.
- Key factors: Develops the background image.

Change vector analysis (CVA)

- Characteristics: Generates two outputs:
  - (1) the spectral change vector describes the direction and magnitude of change from the first to the second date; and
  - (2) the total change magnitude per pixel is computed by determining the Euclidean distance between end points through n-dimensional change space.
- Advantages: Ability to process any number of spectral bands desired and to produce detailed change detection information.
- Disadvantages: Difficult to identify land cover change trajectories.
- Key factors: Defines thresholds and identifies change trajectories

Change vector analysis (CVA)





Category II: Transformation of datasets

- **PCA**
- **Tasseled Cap (KT)**
- **Gramm-Schmidt (GS)**
- **Chi-Square**

1. Principal component analysis (PCA)

➢ Assumes that multi-temporal data are highly correlated and change information can be highlighted in the new components.

➢ Two ways to apply PCA for change detection are:

(1) Put two or more dates of images into a single file, then perform PCA and analyse the minor component images for change information.

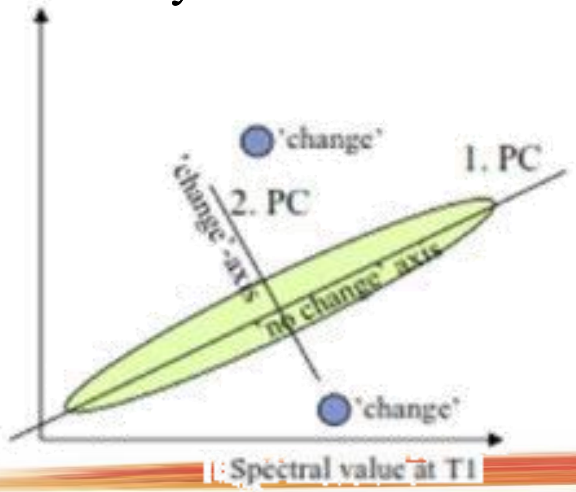
(2) Perform PCA separately, then subtract the second-date PC image from the corresponding PC image of the first date.

Principal component analysis (PCA)

- **Advantages:** Reduces data redundancy between bands and emphasizes different information in the derived components.

- **Disadvantages:**
  - PCA is scene dependent, thus the change detection results between different dates are often difficult to interpret and label.
  - It cannot provide a complete matrix of change class information and requires determining thresholds to identify the changed areas.

- **Key factors:** Analyst's skill in identifying which component best represents the change and selecting thresholds.



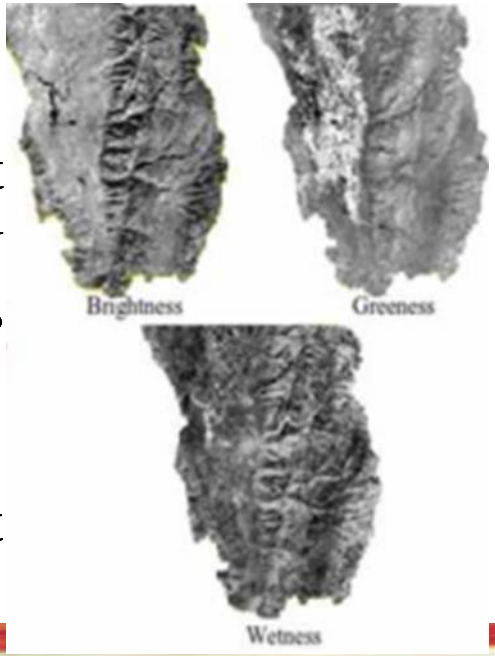
Tasselled cap (KT)

- The principle of this method is similar to PCA.
- The only difference from PCA is that PCA depends on the image scene, and KT transformation is independent of the scene.
- The change detection is implemented based on the three components: brightness, greenness and wetness.

- Advantages: Reduces data redundancy between bands and emphasizes different information in the derived components. KT is scene independent.

- Disadvantages: Difficult to interpret and label change information, cannot provide a complete change matrix; requires determining thresholds to identify the changed areas. Accurate atmospheric calibration for each date of image is required.

- Key factors: Analyst's skill is needed in identifying which component best represents the change and selecting thresholds.



Gramm– Schmidt (GS)

- The GS method orthogonalizes spectral vectors taken directly from bi-temporal images, as does the original KT method, produces three stable components corresponding to multi-temporal analogues of KT brightness, greenness and wetness, and a change component.

- Advantages: The association of transformed components with scene characteristics allows the extraction of information that would not be accessible using other change detection techniques.

- Disadvantages:
  - It is difficult to extract more than one single component related to a given type of change.
  - The GS process relies on selection of spectral vectors from multi-date image typical of the type of change being examined.

- Key factors: Initial identification of the stable subspace of the multi-date data is required.

Chi-square

- $Y=(X-M)^T \Sigma^{-1}*(X-M)$ Y: digital value of change image

  X: vector of the difference of the six digital values between the two dates

  M: vector of the mean residuals of each band

  T: transverse of the matrix,

  Σ^{-1}: inverse covariance matrix of the six bands

- Advantages: Multiple bands are simultaneously considered to produce a single change image.

- Disadvantages: The assumption that a value of Y=0 represents a pixel of no change is not true when a large portion of the image is changed.
- Also the change related to specific spectral direction is not readily identified.

- Key factors: Y is distributed as a Chi-square random variable with p degrees of freedom (p is the number of bands).

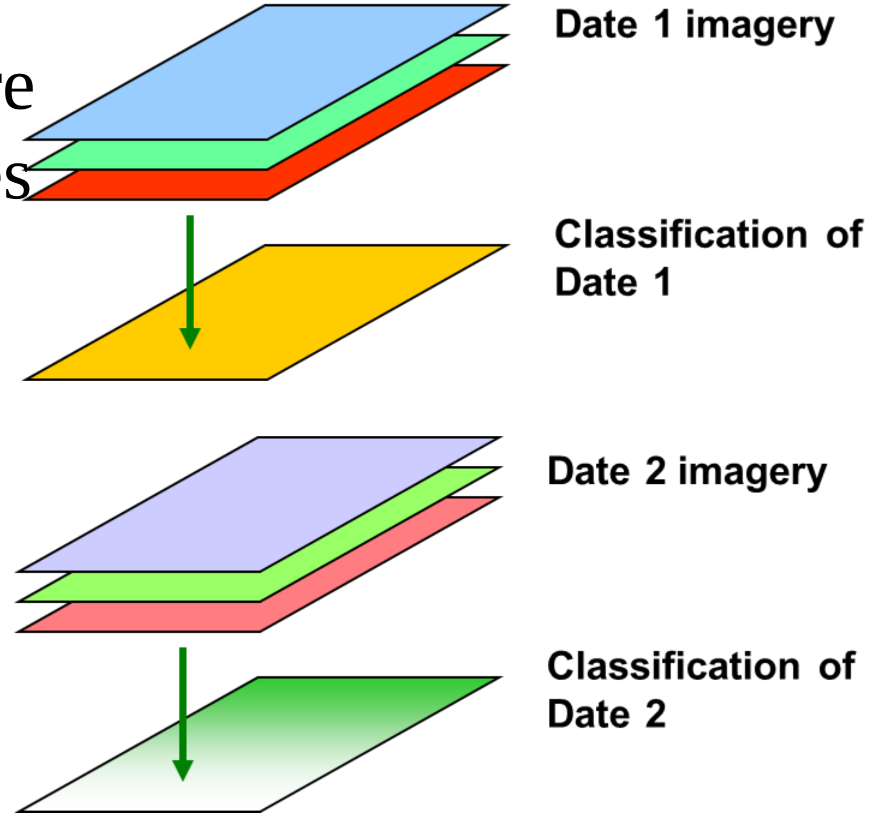
Category III: Classification based approach

1. Post-Classification Comparison
2. Spectral-Temporal Combined Analysis
3. EM Transformation
4. Unsupervised Change Detection
5. Hybrid Change Detection
6. Artificial Neural Networks (ANN)

Post-classification

- Post-classification (delta classification)

– Classify Date 1 and Date 2 separately, compare class values on pixel by pixel basis between dates



- **Advantages:**

– Avoids need for strict radiometric calibration

– Favours classification scheme of user

– Designates type of change occurring

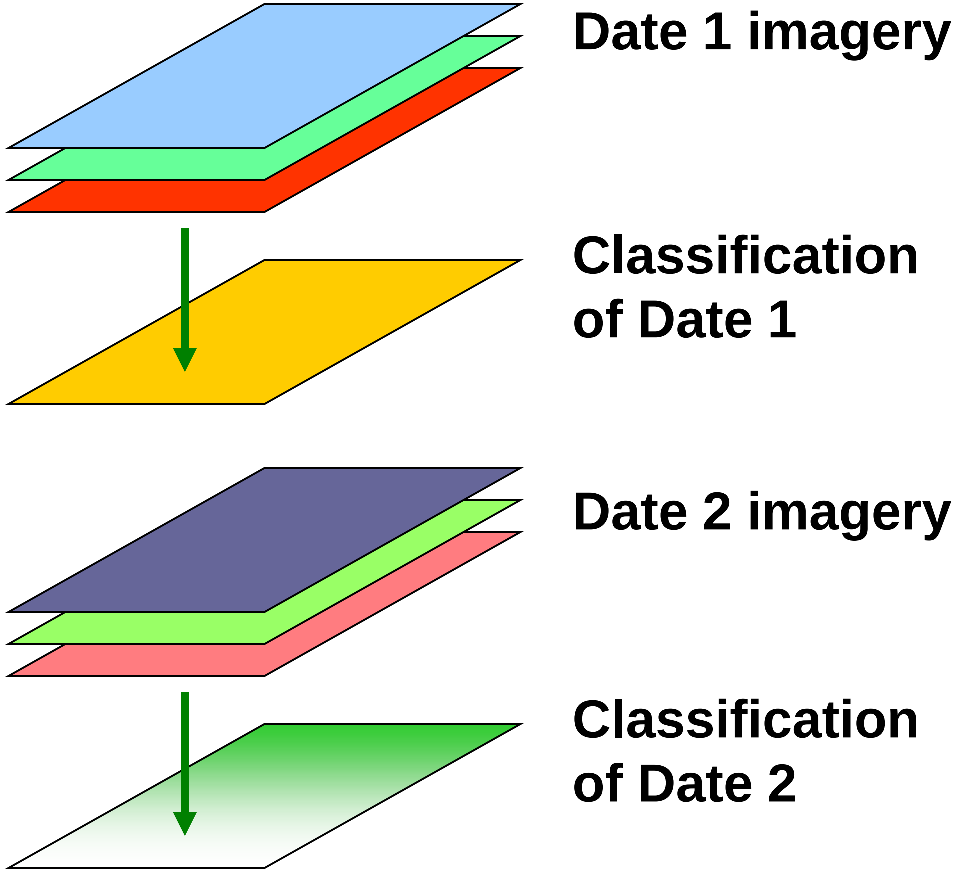
- **Disadvantages:**

– Error is multiplicative from two parent maps

– Changes within classes may be interesting

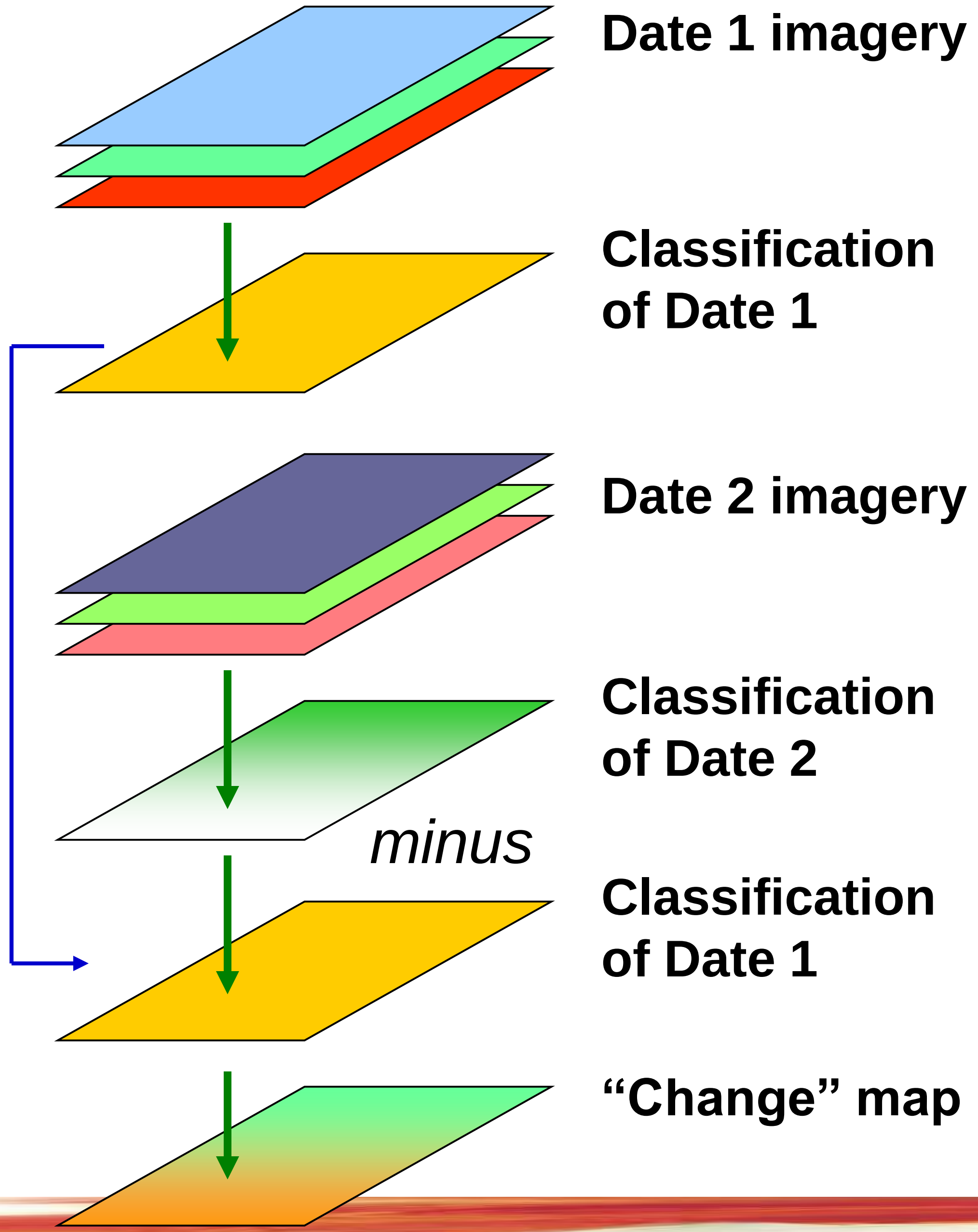
Comparison of Classifications

- Two dates are classified separately



Comparison of Classifications

- Two dates are classified separately
- Classification map of Date 2 is then subtracted from the map of Date 1



Comparison of Classifications

- Advantages
  - **provides “from - to” change class information**
  - **next base year is already completed**
- Disadvantages
  - **accuracy of change map depends on the accuracy of the individual classifications**
  - **requires two classifications**

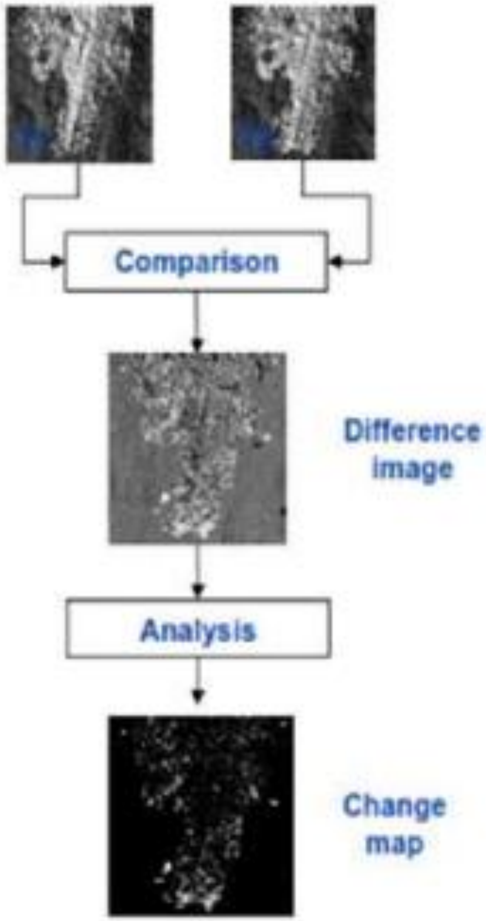
Unsupervised techniques

► Objective
Produce a change detection map in which changed areas are separated from unchanged ones.

► The changes sought are assumed to result in larg changes in radiance values than other factors.

► Comparison is performed directly on the spectral data.

► This results in a difference image which is analysed to separate insignificant from significant changes.



Supervised techniques

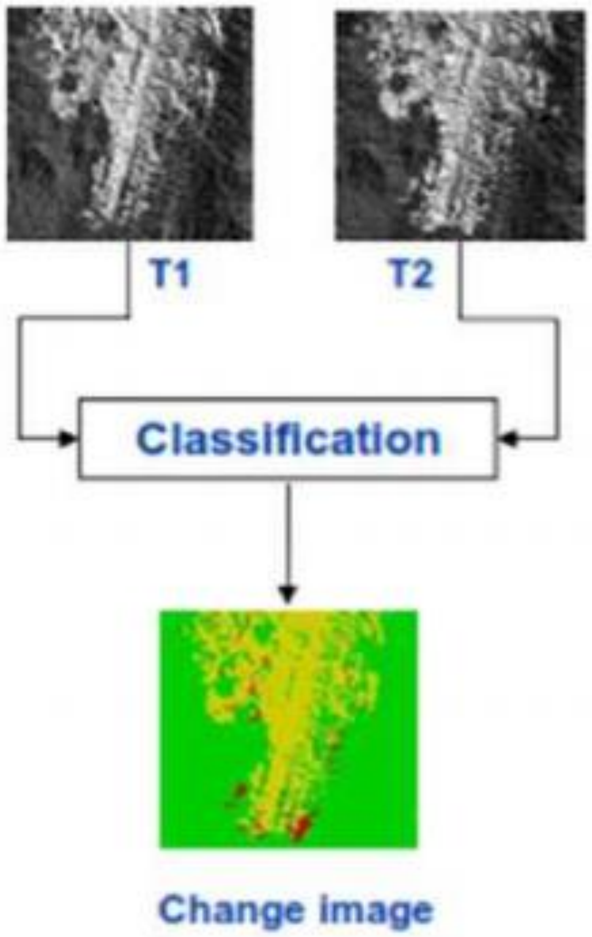
➢Objective:

Generate a change detection map where changed areas are identified and the land-cover transition type can be identified.

➢The changes are detected and labelled using supervised classification approaches.

➢ Main techniques:

- Post-classification comparison
- Multi-date direct classification



Post-classification comparison

► Standard supervised classifiers are used to classify the two images independently.

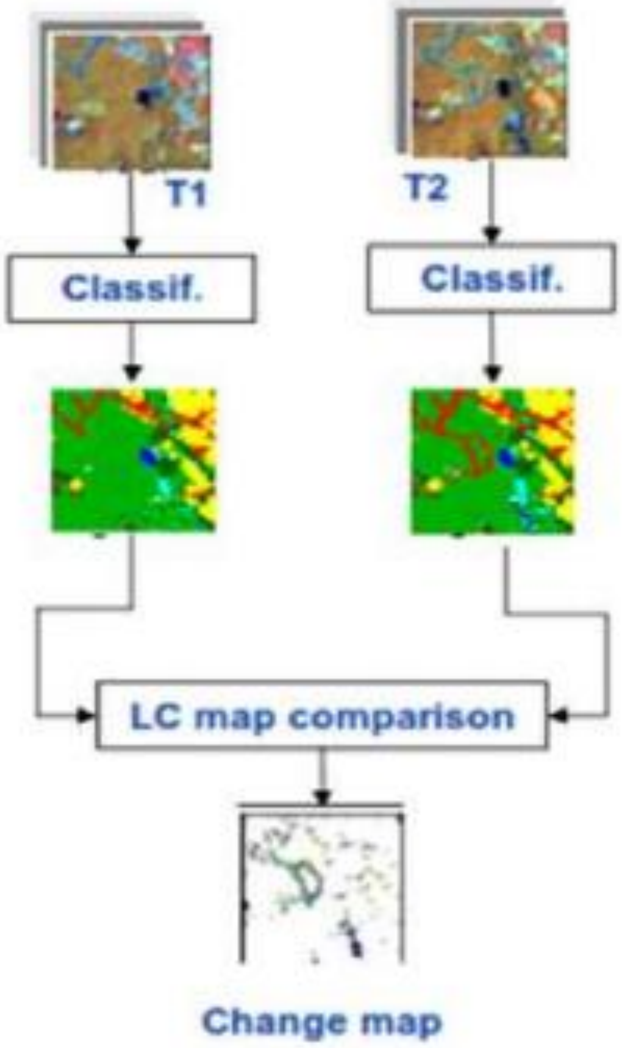
► Changes are detected by comparing the two classified images.

► **Advantage**

- Common and intuitive.
- Provides change matrix.

► **Drawback**

- Critically depends on the accuracy of the classification maps. Accuracy close to the product of the two results.
- Does not exploit the dependence between the information from the two points in time.



Post-classification comparison

A	A	A	B	B	B
A	A	B	B	B	B
A	A	B	B	B	B
B	B	B	C	B	B
B	B	C	B	B	B
B	B	B	B	B	B

A	A	A	B	B	B
A	A	B	B	B	B
A	A	C	C	B	B
B	B	C	C	B	B
B	B	C	C	C	B
B	B	C	B	B	B

Example of change matrix (pixel count). Change appears in bold.

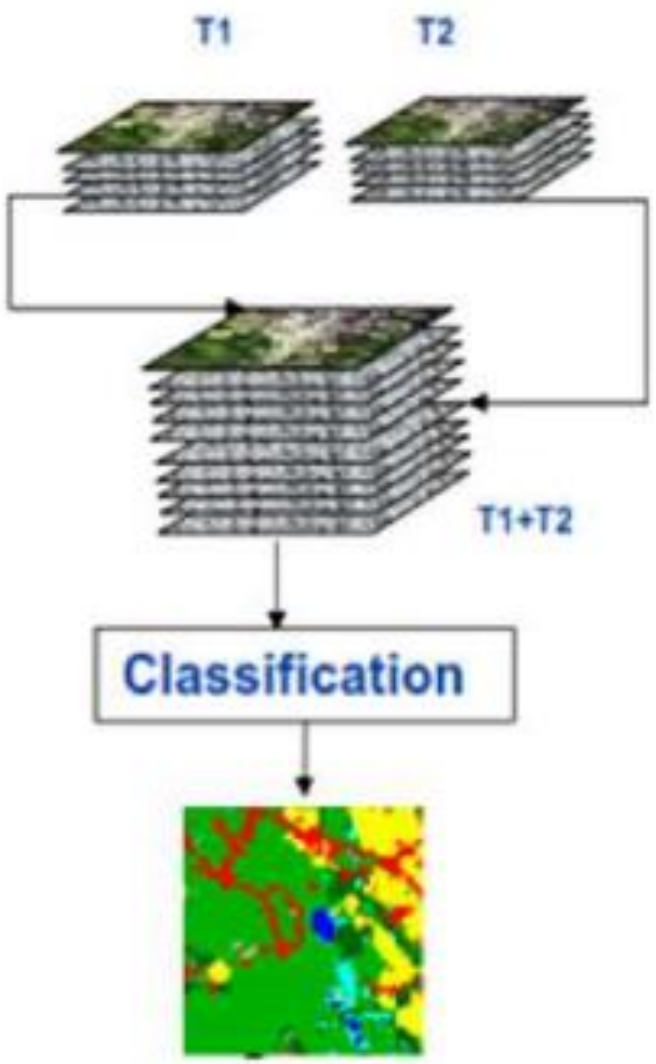
ClassTime x / ClassTime y	A	B	C	Total
A	7	0	0	7
B	0	21	0	21
C	0	**6**	**2**	8
Total	7	27	2	36

Multi-date direct classification

► Two dates are combined into one multi-temporal image and classified.

► Performs joint classification of the two images by using a stacked feature vector.

► Change detection is performed by considering each transition as a class, and training the classifier to recognize all classes and all transitions.



► **Advantage**

- Exploits the multi-temporal information.
- Error rate not cumulative.
- Provides change matrix.

► **Drawback**

- Ground truth required also for transitions

Supervised v/s Unsupervised

	Supervised	Unsupervised
Level of change detection	Change detection at decision level.	Change detection at data level.
Change information	Provides explicit labeling of change and class transitions	Separates ‘change’ from ‘no change’.
Change computation	Obtained directly from the classified images.	Obtained through interpretation of the difference image.
Ground truth	Requires ground truth.	Requires no ground truth.
Spectral information.	Multispectral.	Most methods work on one spectral band.
Data requirements	Not sensitive to atmospheric conditions and sensor differences.	Sensitive to atmospheric conditions and sensor differences.

Other Advanced approaches

An MRF approach to unsupervised change detection

- Based on a technique that exploits the expectation-maximization (EM) algorithm for the estimation of the density functions associated with both the changed and unchanged pixels in the difference image.
- Then, on the basis of such estimates, an automatic method for the unsupervised analysis of the difference image is described.
- The method makes use of Markov random fields (MRFs) for modelling the spatial-contextual information included in the neighbourhood of each pixel.

Markov Chain Analysis

- A technique for predictive change modeling.
- Predictions of future change are based on changes that have occurred in the past.
- It ignores the forces and processes that produced the observed patterns.
- It assumes that the forces that produced the changes will continue to do so in the future.
- Insensitive to space

Cellular Automata

- Creates a “spatially-explicit weighting factor.
- Weighting factor applied to each of the suitabilities, weighing more heavily areas that are in proximity to existing land uses
- Ensures that landuse change occurs in proximity to existing like landuse classes, and not in a wholly random manner
- Adds ***spatial contiguity*** as well as knowledge of the likely spatial distribution of transitions to Markov change analysis.

•Markov model is capable of accurate measurement of the magnitude of change but fails in predicting the direction of change

• Cellular Automata (CA) incorporates the spatial component and thus includes direction into modeling process.

Change detection of remote sensing images : DT-CWT AND MRF

- An unsupervised algorithm is proposed based on the combination between Dual-tree Complex Wavelet Transform (DT-CWT) and Markov random Field (MRF) model.

- This method first performs multi-scale decomposition for the difference image by the DT-CWT and extracts the change characteristics in high-frequency regions by using a MRF-based segmentation algorithm.

- Then this method estimates the final maximum a posterior (MAP) according to the segmentation algorithm of iterative condition model (ICM) based on fuzzy c-means(FCM) after reconstructing the high-frequency and low-frequency sub-bands of each layer respectively.

- Finally, the method fuses the above segmentation results of each layer by using the fusion rule proposed to obtain the mask of the final change detection result.

Remote Sensing Image Change Detection based on Swarm Intelligence Algorithms

- Ant colony optimization (ACO) and Particle swarm optimization (PSO) as the two main algorithms of swarm intelligence.
- Properties of self-organization, cooperation, communication and other intelligent merits, they have great potential for research .
- Algorithms for constructing the change rules, then use these rules to process the data.

Analyzing Nature of Change

•Nature of change can be assessed by analyzing the change trajectories in land cover classes over time.

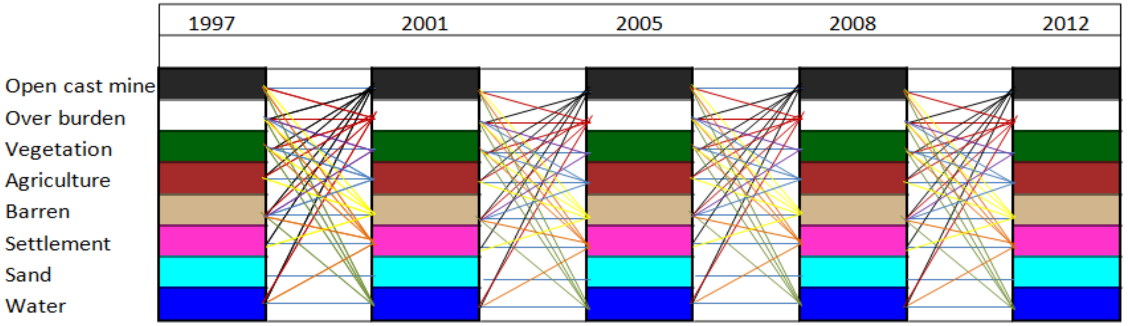
•These trajectories are described as trends over time which is responsible for changes in earth resource dynamics in a particular area .

•Trajectories of land-cover change are generated which refer to successive land-cover types for a given pixel over period of observation.

Analyzing Spatial Pattern of Change

•Knowledge of

- •Changes occurred at particular location
- •the reason for such changes
- •the rate at which the changes have occurred
- •the future scenario if driving forces operate at same pace



All possible change trajectories corresponding to different LULC classes

Factors to consider when choosing a method

- **Objective of the change detection?**
  - Monitor/identify specific changes
  - More efficient mapping at T2
  - Improved quality of mapping at T2
- **What type of change information to extract?**
  - Spectral changes
  - Land cover transitions
  - Shape changes
  - Changes in long temporal series
- **What type of changes to be considered?**
  - Land use and land cover change
  - Forest and vegetation change
  - Wetland change
  - Urban change
  - Environmental change

प्रश्नोत्तरी / Quiz

ELECTRONIC COLLABORATIVE LEARNING AND KNOWLEDGE SHARING SYSTEM

सभी प्रतिभागियों से अनुरोध है कि प्रश्नोत्तरी में भाग लेने हेतु वे ई-क्लास में लॉगिन करें:

URL : https://eclass.iirs.gov.in/login

नोट: प्रतिभागी जो पहले से ही ई-क्लास में लॉगइन हैं , प्रश्नोत्तरी में भाग लेने हेतु कृपया अपने वेब पेज को रिफ्रेश करें ।

All the Participants are requested to login in E-CLASS :

URL : https://eclass.iirs.gov.in/login

Note : Participants who are already logged in, please refresh your Web Page to Participate in the quiz.

Quiz Time…….

In Stratified random sampling:

- points are generated proportionate to the distribution of classes in the image
- each class has an equal number of random points
- no rules are used; points created using a completely random process

Kappa Coefficient expresses:

- Correctly classified pixels in the image
- what proportion of pixels assigned to a class were correctly assigned
- how much of the land in each category was classified correctly
- the proportionate reduction in error generated by the classification in comparison with a completely random process

Image rationing:

- Subtracts the first date image from a second-date image
- Calculates the ratio of registered images of two dates, band by band
- Generates the spectral change vector describes the direction and magnitude of change

THANKYOU