Change Detection Techniques

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General Questions

• Where and when has change taken place in the landscape?
• How much change, and what type of change has occurred?
• What are the cycles and trends in the change?
Types of Change Detection

• Between-class changes
  – Based on classification imagery
  – Answers the question, “Has a pixel changed and what has it changed to?”
  – e.g. forest to agriculture conversion

• Within-class changes
  – Based on continuous spectral or transformed spectral information
  – Answers the question, “How much and in what direction has a pixel changed?”
  – e.g. change in % vegetation cover
Types of Change Detection

• Use of time as an implicit variable
  – The actual time differences are not used in the analysis, just the fact that two images are from different times.

• Use of time as an explicit variable
  – If we are interested in the amount of change/unit time, we need to include time explicitly in our analyses.
Change Detection Process

1. Data Acquisition and Preprocessing
2. Radiometric/Geometric Correction
3. Data Normalization
4. Change Detection Analysis
5. Accuracy Assessment
6. Final Product Generation
Change Detection Analysis

• Landscape is dynamic

• Allows for the monitoring of change over time
  - Rates e.g., \( x \% \) per year deforestation
  - Amounts e.g., \( x \text{ km}^2 \) loss of wetlands

• General steps to perform digital change detection are shown next
General Steps Used to Conduct Digital Change Detection Using Remote Sensor Data

State the Change Detection Problem
- Define the study area
- Specify frequency of change detection (e.g., seasonal, yearly)
- Identify classes from an appropriate land cover classification system

Considerations of Significance When Performing Change Detection
- Remote Sensing System Considerations
  - Temporal resolution
  - Spatial resolution
  - Spectral resolution
  - Radiometric resolution
- Environmental Considerations
  - Atmospheric conditions
  - Soil moisture conditions
  - Phenological cycle characteristics
  - Tidal stage

Image Processing of Remote Sensor Data to Extract Change Information
- Acquire Appropriate Change Detection Data
  - In situ and collateral data
  - Remotely sensed data
    - Base year (Time n)
    - Subsequent Year(s) (Time n-1 or n+1)
- Preprocess the Multiple Date Remotely Sensed Data
  - Geometric registration
  - Radiometric correction (or normalization)
- Select Appropriate Change Detection Algorithm
- Apply Appropriate Image Classification Logic If Necessary
  - Supervised, unsupervised, hybrid
- Perform Change Detection using GIS Algorithms
  - Highlight selected classes using change detection matrix
  - Generate change map products
  - Compute change statistics

Quality Assurance and Control Program
- Assess Statistical Accuracy of:
  - Individual date classifications
  - Change detection products

Distribute Results
- Digital products
- Analog (hardcopy) products
Why do change analysis?

• To map patterns of forest change, specifically deforestation,

• To analyze the rates of such changes in the tropics and elsewhere

• Monitoring of change is frequently perceived as one of the most important contributions of remote sensing technology to the study of global ecological and environmental change.

• Land cover changes can occur in two forms:
  - conversion of land cover from one category to a completely different category (via agriculture, urbanization, etc.),
  - modification of the condition of the land cover type within the same category (thinning of trees, selective cutting, etc.)
Why Detect Changes?

- LULCC
- Forest & vegetation change
- Forest mortality, defoliation, & 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, coastal marine environmental change, desertification, and detection of landslide areas
- Crop monitoring, shifting cultivation monitoring, road segments, and change in glacier mass balance and facies
- Others…
Change detection

- **1982-1992 land use change**
  - 29,860 acres/year

- **1992-1995 land use change**
  - 56,640 acres/year

- **% total non-federal land developed**
  - 1982 = 27.7%
  - 1985 = 32.7%
  - 1992 = 34.4%
  - 1997 = 40.8%
Products of Change Detection

• Change area and rate
• assessing the spatial pattern of the change
• Change trajectories; identifying the nature of the change
• Accuracy assessment of change detection results
Change-Detection Considerations

• Precise geometric registration
• Radiometric normalization/calibration
• Phenology, soil moisture, sun angles (select images of similar solar days)
• Image complexity of the study area and mixel effects (use images of similar spatial resolutions)
• Compatibility of images from different sensors
• Classification and change detection schemes (application oriented – change/non-change vs change directions)
• Change detection methods
• Ground truth data
• Analyst’s skill and experience
• Time and cost restrictions
Before implementing change detection analysis, 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) similar phenological states between multi-temporal images; and
(4) selection of the same spatial and spectral resolution images if possible.
Temporal Resolution

- When performing change detection using RS data from multiple dates, two temporal resolutions must be held constant for optimal results:

1. **Data should be acquired the same time of day** (e.g., Landsat TM is before 9:45 am in U.S.)

2. **Data should be collected on anniversary dates** (removes sun angle & plant phenological differences)
Spatial Resolution & Look Angle

• Accurate spatial registration of at least two images is essential for optimal digital change detection. Ideally the following should be held constant:
  – Data collected with the same Instantaneous-Field-Of-View (IFOV) i.e., *same pixel size*
  – Rectification Root Mean Square Error (RMSE) of < 0.5 of a pixel i.e., *reduce misregistration*
  – Data collected from the same look angle i.e.*reduce reflectance differences*
Spectral Resolution

- Data should be collected from the same sensor in the same bands
  - This achieves the best results but when this is not possible, bands which most closely approximate one another should be used.
Radiometric Resolution

• Data should be collected at the same radiometric precision on both dates
  – When the radiometric resolution of data acquired by one system are compared with data acquired by a higher radiometric resolution instrument (e.g., Landsat TM with 8-bit data) then the lower resolution (e.g., 6-bit data) should be decompressed to 8-bits for change detection purposes. *Note: precision of decompressed brightness values is not as good as original, uncompressed data.*
Environmental Considerations

• When performing change detection it is also desirable to hold environmental variables such as:
  – Atmospheric
  – Soil
  – Vegetative
conditions as constant as possible
Atmospheric Conditions

- Ideal atmospheric conditions for the collection of remotely sensed data include no clouds, haze, or extreme humidity.
- Cloud cover > 20% is usually considered unacceptable.
- If dramatic differences exist in atmospheric conditions across the imagery to be used then atmospheric attenuation in the imagery must be corrected for e.g., using in situ data and atmospheric transmission models or alternate empirical methods.
Soil Moisture Conditions

• Under ideal conditions, soils moisture should be identical across dates.
• This means the dates for imagery must be reviewed before purchase to compare precipitation records in the days and weeks prior to the image date.
Vegetative Conditions

• Similar times of year and moisture conditions usually result in similar phenological stages in vegetation. Hence if the other conditions are met in terms of environmental and resolution considerations, usually vegetative conditions are also.

• Ground data should be available to confirm changes in vegetation, which is usually what we are studying with change detection.
Images must undergo a number of restoration steps that involve radiometric calibration, atmospheric correction, and radiometric rectification to ensure we are obtaining real image differences in our change detection.

These processes remove differences between the images related to:

- sensor differences *(intra-instrument differences, instrument drift, or inter-instrument differences),

- illumination differences *(earth-sun distances, solar incidence angle),

- atmospheric differences *(aerosol content, water droplet concentration)*
Radiometric Calibration/Normalization

1. Absolute correction/calibration:
   • Converting from DN to ground reflectance (or radiance) using atmospheric models

2. Relative normalization:
   • Based on regression or histogram matching techniques to register the radiometric signals of one image to another.
   • Noise reduction
   • Haze reduction
Change Detection: Radiometric Calibration

- Histogram matching
Change Detection: Radiometric Calibration

• Regression Approach
Change Detection

• Atmospheric correction
  – Model atmospheric effects using radiative transfer models
    • Aerosols, water vapor, absorptive gases
Atmospheric Correction Necessary / Not Necessary

• **NECESSARY:** Required when individual date images used in change detection algorithm are based on linear transformation of data, a normalized difference of vegetation index image is produced.

• **NECESSARY:** Imagery should be atmospherically corrected if the change detection is based on multiple-date red/near-infrared ratio images (landsat tm 4 / landsat tm 3).

• **UNNECESSARY:** It is unnecessary to correct for atmospheric effects prior to image classification if the spectral signatures characterizing the desired classes are derived from the image to be classified – images from a single date.
  
  – It is not necessary to atmospherically correct Landsat TM data obtained on Date 1 if it is going to be subjected to a maximum likelihood classification algorithm and all the training data are derived from the Date 1 imagery. The same hold true when a Date 2 image is classified using training data extracted from the Date 2 image. Change between the Date 1 and Date 2 classification maps derived from the individual dates of imagery (corrected or uncorrected can easily be compared in post-classification comparison).

• **UNNECESSARY:** It is also unnecessary when change detection is based on classification of multiple date composite imagery in which the multiple dates of remotely sensed imaged are rectified and placed in a single dataset and then classified as if it were a single image (e.g. multiple date principle components change detection).

• **NECESSARY:** Only when Training data from one time and/or place are applied in another time and/or place is atmospheric correction necessary for image classification and many change detection algorithms.
Some examples of Change Detection and Analysis

• **Classification Algorithms (after Jensen 2005)**
  1. Direct Comparison – “Blinking”
  2. Write Function Memory Insertion
  3. Multi-Date Composite Image
  4. Image Algebra Change Detection
  5. Post-classification Comparison
  6. Multi-date Change with Binary Mask
  7. Multi-date Change with Ancillary Data
  9. Spectral Change Vectors
  10. Knowledge-Based Vision Systems

• **Index Algorithms - Thresholding**
Change Detection: Methods

• Basic model:
  – Inputs:
    • Landsat TM image from Date 1
    • Landsat TM image from Date 2
  – Potential output:
    • Map of change vs. no-change
    • Map describing the types of change
Change Detection: Methods

• Display bands from Dates 1 and 2 in different color guns of display
  – No-change is greyish
  – Change appears as non-grey

• Limited use
  – On-screen delineation
  – Masking
Direct: “Blinking”

Link two composites, “blink” back and forth.

Advantages:
Simple and Immediate.

Disadvantages:
No change class labels, to-from analysis,
Multi-Date Visual Change Detection Using Write-Function Memory Insertion

![Diagram of three image planes representing different dates and bands]

**Red image plane**
**Green image plane**
**Blue image plane**

<table>
<thead>
<tr>
<th>Date 1</th>
<th>band n</th>
</tr>
</thead>
<tbody>
<tr>
<td>Date 2</td>
<td>band n</td>
</tr>
<tr>
<td>Date 3</td>
<td>band n</td>
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</tbody>
</table>

**Advantages:**
- Visual examination of 2 or 3 years of nonspecific change

**Disadvantages:**
- Nonquantitative
- No ‘from-to’ change class information

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**Figure 9-6** Diagram of Multi-Date Visual Change Detection using Write Function Memory insertion.
Write-Function Memory Insertion (RGB Control)

R = Band 4 1975
G = Band 4 1986
B = Band 4 1986
Multi-Date Composite Image Change Detection

Advantages:
- Requires single classification

Disadvantages:
- Difficult to label change classes
- Little ‘from-to’ change class information available

Figure 9-9  Diagram of Multi-date Composite Image change detection.
Multi-date Composite Image Change Detection in Imagine

PC 1

PC 2

PCA

PC 3

Composite
Image Algebra Change Detection

Date 1
Rectified Thematic Mapper bands

Date 2
Rectified Thematic Mapper bands

Composite dataset

Differenced or band ratioed image

Recoded to produce binary ‘change/no-change’ mask

Advantages:
• Efficient method of identifying pixels that have changed in brightness value between dates

Disadvantages:
• No ‘from-to’ change classes available
• Requires careful selection of the ‘change/no-change’ threshold

Figure 9-10  Diagram of Image Algebra change detection.
Image Algebra Change Detection in Imagine
Image Algebra Change Detection in Imagine

Red = > 20% decrease;
Green = > 20% increase in Band 4

Based on non-corrected Digital Numbers
Thresholding

Standard Normal Deviates

\[ Z = \frac{x - \mu}{\sigma} \]

\[ Z = \frac{x - 0.038}{0.114} \]

Threshold = \( \pm 2 \sigma \)
Determining Threshold Values in Image Enhancement Change Detection Methods

- Ground truth data
- Sensitivity analysis identifying the threshold value that produces the highest accuracy (K-hat)

**L₁**: Threshold level of the lower tail of the distribution; **M**: Mean; **L₂**: Threshold level of the higher tail of the distribution.
Change Detection: Methods

• Image differencing
  – Date 1 - Date 2
  – No-change = 0
  – Positive and negative values interpretable
  – Pick a threshold for change
  – Often uses vegetation index as start point, but not necessary
Image Differencing

Image Date 1

<p>| | | | |</p>
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<tr>
<td>240</td>
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<tr>
<td>220</td>
<td>98</td>
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Image Date 2

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<td>7</td>
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<tr>
<td>103</td>
<td>98</td>
<td>254</td>
<td>210</td>
</tr>
</tbody>
</table>

Difference Image = Image 1 - Image 2

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<tr>
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</thead>
<tbody>
<tr>
<td>3</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>143</td>
<td>2</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>107</td>
<td>110</td>
<td>0</td>
<td>-168</td>
</tr>
<tr>
<td>117</td>
<td>0</td>
<td>-166</td>
<td>-164</td>
</tr>
</tbody>
</table>
Change Detection: Methods

• Image differencing: Pros
  – Simple (some say it’s the most commonly used method)
  – Easy to interpret
  – Robust

• Cons:
  – Difference value is absolute, so same value may have different meaning depending on the starting class
  – Requires atmospheric calibration for expectation of “no-change = zero”
Image Differencing

Shadow Fraction, 1986

Shadow Fraction, 2002

Roads
Image Differencing

- Loss of shadow (darker pixels) is related to clearings, gain of shadow (brighter pixels) is related to forest recovery.
Image Differencing
Image Differencing

- If we use a change threshold of 1 stdev, we can classify the image into gain, no-change or loss.
- Red signifies loss of shadow (loss of forest), green gain of shadow (forest recovery), black no-change.
Change Detection: Methods

• Image Ratioing
  – Date 1 / Date 2
  – No-change = 1
  – Values less than and greater than 1 are interpretable
  – Pick a threshold for change
Change Detection: Methods

• Image Ratioing: Pros
  – Simple
  – May mitigate problems with viewing conditions, esp. sun angle

• Cons
  – Scales change according to a single date, so same change on the ground may have different score depending on direction of change; i.e. \( \frac{50}{100} = 0.5 \), \( \frac{100}{50} = 2.0 \)
Change Detection

Image Difference (TM99 – TM88)

Image Ratio (TM99 / TM88)
Multi-date Change Detection Using A Binary Mask Applied to Date 2

- very effective method
- Date 1 – base image
- Date 2 – earlier image or later image
- spectral change image is then recorded in to binary mask file

Diagram of Multiple-Date Change Detection Using a Binary Change Mask Applied to Date 2 (Jensen, 1994).
Change Vector Analysis (CVA)

Change Vector Analysis (CVA) uses two spectral channels to map both the: 1) magnitude of change and, 2) the direction of change between the two (spectral) input images for each date.
Change Detection: Methods

- Change vector analysis
  - In n-dimensional spectral space, determine length and direction of vector between Date 1 and Date 2
Change Detection: Methods

• No-change = 0 length
• Change direction may be interpretable
• Pick a threshold for change
Change Vector Analysis

Band Math followed by change vector

2-D change vector

3-D change vector

Possible Change Sector Code Locations for a Pixel Measured in Three Bands on Two Dates

Figure 9-23  Possible change sector codes for a pixel measured in three bands on two dates.

Figure 9-22  Schematic diagram of the spectral change detection method (after Malila, 1980).
A change vector analysis technique to monitor land use/land cover in SW Brazilian Amazon: Acre State

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Abstract

The Brazilian Amazon is an area where extensive tropical rainforest areas are being destined to agriculture and cattle raising activities, contributing to the environmental and landscape change of this large region. In this context, the main objective of this paper is to present and test a technique for change detection called Change Vector Analysis (CVA) to analyze the variability of land use/land cover dynamics in the region of Peixoto, Acre State, using multitemporal analysis of multispectral TM-Landsat data. The results demonstrate the capacity of the CVA technique to stratify different types of change related to land use/land cover dynamics in this region.
• EXAMPLE CVA: The first step of the example CVA method was to apply a Tasseled Cap transform which generates the components Greenness and Brightness, in order to reduce the amount of redundant information of orbital images to be analyzed. This transform can be understood as defining a new coordinate system, where data from different bands occupy a new system of coordinates, where data from the different bands occupy new axes associated with biophysical properties of targets. In this case, such axes are Greenness, associated with the amount and vigor of vegetation, and Brightness, associated with variations of soil reflectance.

• The position variation of the same pixel during different data-takes within the space formed by these two axes, determines the magnitude and direction of the spectral change vectors.

• The next step in the band transformation process into new coordinates axes was to calculate the magnitude of variation among spectral change vectors between the images pairs.

• The magnitude of vectors was calculated from the Euclidean Distance between the difference in positions of the same pixel from different data-takes within the space generated by the axes Greenness and Brightness, as follows:

\[ R = \sqrt{(yb - ya)^2 + (xb - xa)^2} \]

Where: \( R \) = Euclidean Distance
\( ya = \) DN values of Greenness from date 2
\( yb = \) DN values of Greenness from date 1
\( xa = \) DN values of Brightness from date 1
\( xb = \) DN values of Brightness from date 2
Table 2 - Magnitude thresholds of change for each class during each data-take analyzed.

<table>
<thead>
<tr>
<th>Thresholds</th>
<th>Changes</th>
</tr>
</thead>
<tbody>
<tr>
<td>40</td>
<td>40</td>
</tr>
<tr>
<td>7</td>
<td>22</td>
</tr>
<tr>
<td>17</td>
<td>20</td>
</tr>
<tr>
<td>10</td>
<td></td>
</tr>
<tr>
<td>1997/1999</td>
<td></td>
</tr>
</tbody>
</table>

Classes of Change:

- Class 1
- Class 2
- Class 3
- Class 4

Each of the Classes of Change thresholds was set to trigger only the values that indicated magnitude or change. Preserving just those information that are relevant to the CVA technique is an example of vector change, where the main function of the algorithm is to determine an interactive difference.

A threshold of final magnitude was defined for each one of the change classes through an interactive adjustment to show in Figure 3.

Examples of change classes are transformations of sections with growth of cultures, such as increase in brightness and decrease in greenness, or decrease in growth of cultures, such as increase in greenness and decrease in brightness. Class 1 indicates change in brightness, whereas Class 2 indicates change in greenness.

Table 1 - Possible change classes from both input components and related types of change.

<table>
<thead>
<tr>
<th>Components</th>
<th>Changes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Burning or Water</td>
<td>-</td>
</tr>
<tr>
<td>Biomass Loss</td>
<td>+</td>
</tr>
<tr>
<td>Deforestation</td>
<td>-</td>
</tr>
<tr>
<td>Regrowth</td>
<td>+</td>
</tr>
<tr>
<td>Themes</td>
<td>Greenness</td>
</tr>
<tr>
<td></td>
<td>Brightness</td>
</tr>
</tbody>
</table>

Classes:

- Class 1
- Class 2
- Class 3
- Class 4

Components of greenness and brightness were used in this study. Only four classes of change were possible. Changes through channels of spectral bands, which allows to distinguish 7 types of changes. Since only components used (Table 1) in other words, each vector is a function of the combination of positive or negative
Change Detection: CVA Methods

• Change detection: Pros
  – Conceptually appealing
  – Allows designation of the type of change occurring

• Cons
  – Requires very accurate radiometric calibration
  – Change value is not referenced to a baseline, so different types of change may have same change vector
Example of Change Vector Analysis: Tugend 2001: Lake Kissimmee Littoral Zone “Enhancement”

Decreases in brightness of bands 1, 2, 3 due to increases of vegetation. Increases in brightness due either to decrease of vegetation, or increases of turbidity.
Vegetation Indices in Change Detection

• A useful vegetation or greenness index can be created from a ratio of the visible and near-infrared data, known as the normalized difference vegetation index (NDVI) (Campbell, 1996).

• This index can be used to show the amount of vegetation present at a given time, and can be used in change analyses to indicate how a landscape changes in terms of vegetation amount across a set time period.

• Quite simply we can subtract one image from a second image
e.g., 1990 NDVI – 1980 NDVI = A number > 0.0 means an increase in vegetation since 1980
Figure 4: Frequency of NDVI change values across the La Campa & Gracias study area

0.0 (no change in vegetation)

Decreasing vegetation amount

Increasing vegetation amount

The graph shows the frequency of NDVI change values across the La Campa & Gracias study area. Values above 0.0 indicate increasing vegetation, while values below 0.0 indicate decreasing vegetation amount.
Change Detection: Methods

• Post-classification (delta classification)
  – Classify Date 1 and Date 2 separately, compare class values on pixel by pixel basis between dates
Post-Classification Comparison Change Detection

Date 1

Rectified Thematic Mapper bands

Classification map of Date 1

Date 2

Rectified Thematic Mapper bands

Classification map of Date 2

Classification map of Date 1

Change map produced using ‘change detection matrix’ logic applied to Date 1 and Date 2 classification maps

Advantages:
- Provides ‘from-to’ change class information
- Next base year map is already completed

Disadvantages:
- Dependent on accuracy of individual date classifications
- Requires two separate classifications

Figure 9-12 Diagram of Multi-Date Post-Classification Comparison change detection.
Post-Classification Change Comparison

Use “confusion matrix”

Legend
Class 1 = Blue
Class 2 = Green
Class 3 = Red
Class 4 = Yellow
Class 5 = Cyan

1997 – “Classified”
1994 – “Ground Truth”
Change Detection: Methods

• Post-classification: Pros
  – Avoids need for strict radiometric calibration
  – Favors classification scheme of user
  – Designates type of change occurring

• Cons
  – Error is multiplicative from two parent maps
  – Changes within classes may be interesting
Change Detection Using An Ancillary Data Source as Date 1

Date 1
Ancillary data source, e.g., National Wetlands Inventory map

Date 2
Rectified Thematic Mapper bands

Classification map of Date 2
Classification map of Date 1

Perform Post-Classification Comparison change detection or update Date 1 NWI map with Date 2 change information using GIS dominate function.

Advantages:
- May reduce change detection errors (omission and comission)
- Provides 'from-to' change class information
- Requires a single classification

Disadvantages:
- Dependent on quality of ancillary information

Figure 9-18  Diagram of Multi-date Change Detection Using Ancillary Data Source as Date 1.
Change Detection: Methods

• Composite Analysis
  – Stack Date 1 and Date 2 and run unsupervised classification on the whole stack
Composite Analysis

Steps

1. Geometrically correct images.

2. Merge the images into a single image.
   - The number of bands in the composite image typically = the number of bands in a single image x the number of images used.
   - e.g. if we use 2 MSS images, the composite images will have 4 bands x 2 image = 8 bands.

3. We use the composite image to perform classification.
   “Change” categories should be statistically different from “no change” categories.
Composite Analysis

Benefits

• Only a single classification is needed.
• May extract maximum change variation
• Includes reference for change, so change is anchored at starting value, unlike change vector analysis and image differencing

Drawbacks

• Class choices and interpretation can be complex. This is more of a classification technique that takes change into consideration, than a true change-detection technique.
Principle Components Analysis

Steps

1. Geometrically correct images.
2. Perform PCA transformation.
3. Interpret PCA images (each image will contain a single axis).
Principle Components Analysis

PCA Axis 1

PCA Axis 2

PCA Axis 3

PCA Axis 4
Principle Components Analysis

Benefits
• Relatively easy to do, can reduce a large dataset into a much smaller dataset.

Drawbacks
• Interpretation can be difficult.
Cross-Correlation Analysis (CCA)

Cross-Correlation Analysis (CCA) uses a land cover map to delineate spectral cluster statistics between the baseline image year (Time 1) and each scene in the temporal sequence (Time 2). Calculating the Z-statistic deviations from the cluster mean identifies change pixels within each land cover cluster.

![Diagram of CCA process]

- Land cover, Time 1 (circa 2000)
- Landsat image Time 2
- Histogram under each land cover
- Z-score map showing large deviations from the mean
Cross-correlation Analysis

CCA calculates the sum of the distance of each pixel in each band from the norm

\[
Z = \sum_{i=1}^{n} \left( \frac{\text{Observed}_i - \text{Expected}_i}{\text{Std. Dev.}_i} \right)^2
\]

- \( Z \) is the distance measure
- \( \text{Observed} \) is the pixel value for each band
- \( \text{Expected} \) is the mean value of all extracted pixels for each band
- \( \text{Std. Dev.} \) is the standard deviation of all extracted pixels for each band
Cross-correlation Analysis

- **Step 1**
  - Use 1989 classification as base land cover
  - Extract vegetated class areas to be analyzed from 1999/2000 ETM image (turf & grass, agriculture & barren, deciduous, and coniferous)
Cross-correlation Analysis

• **Step 2**
  – Perform CCA on 1999/2000 imagery
  – Identify thresholds separating unchanged pixels and changed pixels

$Z$-values range from 1 to 5,794
Cross-correlation Analysis

- **Step 3**
  - Create a mask from changed pixels for all categories analyzed (turf & grass, agriculture & barren, deciduous, and coniferous)
Cross-correlation Analysis

- **Step 4**
  - Extract changed pixels from 1999/2000 image data
  - Perform unsupervised classification to identify new categories
Cross-correlation Analysis

- **Step 4**
  - Merge new classes with historic classification to produce updated land cover
Cross-correlation Analysis

Site 1

1989 Classification

2000 Classification
Cross-correlation Analysis

1939 Classification

Site 2

2000 Classification
Theil-Sen Regression Analysis (TSA)

Much like typical image regression change, we use Theil-Sen as it is more robust to sample outliers than ordinary least-squares regression.

• Medians are outlier resistant measures of central tendency and the method uses the median of all pairwise slopes to calculate the slope of the regression line.

• The median value of the sample offsets represents the intercept.
TSA con’t…

• Generate mask to sample pixels in each land cover
• Samples are used to build a regression equation for each cover type using the baseline data as the regressor and each scene in the temporal sequence as the response.
• A change mask is created by mapping pixels characterizing large residuals away from the regression line.
## Change Detection Techniques

<table>
<thead>
<tr>
<th>Techniques</th>
<th>Specific Methods</th>
<th>Lu et al. 2004</th>
<th>Mas 1999</th>
</tr>
</thead>
<tbody>
<tr>
<td>Algebra (Image Enhancement)</td>
<td>• Image differencing</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>• Vegetation index differencing</td>
<td>✓</td>
<td>✓</td>
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<tr>
<td></td>
<td>• Change vector analysis</td>
<td>✓</td>
<td>X</td>
</tr>
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<td></td>
<td>• Image regression</td>
<td>✓</td>
<td>X</td>
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<td></td>
<td>• Ratioing</td>
<td>✓</td>
<td>X</td>
</tr>
<tr>
<td>Transformation (Image Enhancement)</td>
<td>• Selective principal component analysis (SPCA)</td>
<td>X</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>• PCA</td>
<td>✓</td>
<td>X</td>
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<tr>
<td></td>
<td>• Tasseled Cap (KT)</td>
<td>✓</td>
<td>X</td>
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<tr>
<td></td>
<td>• Gramm-Schmidt (multi-date KT)</td>
<td>✓</td>
<td>X</td>
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<tr>
<td></td>
<td>• Chi-square</td>
<td></td>
<td></td>
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<tr>
<td>Classification</td>
<td>• Direct multi-date unsupervised classification</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>• Post-classification change differencing</td>
<td>✓</td>
<td>X</td>
</tr>
<tr>
<td></td>
<td>• Unsupervised change detection</td>
<td>✓</td>
<td>X</td>
</tr>
<tr>
<td></td>
<td>• Expectation maximization (EM)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Advanced Models</td>
<td>• Li-Strahler reflectance model</td>
<td>✓</td>
<td>X</td>
</tr>
<tr>
<td></td>
<td>• Spectral mixture model</td>
<td>✓</td>
<td>X</td>
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<tr>
<td></td>
<td>• Biophysical parameter method</td>
<td>✓</td>
<td>X</td>
</tr>
<tr>
<td>GIS</td>
<td>• GIS + Remote Sensing</td>
<td>✓</td>
<td>X</td>
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<td></td>
<td>• GIS</td>
<td>✓</td>
<td>X</td>
</tr>
<tr>
<td>Visual analysis</td>
<td></td>
<td>✓</td>
<td>X</td>
</tr>
<tr>
<td>Image Enhancement + Post-Class Comparison</td>
<td>• Hybrid change detection</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>
## Results (Mas 1999)

Table 5. Comparison of the performances of the change detection procedures.

<table>
<thead>
<tr>
<th>Change detection procedure</th>
<th>Change no change level</th>
<th>From-to change level</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Kappa</td>
<td>Global accuracy</td>
</tr>
<tr>
<td>Band 2 differencing</td>
<td>0.4100</td>
<td>80.40</td>
</tr>
<tr>
<td>Band 4 differencing</td>
<td>0.2210</td>
<td>73.90</td>
</tr>
<tr>
<td>NDVI differencing</td>
<td>0.3981</td>
<td>81.84</td>
</tr>
<tr>
<td>SPCA band 2</td>
<td>0.4155</td>
<td>82.05</td>
</tr>
<tr>
<td>SPCA band 4</td>
<td>0.2222</td>
<td>73.20</td>
</tr>
<tr>
<td>Multi-date classification</td>
<td>0.2850</td>
<td>80.71</td>
</tr>
<tr>
<td>Post-classification comparison</td>
<td>0.6191</td>
<td>86.87</td>
</tr>
<tr>
<td>Masking + post-classification comparison</td>
<td>0.4201</td>
<td>84.52</td>
</tr>
</tbody>
</table>

- Post-classification is the best.
- Band 2 is better than Band 4 in change detections.
Table 1. Summary of change detection techniques. (The five levels indicate the complexity of the change detection techniques, from simplest 1 to the most complex 5.)

<table>
<thead>
<tr>
<th>Techniques</th>
<th>Characteristics</th>
<th>Advantages</th>
<th>Disadvantages</th>
<th>Examples</th>
<th>Level</th>
<th>Key factors</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Category I. Algebra</strong></td>
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<tr>
<td>1. Image differencing</td>
<td>Subtracts the first-date image from a second-date image, pixel by pixel</td>
<td>Simple and straightforward, easy to interpret the results</td>
<td>Cannot provide a detailed change matrix, requires selection of thresholds</td>
<td>Forest defoliation (Muchoney and Haack 1994), land-cover change (Sohl 1999) and irrigated crops monitoring (Manavalan et al. 1995)</td>
<td>1</td>
<td>Identifies suitable image bands and thresholds</td>
</tr>
<tr>
<td>2. Image regression</td>
<td>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</td>
<td>Reduces impacts of the atmospheric, sensor and environmental differences between two-date images</td>
<td>Requires to develop accurate regression functions for the selected bands before implementing change detection</td>
<td>Tropical forest change (Singh 1986) and forest conversion (Jha and Unni 1994)</td>
<td>1</td>
<td>Develops the regression function; identifies suitable bands and thresholds</td>
</tr>
<tr>
<td>3. Image ratioing</td>
<td>Calculates the ratio of registered images of two dates, band by band</td>
<td>Reduces impacts of Sun angle, shadow and topography</td>
<td>Non-normal distribution of the result is often criticized</td>
<td>Land-use mapping and change detection (Prakash and Gupta 1998)</td>
<td>1</td>
<td>Identifies the image bands and thresholds</td>
</tr>
<tr>
<td>Techniques</td>
<td>Characteristics</td>
<td>Advantages</td>
<td>Disadvantages</td>
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<tr>
<td>4. Vegetation index differencing</td>
<td>Produces vegetation index separately, then subtracts the second-date vegetation index from the first-date vegetation index</td>
<td>Emphasizes differences in the spectral response of different features and reduces impacts of topographic effects and illumination</td>
<td>Enhances random noise or coherence noise</td>
<td>Vegetation change (Townshend and Justice 1995, Guerra et al. 1998, Lyon et al. 1998) and forest canopy change (Nelson 1983)</td>
<td>1</td>
<td>Identifies suitable vegetation index and thresholds</td>
</tr>
<tr>
<td>5. Change vector analysis (CVA)</td>
<td>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</td>
<td>Ability to process any number of spectral bands desired and to produce detailed change detection information</td>
<td>Difficult to identify land cover change trajectories</td>
<td>Change detection of landscape variables (Lambin 1996), land-cover changes (Johnson and Kasischke 1998), disaster assessment (Johnson 1994, Schopppmann and Tyler 1996), and conifer forest change (Cohen and Fiorella 1998, Allen and Kupfer 2000)</td>
<td>3</td>
<td>Defines thresholds and identifies change trajectories</td>
</tr>
<tr>
<td>Techniques</td>
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<tr>
<td>6. Background subtraction</td>
<td>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.</td>
<td>Easy to implement</td>
<td>Low accuracy</td>
<td>Tropical forest change (Singh 1989).</td>
<td>1</td>
<td>Develops the background image</td>
</tr>
<tr>
<td>Category II. Transformation</td>
<td></td>
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<tr>
<td>7. Principal component analysis (PCA)</td>
<td>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; and (2) perform PCA separately, then subtract the second-date PC image from the corresponding</td>
<td>Reduces data redundancy between bands and emphasizes different information in the derived components</td>
<td>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</td>
<td>Land-cover change (Byrne <em>et al.</em> 1980, Ingebritsen and Lyon 1985, Parra <em>et al.</em> 1996, Kwarteng and Chavez 1998), urban expansion (Li and Yeh 1998), tropical forest conversion (Jha and Unni 1994), forest mortality (Collins and Woodcock 1996) and forest defoliation (Muchoney and Haack 1994)</td>
<td>2</td>
<td>Analyst’s skill in identifying which component best represents the change and selecting thresholds</td>
</tr>
<tr>
<td>Techniques</td>
<td>Characteristics</td>
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<td>8. Tasselled cap (KT)</td>
<td>PC image of the first date. 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.</td>
<td>Reduces data redundancy between bands and emphasizes different information in the derived components. KT is scene independent.</td>
<td>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. 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.</td>
<td>Monitoring forest mortality (Collins and Woodcock 1996), monitoring green biomass change (Coppin et al. 2001) and land-use change (Seto et al. 2002)</td>
<td>2</td>
<td>Analyst’s skill is needed in identifying which component best represents the change and selecting thresholds</td>
</tr>
<tr>
<td>9. Gramm–Schmidt (GS)</td>
<td>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.</td>
<td>The association of transformed components with scene characteristics allows the extraction of information that would not be accessible using other change detection techniques.</td>
<td></td>
<td>Monitoring forest mortality (Collins and Woodcock 1994, 1996)</td>
<td>3</td>
<td>Initial identification of the stable subspace of the multi-date data is required</td>
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<td>Techniques</td>
<td>Characteristics</td>
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<tr>
<td>10. Chi-square</td>
<td>$Y = (X - M)^T \Sigma^{-1} (X - M)$ $Y$: 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, $\Sigma^{-1}$: inverse covariance matrix of the six bands</td>
<td>Multiple bands are simultaneously considered to produce a single change image.</td>
<td>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</td>
<td>Urban environmental change (Ridd and Liu 1998)</td>
<td>3</td>
<td>$Y$ is distributed as a Chi-square random variable with $p$ degrees of freedom ($p$ is the number of bands)</td>
</tr>
<tr>
<td>Category III. Classification</td>
<td></td>
<td>Minimizes impacts of atmospheric, sensor and environmental differences between multi-temporal images; provides a complete matrix of change information</td>
<td>Requires a great amount of time and expertise to create classification products. The final accuracy depends on the quality of the classified image of each date</td>
<td>LULC change (Brondizio et al. 1994, Dimyati et al. 1996, Mas 1997, Castelli et al. 1998, Miller et al. 1998, Mas 1999, Foody 2001), wetland change (Jensen et al. 1987, 1995, Munyati 2000) and urban expansion (Ward et al. 2000)</td>
<td>2</td>
<td>Selects sufficient training sample data for classification</td>
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<tr>
<td>Techniques</td>
<td>Characteristics</td>
<td>Advantages</td>
<td>Disadvantages</td>
<td>Examples</td>
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<tr>
<td>12. Spectral–temporal combined</td>
<td>Puts multi-temporal data into a single file, then classifies the combined</td>
<td>Simple and time-saving in classification</td>
<td>Difficult to identify and label the change classes; cannot provide a complete</td>
<td>Changes in coastal zone environments (Weismiller et al. 1977) and forest</td>
<td>3</td>
<td>Labels the change classes</td>
</tr>
<tr>
<td>analysis</td>
<td>dataset and identifies and labels the changes</td>
<td></td>
<td>matrix of change information</td>
<td>change (Soares and Hoffer 1994)</td>
<td></td>
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</tr>
<tr>
<td>13. EM detection</td>
<td>The EM detection is a classification-based method using an</td>
<td>This method was reported to provide higher change detection</td>
<td>Requires estimating the ( a ) priori joint class probability.</td>
<td>Land-cover change (Bruzzone and Serpico 1997b, Serpico and Bruzzone 1999)</td>
<td>3</td>
<td>Estimates the ( a ) priori joint class probability</td>
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<td></td>
<td>expectation–maximization (EM) algorithm to estimate the ( a ) priori joint</td>
<td>accuracy than other change detection methods</td>
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<td>class probabilities at two times. These probabilities are estimated</td>
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<td>directly from the images under analysis</td>
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<tr>
<td>14. Unsupervised change detection</td>
<td>Selects spectrally similar groups of pixels and clusters date 1 image into</td>
<td>This method makes use of the unsupervised nature and automation of the</td>
<td>Difficulty in identifying and labelling change trajectories</td>
<td>Forest change (Hame et al. 1998)</td>
<td>3</td>
<td>Identifies the spectrally similar or relatively homogeneous units</td>
</tr>
<tr>
<td>Techniques</td>
<td>Characteristics</td>
<td>Advantages</td>
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<tr>
<td>15. Hybrid change detection</td>
<td>identifies changes and outputs results. Uses an overlay enhancement from a selected image to isolate changed pixels, then uses supervised classification. A binary change mask is constructed from the classification results. This change mask sieves out the changed themes from the LULC maps produced for each date. The input used to train the neural network is the spectral data of the period of change. A back-propagation algorithm is often used to train the multi-layer perceptron neural network model.</td>
<td>This method excludes unchanged pixels from classification to reduce classification errors.</td>
<td>Requires selection of thresholds to implement classification; somewhat complicated to identify change trajectories.</td>
<td>LULC change (Pilon et al. 1988, Luque 2000), vegetation change (Petit et al. 2001) and monitoring eelgrass (MacLeod and Congalton 1998)</td>
<td>3</td>
<td>Selects suitable thresholds to identify the change and non-change areas and develops accurate classification results.</td>
</tr>
<tr>
<td>16. Artificial neural networks (ANN)</td>
<td></td>
<td>ANN is a non-parametric supervised method and has the ability to estimate the properties of data based on the training samples.</td>
<td>The nature of hidden layers is poorly known; a long training time is required. ANN is often sensitive to the amount of training data used. ANN functions are not common in image processing software.</td>
<td>Mortality detection in Lake Tahoe Basin, California (Gopal and Woodcock 1996, 1999), land-cover change (Abuelgasim et al. 1999, Dai and Khorram 1999), forest change (Woodcock et al. 2001) urban change (Liu and Lathrop 2002)</td>
<td>5</td>
<td>The architecture used such as the number of hidden layers, and training samples.</td>
</tr>
<tr>
<td>Techniques</td>
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<td>Category IV. Advanced models</td>
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<td>17. Li–Strahler reflectance model</td>
<td>The Li–Strahler canopy model is used to estimate each conifer stand crown cover for two dates of imageries separately. Comparison of the stand crown covers for two dates is conducted to produce the change detection results</td>
<td>This method combines the techniques of digital image processing of remotely sensed data with traditional sampling and field observation methods. It provides statistical results and maps showing the geometric distribution of changed patterns</td>
<td>This method requires a large number of field measurement data. It is complex and not available in commercial image processing software. It is only suitable for vegetation change detection</td>
<td>Mapping and monitoring conifer mortality (Macomber and Woodcock 1994)</td>
<td>5</td>
<td>Develops the stand crown cover images and identifies the crown characteristics of vegetation types</td>
</tr>
<tr>
<td>18. Spectral mixture model</td>
<td>Uses spectral mixture analysis to derive fraction images. Endmembers are selected from training areas on the image or from spectra of materials occurring in the study area or from a relevant spectral library. Changes are detected by comparing the 'before' and 'after'</td>
<td></td>
<td></td>
<td>Land-cover change in Amazonia (Adams et al. 1995, Roberts et al. 1998), seasonal vegetation patterns using AVIRIS data (Ustin et al. 1998) and vegetation</td>
<td>5</td>
<td>Identifies suitable endmembers; defines suitable thresholds for each land-cover class based on fractions</td>
</tr>
<tr>
<td>Techniques</td>
<td>Characteristics</td>
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<tr>
<td>19. Biophysical parameter</td>
<td>fraction images of each endmember. The quantitative changes can be measured by classifying images based on the endmember fractions. Develops a biophysical parameter estimation model through integration of field measurements and remotely sensed data and estimates the parameter for the study area. The vegetation types are classified based on the biophysical parameter. The model is also transferred to other image data with different dates to estimate the selected parameters after reflectance calibration or normalization. Change detection is implemented through comparing the biophysical parameters.</td>
<td>This method can accurately detect vegetation change based on vegetation physical structures</td>
<td>Requires great effort to develop the model and implement accurate image calibration to eliminate the difference in reflectance caused by different atmospheric and environmental conditions. Requires a large number of field measurement data. The method is only suitable for vegetation change detection.</td>
<td>Tropical successional forest detection in Amazon basin (Lu 2001, Lu et al. 2002)</td>
<td>5</td>
<td>Develops relevant models for estimation of biophysical parameters and defines each vegetation class based on biophysical parameters.</td>
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<tr>
<td>Techniques</td>
<td>Characteristics</td>
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<tr>
<td>Category V. GIS 20. Integrated GIS and remote sensing method</td>
<td>Incorporates image data and GIS data, such as the overlay of GIS layers directly on image data; moves results of image processing into GIS system for further analysis</td>
<td>Allows access of ancillary data to aid interpretation and analysis and has the ability to directly update land-use information in GIS</td>
<td>Different data quality from various sources often degrades the results of LULC change detection</td>
<td>LULC (Price et al. 1992, Westmoreland and Stow 1992, Mouat and Lancaster 1996, Slater and Brown 2000, Petit and Lambin 2001, Chen 2002, Weng 2002) and urban sprawl (Yeh and Li 2001, Prol-Ledesma et al. 2002)</td>
<td>4</td>
<td>The accuracy of different data sources and their registration accuracies between the thematic images</td>
</tr>
<tr>
<td>21. GIS approach</td>
<td>Integrates past and current maps of land use with topographic and geological data. The image overlaying and binary masking techniques are useful in revealing quantitatively the change dynamics in each category</td>
<td>This method allows incorporation of aerial photographic data of current and past land-use data with other map data</td>
<td>Different GIS data with different geometric accuracy and classification system degrades the quality of results</td>
<td>Urban change (Lo and Shipman 1990) and landscape change (Taylor et al. 2000)</td>
<td>4</td>
<td>The accuracy of different data sources and their registration accuracies between the thematic images</td>
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<td>Techniques</td>
<td>Characteristics</td>
<td>Advantages</td>
<td>Disadvantages</td>
<td>Examples</td>
<td>Level</td>
<td>Key factors</td>
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<td>Category VI. Visual analysis</td>
<td>One band (or VI) from date1 image as red, the same band (or VI) from date2 image as green, and the same band (or VI) from date3 image as blue if available. Visually interprets the colour composite to identify the changed areas. An alternative is to implement on-screen digitizing of changed areas using visual interpretation based on overlaid images of different dates.</td>
<td>Human experience and knowledge are useful during visual interpretation. Two or three dates of images can be analysed at one time. The analyst can incorporate texture, shape, size and patterns into visual interpretation to make a decision on the LULC change.</td>
<td>Cannot provide detailed change information. The results depend on the analyst’s skill in image interpretation. Time-consuming and difficulty in updating the results.</td>
<td>Land-use change (Sunar 1998, Ulbricht and Heckendorff 1998), forest change (Sader and Winne 1992), monitoring selectively logged areas (Stone and Lefebvre 1998, Asner et al. 2002) and land-cover change (Slater and Brown 2000)</td>
<td>1</td>
<td>Analyst’s skill and familiarity with the study area</td>
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</table>

Category VII. Other change detection techniques
23. Measures of spatial dependence (Henebry 1993)
24. Knowledge-based vision system (Wang 1993)
25. Area production method (Hussin et al. 1994)
26. Combination of three indicators: vegetation indices, land surface temperature, and spatial structure (Lambin and Strahler 1994b)
27. Change curves (Lawrence and Ripple 1999)
28. Generalized linear models (Morissette et al. 1999)
29. Curve-theorem-based approach (Yue et al. 2002)
30. Structure-based approach (Zhang et al. 2002)
31. Spatial statistics-based method (Read and Lam 2002)
Summary (Lu et al. 2004)

- Red band is better for single band CD
- Band ratio is better than single band CD
- CVA and NDVI are better for multi-band CD
Change Detection: Summary

- Radiometric, geometric calibration critical
- Minimize unwanted sources of change (phenology, sun angle, etc.)
- Differencing is simple and often effective
- Post-classification may have multiplicative error
- Better to have a reference image than not