UNIT 15

CHANGE DETECTION TECHNIQUES

Structure

15.1 INTRODUCTION

This unit mainly deals with various aspects of change detection techniques and factors responsible to understand the changes. In this unit, we will discuss about change detection necessity, their change agents, requirement of image processing change detection, steps involved for spectral change detection, and applications of change detection. You will also comprehend the significance of change detection.

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Expected Learning Outcomes

After studying this unit, you should be able to:

- ❖ define change detection and write suitability of remote sensing data;
- ❖ discuss basic steps in a change detection study;
- ❖ describe various methods of change detection;
- ❖ describe considerations in change detection studies; and
- ❖ list recent trends in the field.

15.2 CHANGE DETECTION

Human activity, sudden natural events, or long-term climatological or environmental trends can all lead to change on the earth's surface. Natural hazards are part of human history and the human population is sensitive to a number of hazards such as cyclones, flooding, tsunamis and disease epidemics. According to an estimate, around 50 billion people could be at risk by eighth decade of this century from these hazards because of increasing population densities and environmental changes. One of the core uses of images and remote sensing is the detection of that change. Let us see the definition of change detection.

15.2.1 Definition

In the context of remote sensing, **change detection** refers to the process of identifying differences in the state of an object or phenomenon by observing it at different times (Singh, 1989). This is achieved by comparing images or data captured by remote sensing sensors, such as satellites or aerial photography, taken at different time periods. In order to identify the kind, size, and location of a change, numerous raster datasets that were typically collected for the same area at various dates are compared. This could be done by detecting changes from one image to the next, across a stack of images, or throughout the course of an image time series. The goal of change detection is to monitor and analyse changes in the Earth's surface or atmosphere over time (Fig. 15.1). These changes could be due to various factors, such as:

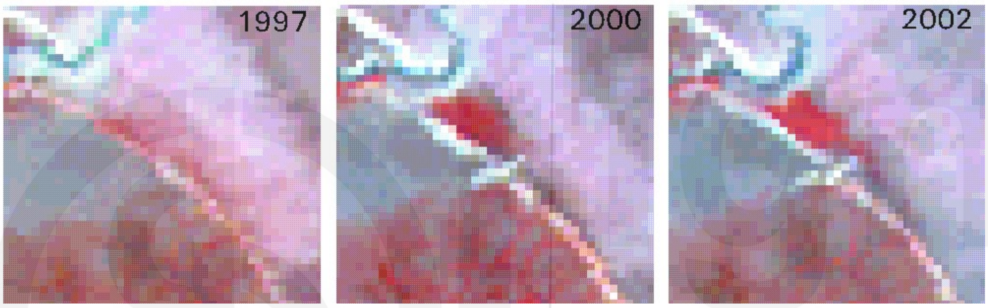
- Natural events: such as deforestation, wildfires, floods, volcanic eruptions, or changes in vegetation.
- Human activities: including urbanisation, agriculture expansion, or infrastructure development.

The aspects of change that are of interest are (Deer, 1995):

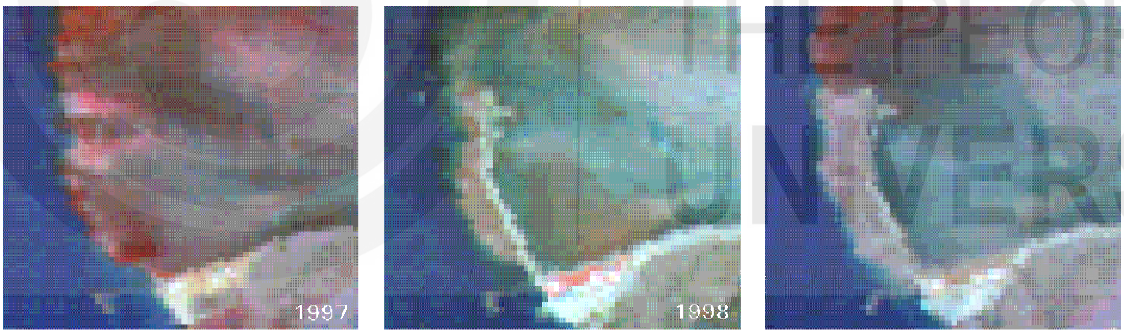
- Has it occurred? (detection)
- Where? (location and extent)
- What change occurred? (identification)
- What are the causes and implications of this? (analysis)

According to Deer (1995), the term ‘change detection’ is loosely applied. It invariably involves the first aspect, normally the second and sometimes the third. The fourth aspect is normally left to the human analyst.

(a)



(b)



(c)

Fig. 15.1: a) LISS III images of pre (left panel) and post tsunami (right panel) periods showing changes in the islands of A&N due to tsunami event of December 2004; LISS III images of an island in the Gulf of Kachchh showing change in b) landforms and c) land use /land cover with time. (Source: Prof. Benidhar Deshmukh)

According to Lu et al. (2004), a good change detection research should provide the following information:

- area change and change rate;
- spatial distribution of changed types;
- change trajectories of land-cover types, and
- accuracy assessment of change detection results.

In the context of remote sensing, change detection can be done using images of two time periods, multiple time periods and even for time series data depending upon the objective of the study.

15.2.2 Importance

Accurate and timely change detection of Earth's surface features helps improve our understanding of the relationships and interactions between human and natural phenomena, aiding in better resource management and utilisation (Lu et al., 2004). There are several attributes or indicators which are useful in natural resource monitoring and management and also for land use planning as shown in the Table 15.1.

Table 15.1: Common human-made and natural resource attributes or indicators that are often the focus of land-use planning and natural resource monitoring programs (adapted from Jensen, 2017 and Kennedy et al., 2009)

Man-made and/or Natural Resource Attributes or Indicators	Process of Interest or Threat
Change in the size or shape of areal patches (polygons) of related cover types	Urban expansion (sprawl), vegetation expansion; sea-level rise, consolidation, fragmentation; infilling, encroachment, erosion/dilution
Change in width or character of linear features	Densification of road, utility, or hydrologic network, impact of use of paths or roads; impact of flooding on riparian vegetation; dynamics of terrestrial and submerged near-shore aquatic vegetation
Slow changes in surface cover types of species composition	Succession, competition, eutrophication, consolidation, fragmentation, exotic species invasion
Abrupt changes in surface cover, water, and/or atmospheric condition	Catastrophic event (e.g., hurricane, flood, tornado, volcanic eruption, fire, wind, landslides), disturbance, human activity (e.g., land clearing; urban and/or environmental terrorism), land management practices (e.g., no-till farming, prescribed burning)
Slow changes in condition of a single cover type	Climate-related changes in vegetation species composition and/or productivity; sea surface temperature, slowly-spreading forest mortality caused by insect or diseases; changes in moisture regime
Changes in timing or the extent of diurnal and/or seasonal processes	Coastal zone dynamics, snow cover dynamics, natural vegetation and agriculture phenology

Change detection plays a crucial role in monitoring environmental changes, urban expansion, deforestation, agricultural trends, and natural disasters. Remote sensing based change detection approach is widely applied across various fields to monitor and analyse changes in the environment. Change detection helps in assessing how a region has transformed over time by comparing multi-temporal remote sensing images.

Objectives of change detection are generally the following:

- Identify and quantify changes in land cover and land use.
- Detect environmental and climatic variations.

- Monitor natural disasters such as floods, wildfires, and deforestation.
- Support urban and infrastructure development planning.

Some of the areas where change detection is generally carried out and where remote sensing plays an important role are the following:

- Land Use and Land Cover Change (LULC) for monitoring the expansion of cities, infrastructure development, and changes in land use patterns over time; detecting changes in agricultural practices, or land conversion for farming, and tracking changes in forest cover, especially in tropical areas, to assess the extent of deforestation or reforestation.
- Environmental monitoring for monitoring changes in wetland ecosystems, which are sensitive to human activities and climate change; detecting changes in coastline shape, coastal erosion, and the impacts of sea-level rise, and identifying areas affected by desertification or land degradation, especially in arid and semi-arid regions.
- Disaster management and assessment is another important area where remote sensing is used to assess changes caused by flooding, wildfires, earthquakes, volcanic activity, landslides, cyclones, etc.
- Climate change studies is carried out to generally for monitoring glaciers to track changes in their size and extent, monitoring changes in vegetation growth patterns due to climate change, such as the timing of plant growth and flowering and also tracking the extent and duration of snow cover, which is crucial for understanding regional climate trends.
- In the field of water resources management, monitoring water quality, change in extent of water bodies, fluctuations in water levels in reservoirs and rivers, changes in wetland areas, especially in terms of area reduction due to human activities or natural changes are some common examples.
- In the field of forestry and natural resource management, monitoring of forests to detect illegal logging, changes in forest health, or impacts from pests and diseases; effects of logging operations on forest cover, biomass, and ecosystem health. Observing the recovery of forests following disturbances or logging events is another important area.
- In the field of biodiversity and habitat change, forest fragmentation is generally detected and monitored, which can affect biodiversity and ecosystems. Monitoring changes in habitats that affect species distribution and migration patterns, including human-induced habitat fragmentation.
- In the field of agriculture, crop monitoring in terms of their health, yield prediction, soil quality, erosion are carried out.
- In the field of infrastructure and urban development monitoring of urban expansion and the development of new buildings, roads, or other infrastructure over time; detection of land subsidence, tracking development of transportation infrastructure, including roads, railways, and airports are some of the common examples.
- For the coastal and marine environments, coastal erosion due to wave action, storms, and sea-level rise; tracking the health and area of mangrove forests, which are vital for coastal protection and biodiversity; and monitoring coral reefs and parameters indicating their health such as sea surface temperature, coral bleaching, turbidity, etc. are some of the common examples.

Understanding the linkages and interactions between human and natural events is crucial for better decision-making, and this requires timely and accurate change detection of Earth's surface features. Timely and accurate change detection of Earth's surface features helps us understand the interactions between human and natural phenomena, supporting better resource management. It typically involves using multi-temporal datasets to analyse changes over time. Remote sensing has become a key source for change detection due to its repetitive data acquisition, broad coverage, and digital format, making it suitable for computer processing in various applications over the years.

15.2.3 Suitability of Remote Sensing Data

There are different types of remote sensing data available. Their suitability for change detection studies are given in Table 15.2:

Table 15.2: Advantage and limitations of various types of remote sensing data for change detection studies:

Remote Sensing Data	Advantage	Disadvantages
Panchromatic	• High spatial resolution (often <1m) • Provides detailed imagery, useful for detecting fine changes like urban expansion or infrastructure • Simple to process and analyse	• Only captures data in a single band (usually visible light) • Limited spectral information, making it unsuitable for detailed land cover classification or vegetation studies
Multispectral	• Captures data across several bands (typically 3-10), enabling detection of land cover, vegetation, and water features • Widely available (e.g., Landsat, SPOT, LISS-III & LISS IV, Sentinel) • Provides enough spectral data for basic classification and change detection	• Lower spectral resolution compared to hyperspectral sensors • Limited ability to detect subtle changes or materials with similar spectral signatures • Less effective for detailed environmental monitoring (e.g., distinguishing between species of vegetation)
Hyperspectral	• Captures data across hundreds of narrow spectral bands, allowing for precise identification of materials (e.g., minerals, specific vegetation types) • Excellent for detecting subtle changes and identifying specific chemical compositions or land features	• Lower spatial resolution compared to panchromatic or multispectral data • Large data volumes, requiring significant storage and processing power • Generally, high cost of data acquisition, and data availability could be an issue
Radar (Synthetic Aperture Radar - SAR)	• Can penetrate clouds, fog, and work in all weather conditions (day or night) • Provides data on surface deformation (e.g., subsidence, landslides) • High temporal resolution, suitable for monitoring rapid changes (e.g., flood extent)	• Lower spatial resolution compared to optical sensors • Interpretation is complex, requiring expertise in radar data processing, • Can be affected by terrain and surface roughness, affecting accuracy in some regions
Lidar	• Provides high-resolution 3D data (surface elevation, vegetation height) • Excellent for detecting subtle topographical or structural changes (e.g., building height, forest canopy changes) • Highly accurate for detecting surface changes (e.g., vegetation, urban infrastructure)	• Expensive and often limited to specific areas or campaigns • Limited by weather conditions (e.g., performance degraded in heavy rain or fog) • Lower spectral information compared to multispectral or hyperspectral data, focusing mostly on spatial attributes

You have learned now that each of the remote sensing data type has its unique advantages and limitations, making them more or less suitable depending on the specific objectives of the change detection study, such as scale, resolution, type of change, and environmental conditions.

15.3 STEPS IN CHANGE DETECTION STUDIES

There are several steps in which remote sensing based change detection studies are carried out. According to Lu et al., 2004, there are three major steps:

- image preprocessing including geometrical rectification and image registration, radiometric and atmospheric correction, and topographic correction if the study area is in mountainous regions;
- selection of suitable techniques to implement change detection analyses; and
- accuracy assessment.

We discuss these into five steps which are given here:

Step 1: Image Acquisition and Selection

Collection of remote sensing data suitable for change detection for the objects and phenomenon under investigation is the first step. It could be panchromatic, multispectral, hyperspectral, radar or lidar multi-temporal data and may be from sources like Landsat, Sentinel, MODIS, SPOT, or high-resolution commercial satellites. One needs to ensure that images cover the same geographical extent and are taken during similar seasonal periods to minimise inconsistencies.

Step 2: Image Preprocessing

The images collected need to be preprocessed for geometric correction, image registration, atmospheric correction, radiometric normalisation, topographic corrections, masking of clouds and to standardise the pixel sizes, Georeferencing converts raw images into a standard coordinate reference system (e.g., UTM, WGS84) and co-registration align multi-temporal images by selecting control points and performing transformations. Resampling is done standardise pixel size if images have different spatial resolutions. It interpolates pixel values to match spatial resolution (e.g., nearest neighbour, bilinear, or cubic convolution).

Radiometric calibration converts digital numbers (DN) of images into physical reflectance values and corrects sensor-specific variations (e.g., gain and offset correction). Some of the common methods of atmospheric correction are used are:

- Dark Object Subtraction (DOS) – It assumes that certain pixels (e.g., deep water or shadows) should have near-zero reflectance in infrared bands. It subtracts minimum reflectance values to reduce haze effects. Steps include identification of the darkest objects in the image, estimation of atmospheric scattering in each band and the subtraction of the estimated atmospheric contribution from all pixels.

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- FLAASH (Fast Line-of-Sight Atmospheric Analysis of Spectral Hypercubes) – It is a physical model based atmospheric correction generally used for hyperspectral data.
- 6S (Second Simulation of the Satellite Signal in the Solar Spectrum) – It is also a physical model based atmospheric correction method which models atmospheric conditions to simulate atmospheric scattering and absorption. These methods are more accurate but computationally intensive.

Radiometric normalisation is carried out to adjust for sensor variations, illumination differences, and atmospheric effects to ensure spectral consistency between images. It ensures that pixel values are consistent across multi-temporal images.

Relative radiometric normalisation does not convert images to absolute reflectance but instead normalises one image (Target) using a reference image (Base). It is faster and widely used in change detection when absolute calibration is not required. Radiometric normalisation prevents brightness differences from being misinterpreted as land cover changes.

Some of the common techniques for relative radiometric normalisation are:

- Dark Object Subtraction (DOS) – it is also used to reduce inter-image variations.
- Histogram Matching – it is used to reduce inter-image variations. It adjusts the histogram of the target image to match that of the base image. It assumes that the general brightness and contrast distribution should be similar between images. For this, the first step is to compute histograms of base and target images. Then pixel values in the target image are adjusted to match the statistical distribution of the base image.
- Pseudo-Invariant Features (PIFs) – Identifies stable ground features (e.g., roads, deep water bodies) that exhibit minimal reflectance changes over time to normalise radiometric values. It normalises radiometric differences based on these invariant features. For this, the first step is to select pseudo-invariant features (PIFs) from both images using scatter plots or machine learning techniques and then apply a linear regression model.
- No-Change Method (Multivariate Alteration Detection - MAD) – It identifies areas that have not changed between two images using statistical analysis. It normalises the target image based on the unaltered pixels. The major steps are use of statistical tests (e.g., Principal Component Analysis (PCA)) to detect unchanged pixels and applying a normalisation function to adjust radiometric values of the target image.
- Empirical Line Calibration (ELC) – It uses field measurements of surface reflectance and image pixel values to create a linear correction model. Steps include collection of ground truth spectral reflectance of known targets (e.g., white calibration panels, asphalt roads) and performing linear regression to calibrate image pixel values. It is generally applied in hyperspectral image calibration where field spectral data is available.

These radiometric normalisation methods are summarised in the Table 15.3.

Table 15.3: Comparison of radiometric normalisation methods:

Method	Absolute/ Relative	Complexity	Best Used For
Radiometric Calibration	Absolute	High	High-precision change detection
Dark Object Subtraction (DOS)	Absolute	Medium	Haze correction in optical imagery
Histogram Matching	Relative	Low	Large-area multi-temporal analysis
Pseudo-Invariant Features (PIF)	Relative	Medium	Urban and infrastructure monitoring
Multivariate Alteration Detection (MAD)	Relative	High	Large-scale environmental change detection
Empirical Line Calibration (ELC)	Absolute	High	Hyperspectral image calibration

Cloud masking is done to minimise errors caused by cloud cover, cloud shadows, and terrain shadows in optical images.

Step 3: Selection of Change Detection Method

The next step is to choose an appropriate change detection technique based on the study objective and data availability.

Step 4: Change Analysis and Interpretation

Now the next step is to apply the selected change detection methods on the your data. You need to identify and quantify changed and unchanged areas and interpret results based on domain knowledge and ancillary data.

Step 5: Accuracy Assessment and Validation

After change analysis, the next step is to compare detected changes with ground truth data, historical records, or field surveys. For this purpose you may generate a confusion matrix to calculate accuracy metrics such as overall accuracy, user's accuracy, producer's accuracy, and kappa coefficient as discussed earlier in the course MGY-102 and also in the next unit.

Effective preprocessing ensures that change detection analysis is reliable and free from errors caused by geometric, radiometric, atmospheric, and sensor inconsistencies. Each preprocessing step from co-registration and radiometric normalisation to cloud removal and data fusion plays a critical role in enhancing the accuracy of change detection results. Proper implementation of these steps leads to more precise identification of land cover transformations, environmental changes, and disaster impacts in remote sensing applications.

15.4 METHODS OF CHANGE DETECTION

There are several methods of change detection applied for variety of remote sensing data. These methods can be broadly categorised into pixel based, object based, and spatial data mining based techniques (Hussain et al., 2013).

However, commonly adopted terms are pixel based, classification based, object based, spectral index based, and machine learning and AI based change detection methods. Let us discuss these methods one by one here. So let us first discuss the pixel based methods.

15.4.1 Pixel Based Methods

Pixel-based change detection methods are among the most widely used approaches in remote sensing for detecting changes in Earth's surface over time. These methods focus on the comparison of individual pixels in multi-temporal remote sensing images to identify changes. Some of the most common pixel-based change detection methods used in remote sensing are described here.

1. Image Differencing

Image differencing is one of the simplest and most intuitive change detection methods. It involves subtracting the pixel values of two images from different times (pre-change and post-change images) to highlight the differences. The result is a difference image, where the intensity of each pixel represents the change between the two time points.

This method has several advantages such as it is easy to implement, computationally efficient and is effective for detecting large changes in homogeneous areas. However, it has some disadvantages such as it is sensitive to misalignment (image registration errors), can be influenced by noise and atmospheric variations and using this method it is difficult to detect subtle or gradual changes.

2. Post-Classification Comparison

This method involves classifying each image (i.e. of pre-change and post-change time periods) separately into different land cover categories using classification algorithms (e.g., supervised or unsupervised classification). The two classified images are then compared to detect changes in land use land cover features. The comparison generates a change matrix, which identifies areas that have changed, stayed the same, or experienced different types of changes.

This method has several advantages such as it is effective for land cover/land use change detection as it can handle complex changes by using sophisticated classification techniques and provides clear identification of change types (e.g., forest to urban, water to vegetation). Disadvantage of this method include: it is sensitive to classification errors, especially when classes are similar; requires high-quality classification results and can be time-consuming and requires accurate ground truth data for classification.

3. Change Vector Analysis

Change Vector Analysis (CVA) is a method that looks at both the magnitude and direction of changes between two time points. It is based on the concept of vector analysis, where the difference between pixel values in the feature space (e.g., multi-spectral bands) is treated as a vector. A change vector of a pixel is the vector difference between the multi-band digital vector of the pixel on two different dates. The amplitude and direction of change from date one to date two are described by a spectral change vector. The output consists of two images, one of which shows the change vector's magnitude and the other its direction. If the magnitude of changes exceeds a certain threshold, the change is determined, and the type of change is indicated by the direction of the change vector. The magnitude and direction of this vector indicate the extent and type of change. Advantages of this method include: effective for detecting subtle changes; can detect both changes in the magnitude and direction of pixel values and can be applied to multiple spectral bands for a more robust analysis. Disadvantages of this approach are that it is computationally intensive; requires high-quality data, particularly in terms of radiometric calibration and is sensitive to noise and may require sophisticated filtering techniques.

4. Principal Component Analysis (PCA)

As you know, PCA is a dimensionality reduction technique that transforms multi-spectral data into a new set of uncorrelated variables called principal components. By applying PCA to multi-temporal images, the changes between the images can be detected by examining the variation in the first few principal components. The principal component images are then analysed to identify changes.

In the Multi-date Principal Component Analysis method, two images from the same location taken at different times are superimposed and analysed as a single image. The local alterations are revealed by the minor component images, while the major component images display the reflectance and radiometric variances (minor changes). This method is more useful than the post classification method for tracking rapid changes in land use and urban growth.

Advantages of this method are that it reduces data complexity by transforming data into fewer components; can highlight large-scale changes across multiple spectral bands and is useful for large datasets with many spectral bands. Disadvantage of this method is that it does not provide detailed change information (only the variation in data); requires interpretation of principal components, which can be difficult and is sensitive to the selection of bands used in the PCA transformation.

5. Thresholding

Thresholding is a simple technique which is often applied to the result of image differencing or change vector analysis. A threshold value is set, and pixels with change values above or below that threshold are considered to have undergone a significant change. This method is commonly used in conjunction with other methods like image differencing or PCA to segment areas of change. Advantages of this method are that it is simple and easy to apply; suitable for detecting large-scale, significant changes and has low computational cost. Disadvantages of this method are: the arbitrary threshold selection can influence the results; is sensitive to noise and atmospheric conditions and is not effective for detecting small, subtle changes.

6. Vegetation Index Differencing

In studies of vegetation, a ratio (sometimes referred to as a vegetation index) is employed to emphasise spectral contrasts between vegetation's strong near-infrared reflectance and the chlorophyll-absorption band (red portion) of the spectrum. Ratio Vegetation Index, Normalised Vegetation Index, and Transformed Vegetation Index are examples of common vegetation indices. NDVI is a commonly used vegetation index that quantifies the density of green vegetation. By comparing NDVI values of two images taken at different times, change detection can be performed to identify changes in vegetation cover. The NDVI difference is often used for monitoring forest cover change, agriculture, or urbanisation.

Advantages of this method are that it is specifically designed for vegetation monitoring; is simple and effective in detecting changes in vegetation cover and is useful for agriculture, deforestation, and other land cover changes. And the limitations are that it is limited to vegetation monitoring (not effective for non-vegetative changes); is sensitive to atmospheric conditions and seasonal variations and does not capture other types of land cover changes.

7. Image Ratioing

Image ratioing involves dividing the pixel values of the post-change image by the pixel values of the pre-change image. This method highlights areas of significant change based on the ratio. The result is a ratio image, where values significantly greater than or less than 1 indicate change.

This method is simple to implement and computationally efficient; is effective for detecting large changes and can highlight areas where change is significantly different from the background. However, it is sensitive to misregistration and noise; may not effectively detect small or subtle changes and assumes that the pixel values of both images are comparable, which may not always be the case due to differences in illumination or atmospheric conditions.

8. Multivariate Statistical Methods

Multivariate statistical methods involve comparing multi-temporal data using statistical techniques, such as the Mahalanobis distance or the Kullback-Leibler divergence. These methods assess the likelihood of change by comparing the statistical distributions of pixel values from different time points. The result is a change map indicating areas where the statistical characteristics of the data have shifted.

This method is effective for detecting complex and subtle changes; can incorporate several spectral bands to account for multi-dimensional change and is robust to some types of noise and environmental conditions. However, disadvantages of this method are that it is computationally intensive; requires careful statistical modelling and understanding of the data and can be challenging to interpret without sufficient ground truth data.

Pixel-based change detection methods are essential tools for analysing spatial changes over time using remote sensing data. While methods like image differencing and post-classification comparison are simple and widely used, more advanced techniques such as Change Vector Analysis and Principal Component Analysis can be applied to detect more subtle or complex changes. However, each method has its strengths and limitations, and selecting the most suitable approach depends on the type of change being studied, the available data, and the desired level of accuracy.

The pixel based methods discussed here are summarised in the Table 15.4.

Table 15.4: Comparison of various pixel-based change detection methods:

Method	Description	Advantage	Limitation
Image Differencing	Subtracts pixel values of two images taken at different times	Simple and fast, easy to implement	Sensitive to noise, requires images with similar conditions
Post-Classification Comparison	Compares classified images from different dates	Identifies changes in land cover types	Requires accurate classification, affected by classification errors
Change Vector Analysis (CVA)	Uses vector difference between pixel values in multi-temporal images	Detects subtle changes, considers multi-spectral information	Complex, requires careful parameter selection
Principal Component Analysis (PCA)	Reduces dimensionality of multi-temporal images	Highlights significant changes, reduces redundancy	May miss small changes, requires multiple images
Thresholding	Sets a threshold to identify changes based on pixel value differences	Simple and intuitive	Requires manual threshold setting, sensitive to threshold choice
Vegetation Index Differencing	Uses vegetation indices (e.g., NDVI) to detect changes in vegetation cover	Effective for vegetation monitoring, reduces atmospheric effects	Limited to vegetation changes, requires consistent image quality
Image Ratioing	Divides pixel values of one image by another	Normalises differences, reduces effects of illumination changes	Sensitive to image quality, requires consistent conditions

Each method has its strengths and weaknesses, and the choice of method depends on the specific application and data characteristics.

Let us spend 5 minutes to check your progress.

SAQ I

a) What is the objective of change detection?

b) Which are the major steps in a change detection study?

c) List the pixel based change detection methods.

Let us now discuss the classification based methods.

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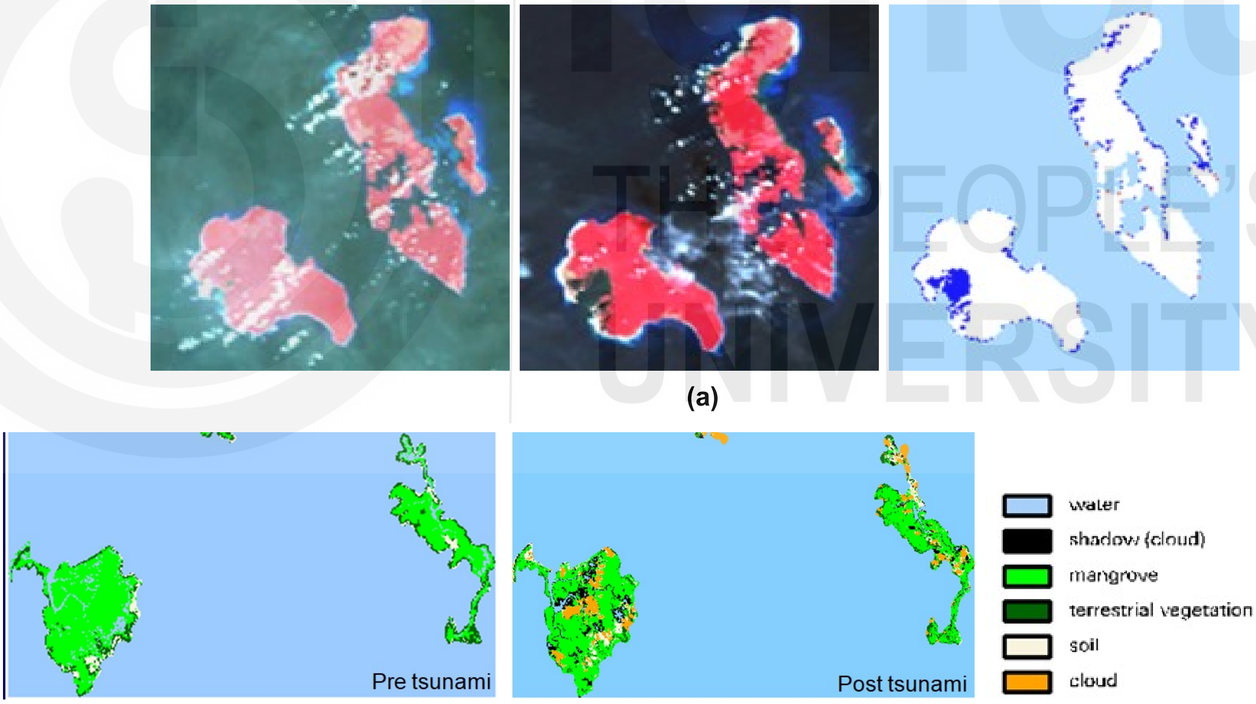
15.4.2 Classification Based Methods

Second type of change detection methods is classification-based change detection methods that focus on identifying changes in land cover or land use by comparing classified images from different time periods. These methods involve classifying both pre-change and post-change images and then comparing the resulting classified images to detect changes. The approach typically requires an intermediate step of image classification, which assigns each pixel in the image to a predefined class (e.g., water, forest, urban). The commonly used classification based change detection methods are discussed here:

1. Post-Classification Comparison

The post-classification comparison method involves separately classifying two or more multi-temporal images (e.g., pre-change and post-change images) and then comparing the resulting classification maps. The comparison helps detect land cover or land use changes by identifying pixels that have changed from one class to another between the two time points. A change detection matrix (or change detection map) is then generated, highlighting areas of no change, as well as the types of land cover transitions (e.g., forest to urban). The classification outputs may have binary (i.e. two classes) or multi-class as shown in Fig. 15.2.



(a)

(b)

Fig. 15.2: Classification based change detection study showing classified images of LISS III images of: a) pre (left panel), post tsunami (middle) periods and the image on right [generated by subtraction of binary class (i.e. land and water) classified outputs] shows the areas where there are change of pixels from land to water as represented in dark blue colour; b) pre and post tsunami periods showing changes in the spatial extent of mangroves in the islands of A&N due to tsunami event of December 2004 as obtained in the multiclass classified outputs. Note the effect of cloud cover on classification in the post tsunami image. (Source: Prof. Benidhar Deshmukh)

Advantages of this method is that it provides detailed information about the nature of changes (specific class transitions); is simple to implement with widely available software tools and is effective for detecting large or abrupt changes in land cover. However, there are certain disadvantages such as classification errors can propagate, leading to inaccurate change detection results; is sensitive to misclassification due to similar spectral signatures for different classes, and requires careful selection of classification techniques and parameters to ensure consistency across time periods.

2. Change Vector Analysis (CVA) with Classification

Change Vector Analysis (CVA) can be applied to classified images also to capture both the magnitude and direction of change. After classifying the images, CVA computes a "change vector" that measures the difference between corresponding pixel values (or classes) from the pre- and post-change images. The magnitude of the change vector reflects the extent of the change, while the direction represents the type of change (e.g., forest to urban). This method can be enhanced by incorporating classification maps to understand how specific land cover types are changing over time.

Advantages of this method is that it can detect both the type and magnitude of changes; is useful for identifying subtle changes in land cover or land use and can be applied to multi-temporal datasets, enabling long-term monitoring of changes. However, there are certain disadvantages of this method such as it requires accurate classification and data alignment; is sensitive to classification errors and spatial misalignment and is computationally intensive, particularly for large datasets.

3. Change Detection Using Decision Trees or Machine Learning

In this method, machine learning algorithms such as decision trees, random forests, or support vector machines (SVMs) are used to classify both pre-change and post-change images. After classification, the results are compared to detect changes. These algorithms can learn complex, non-linear relationships between the pixel values and land cover types, improving classification accuracy. Additionally, machine learning methods can be trained on multi-temporal data to identify patterns in land cover change more effectively than the traditional methods.

Advantage of this method is that machine learning algorithms can achieve high classification accuracy, even with complex or non-linear data. Decision trees and random forests are particularly good at handling large, high-dimensional datasets. These methods can account for spatial, temporal, and spectral data for improved change detection. Disadvantages of this method are that it requires a large amount of training data (ground truth or labelled data) for model training; may require specialised expertise in machine learning techniques; and is computationally intensive, especially when training on large datasets.

4. Post-Classification Fusion

Another classification based method is the post-classification fusion, which involves the combination of classifications from multiple temporal images into a single output by fusing them using statistical methods or by applying a decision rule. This method may involve applying multiple classifiers to a set of temporal

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images and combining their results. It can also use consensus methods to combine classifications from different classification techniques or sensor data. The resulting output is a fused classification map, which identifies land cover changes more effectively than any single classification method.

Advantages of this method are: it combines strengths of multiple classifiers for higher accuracy; it allows integration of different sensor types or temporal data sources, and is effective for handling complex or heterogeneous environments. Disadvantages of this method are: it is complex to implement and interpret; requires good alignment and registration of multi-temporal images; it can be computationally intensive and may require significant post-processing.

5. Multi-Temporal Supervised Classification

This method uses supervised classification techniques (such as maximum likelihood, support vector machines, or random forests) applied to multi-temporal image data. Rather than classifying the images separately, this technique integrates the multi-temporal data and classifies the images simultaneously or sequentially to identify land cover changes. The idea is to use the temporal features of each pixel to aid in the classification of changes.

Advantages of this method are that it takes advantage of the temporal information to improve classification accuracy; is useful for detecting both gradual and sudden changes in land cover and can be applied to a variety of land cover types and sensor data. Disadvantages of this method are that it requires careful training to handle temporal variability and avoid misclassifications; requires labelled training data from both time periods, which may be difficult to acquire, and it can be computationally intensive when using multiple data layers.

6. Hybrid Classification Approaches

As you have read earlier, hybrid classification methods combine different techniques to take advantage of their individual strengths. For example, a hybrid method might use an object-based approach combined with a machine learning classifier, or integrate post-classification with decision tree classification. These hybrid methods aim to improve classification accuracy by leveraging multiple data sources and methods in a complementary manner.

Advantages of this method are that it maximises the strengths of multiple techniques to improve overall accuracy; is suitable for complex environments where a single classification approach may not suffice, and it can handle large datasets and complex classification tasks effectively. Disadvantages of this method are that it is complex to implement and tune; it requires expertise in multiple classification and processing techniques, and it may be computationally expensive and require significant processing power.

Classification-based change detection methods are widely used for detecting and analysing land cover or land use changes using remote sensing data. While traditional methods like post-classification comparison are still common, more advanced techniques such as object-based change detection, machine learning-based approaches, and hybrid methods have significantly improved the accuracy and reliability of change detection studies. Each method has its strengths and limitations, and the choice of method often depends on the nature of the study, the available data, and the type of changes being monitored.

Let us now study about the object based change detection methods.

15.5.3 Object Based Methods

Object-based change detection (OBCD) methods focus on analysing changes at the level of image objects rather than individual pixels. These methods group pixels into objects (or segments) based on similar spectral, spatial, and contextual properties, which are then classified and compared to detect changes. Object-based approaches are particularly useful for complex land covers (e.g., urban areas, forests, agricultural fields) where pixel-based methods may struggle due to noise or the heterogeneity of the landscape.

Some of the object-based change detection methods used are discussed here.

1. Object-Based Change Detection Using Image Segmentation

In this method, the images (pre- and post-change) are first segmented into objects or homogeneous regions using segmentation algorithms (e.g., watershed, region-growing, or multiresolution segmentation). These segments represent meaningful land cover objects (e.g., trees, buildings, roads) rather than individual pixels. After segmentation, each object is classified, and then the pre- and post-change classified objects are compared to identify changes. This comparison can be done using similarity metrics (e.g., intersection-over-union, Euclidean distance) or by directly comparing the class assignments for each object.

2. Change Detection Based on Object Matching

Object matching involves comparing objects identified in the pre-change and post-change images by matching similar objects based on certain criteria (e.g., size, shape, texture, spectral properties). If the objects from the two images are similar (i.e., match based on predefined thresholds or similarity metrics), they are considered unchanged; otherwise, they are marked as changed. This method is particularly useful when comparing objects that are expected to remain stable or have only experienced slight changes.

3. Object-Based Change Detection with Texture and Contextual Features

This method incorporates texture information into the object-based approach by calculating texture features (e.g., entropy, contrast, correlation, etc.) for image segments. Texture features capture the spatial arrangement and structure of pixel values within an object, which can be useful for distinguishing between different types of land cover or detecting subtle changes in the environment. The texture features are then used in combination with spectral features to classify objects and detect changes.

Contextual information such as neighbouring object characteristics, land cover relationships, or topological features (e.g., adjacency, connectivity) can also be incorporated into the change detection process. For example, if a forest patch is surrounded by urban areas, the detection algorithm may prioritise changes based on spatial context (e.g., deforestation or construction). Contextual analysis helps refine object classification by considering the broader spatial arrangement of land cover types.

4. Change Detection with Object-Based Classification Fusion

Object-based classification fusion combines multiple classification methods or sensor data to improve change detection results. For example, it might combine

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a spectral classification with a texture-based classification or integrate data from different sensors (e.g., optical and radar). The fusion of multiple data sources can provide a more comprehensive understanding of land cover change by leveraging the strengths of each classification approach.

Object-based change detection (OBCD) methods offer a more robust alternative to traditional pixel-based methods, particularly in environments where the land cover is heterogeneous or complex. By focusing on image objects rather than individual pixels, these methods better capture spatial and contextual relationships, leading to more accurate change detection, especially in urban and natural landscapes. However, they require high-quality segmentation, careful parameter selection, and often involve more complex processing and computational demands compared to simpler pixel-based approaches.

Let us now study about the spectral index based change detection methods.

15.4.4 Spectral Index Based Methods

Spectral index-based change detection methods use specific spectral indices derived from remotely sensed data to detect changes in the Earth's surface. We have read in earlier courses that spectral indices are mathematical combinations of different spectral bands designed to highlight certain features, such as vegetation, water bodies, or soil. These indices can be computed for both pre- and post-change images, and the differences between the resulting index values are analysed to identify changes in land use and land cover features over time.

Some of the common spectral index-based change detection methods used in remote sensing are NDVI (Fig. 15.3), Soil Adjusted Vegetation Index (SAVI), Enhanced Vegetation Index (EVI), Difference Vegetation Index (DVI), Normalised Difference Built-up Index (NDBI), Normalised Difference Water Index (NDWI), Normalised Difference Snow Index (NDSI), etc.

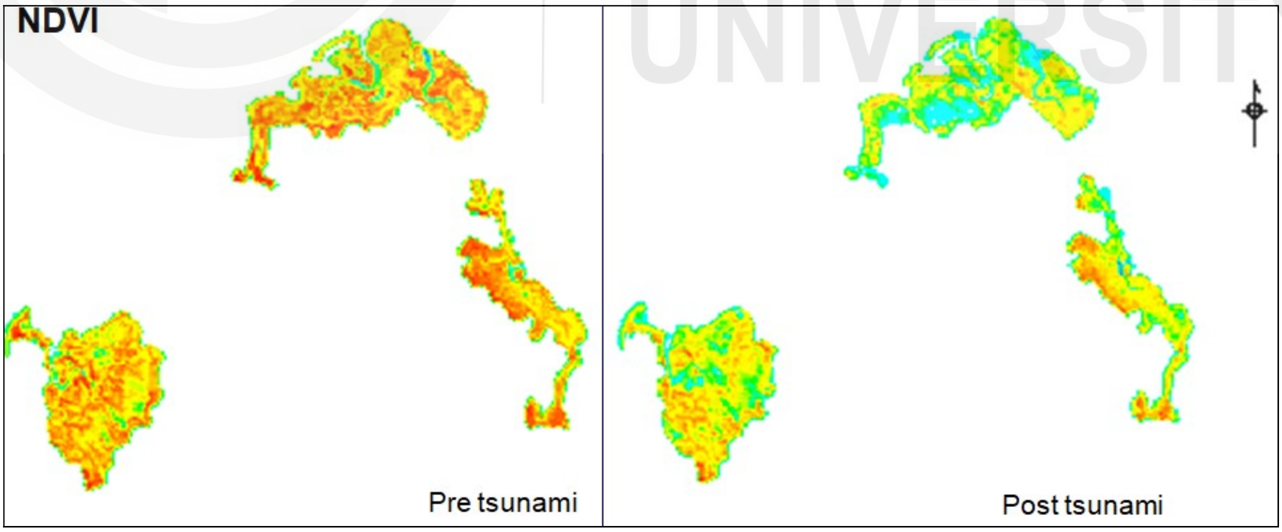

Fig. 15.3: NDVI based change detection result showing NDVI images (in pseudocolour) created from LISS III images of pre (left panel) and post tsunami (right panel) periods showing changes in mangrove cover and also the variations within the mangrove areas the islands of A&N due to tsunami event of December 2004. Note the effect of cloud cover on classification in the post tsunami image. (Source: Prof. Benidhar Deshmukh)

Spectral index-based change detection methods are popular in remote sensing because they offer a simple, fast, and effective way to detect changes in specific land cover types, such as vegetation, water bodies, or built-up areas. By comparing the differences in spectral indices between multi-temporal images, these methods can highlight changes like vegetation loss, urbanisation, water fluctuations, or snow melt. However, the choice of spectral index depends on the specific application, and users must account for factors such as atmospheric conditions, sensor limitations, and the availability of suitable index formulas for the target feature.

Let us now study the machine learning and AI based methods.

15.4.5 Machine Learning and AI Based Methods

Machine learning (ML) and artificial intelligence (AI)-based change detection methods have gained popularity in recent years due to their ability to handle complex datasets, automate processes, and improve detection accuracy. These methods leverage advanced computational techniques to analyse multi-temporal remote sensing data and identify significant changes in the Earth's surface, even in the presence of noise, mixed pixels, or subtle alterations. Some of the machine learning (ML) and AI-based change detection methods used in remote sensing are discussed here.

1. Unsupervised Classification-Based Change Detection

Unsupervised machine learning methods like k-means clustering, ISODATA, or self-organising maps (SOM) are used for change detection without the need for labelled training data. These methods automatically group the image pixels into clusters based on their spectral characteristics, and the differences in pixel groupings between pre- and post-change images are analysed to detect change. The analysis may be carried out by comparing the number or position of clusters, identifying new or lost clusters, or observing changes in cluster characteristics.

This approach does not require labelled data, making it suitable for areas with no ground truth. It can be applied in a variety of regions, even when no prior knowledge of the land cover is available. It is faster than supervised methods in some cases due to its reliance on automated clustering. However, there are some disadvantages of this approach. It may produce less accurate results, especially in areas with complex land cover or mixed pixels. It is difficult to interpret results, as clustering does not directly correspond to real-world classes (e.g., urban, forest, water). And it is sensitive to the number of clusters chosen, which may require manual tuning.

2. Supervised Classification-Based Change Detection

In supervised classification-based change detection, machine learning algorithms (such as support vector machines (SVM), random forests, or artificial neural networks (ANNs)) are trained to classify land cover types in pre- and post-change images. The training is performed using labelled data (ground truth), and the classifier learns to differentiate between changed and unchanged areas based on the spectral, spatial, and temporal features of the pixels. After training, the model is applied to classify both pre- and post-change images. The changes are detected by comparing the classified results from the two time periods.

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Advantages of this approach are that it is accurate for detecting large, distinct changes. It works well when enough labelled data (ground truth) is available for training. There is high flexibility in dealing with various land cover types and change scenarios. The disadvantages of this approach are that it requires a large amount of labelled training data, which may not always be available; it can be computationally expensive for large datasets and is sensitive to class imbalances (e.g., changes may be rare compared to non-changes).

3. Change Vector Analysis (CVA) with Machine Learning

You have read earlier, that Change Vector Analysis (CVA) is a technique where changes are detected by analysing the vector of differences between pre- and post-change image pixels in a multi-dimensional feature space. Machine learning models can be employed to improve the classification of change vectors, by identifying the most relevant features and classifying the change vector into different change types (e.g., vegetation loss, urban expansion, etc.).

Advantage of this approach is that it is effective for detecting changes at a pixel level, particularly in areas where changes are subtle or gradual. Machine learning algorithms can improve the robustness of CVA, enhancing accuracy in change detection. It is adaptable to multi-temporal datasets with varying levels of change intensity. There are some disadvantages of this approach such as it is sensitive to the selection of the feature space and dimensionality reduction. It requires significant computational resources, especially for large datasets with multiple bands or high resolution and accuracy of the results depends on the chosen machine learning algorithm and its hyperparameters.

4. Deep Learning-Based Change Detection

Deep learning, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), has become a powerful tool for change detection in remote sensing. CNNs can automatically learn hierarchical features from multi-temporal satellite imagery, making them effective for detecting changes in complex landscapes, such as urban expansion or land cover transitions. Recurrent neural networks (RNNs) or long short-term memory (LSTM) networks can be applied to handle sequential data, where temporal dependencies play a crucial role (e.g., monitoring changes over time in vegetation dynamics or land use).

Advantages of this approach are that deep learning models can automatically extract features from the raw image data, reducing the need for manual feature engineering. It has high accuracy and robustness, especially for large and complex datasets and it can handle high-dimensional data, including multispectral, multi-temporal, and high-resolution imagery. Disadvantages of this approach include the following: it requires large amounts of labelled data for training, which can be difficult or expensive to obtain it is computationally intensive, requiring high-performance hardware (e.g., GPUs) for training and these models can be "black-box", making it difficult to interpret the underlying mechanisms of change detection.

5. Ensemble Learning-Based Change Detection

Ensemble learning methods combine predictions from multiple models to improve the accuracy of change detection. Popular ensemble techniques include bagging, boosting, and stacking. In remote sensing, ensemble models like Gradient Boosting Machines (GBM) or AdaBoost can be used to combine the results from various classifiers (e.g., random forests, decision trees, support vector machines) to produce a final prediction. These methods are particularly useful in capturing different aspects of changes that may be missed by individual models.

Results of this approach generally have higher accuracy compared to individual models by reducing bias and variance. It is robust to overfitting, especially with large and diverse datasets and is capable of handling both spectral and spatial information for comprehensive change detection. However, this approach is computationally intensive, especially for large datasets and is more complex to implement and tune compared to single models and requires significant data preprocessing and feature engineering.

Machine learning and AI-based change detection methods offer powerful tools for detecting complex and subtle changes in remote sensing data. These methods, especially deep learning, random forests, and SVMs, can provide high accuracy and robustness, handling large and multi-temporal datasets effectively. However, they generally require high-quality labelled data for supervised methods, large computational resources, and careful tuning of models.

15.4.5 GIS Based Method

The methods discussed in this section deal mostly with remote sensing data i.e. raster data. For certain applications such as shoreline mapping, etc. vector data based change detection is required to be performed. The techniques used for vector data based change detection is generally different then the raster based techniques. In most of the cases, vector data is created by visual interpretation and onscreen digitisation of the features of interest for different time periods from remote sensing data. Then the vector data of different time periods are processed and analysed to visualise and quantify the degree of change.

15.5 CONSIDERATIONS IN CHANGE DETECTION STUDIES

When we are using remote sensing data to detect changes in land use and land cover or other features, significant changes in radiance values should be attributed to the land use and land cover changes, rather than other factors like atmospheric conditions, sun angle, and soil moisture. Impact of these factors' can be minimised by selecting suitable data.

There are several factors that need to be considered and carefully taken care of while carrying out a remote sensing data based change detection study. Each of these factors plays an important role in ensuring accurate, reliable, and actionable results. Some of the factors are given in the Table 15.5:

Table 15.5: Considerations for remote sensing based change detection studies:

Consideration	Description
Selection of remote sensing data	• Spatial resolution: Data should match the scale of change (e.g., high-resolution for urban changes, moderate-resolution for large-scale phenomena) • Temporal resolution: Frequency of data acquisition should be high enough to detect changes, especially for dynamic phenomena

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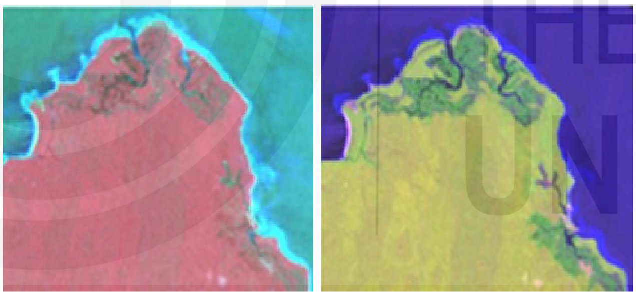
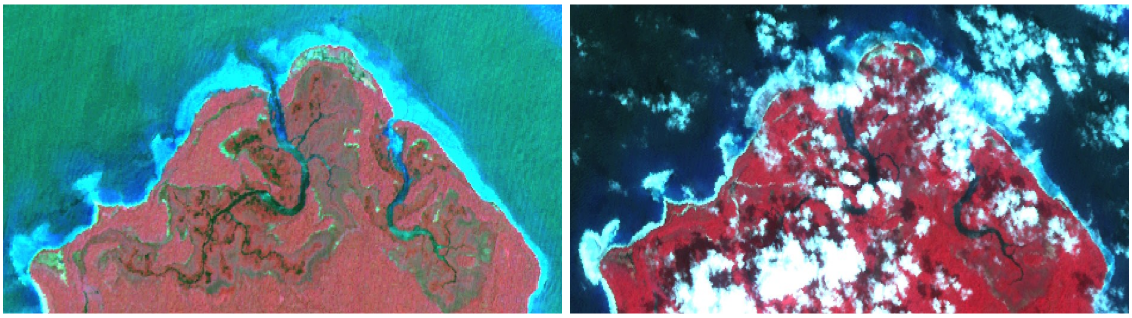
	• Spectral resolution: Suitable (Fig. 15.4a) and higher number of spectral bands allow for more detailed material differentiation (e.g., hyperspectral for specific minerals, multispectral for land cover) • Data availability: Availability of historical data (e.g., Landsat, Sentinel-2) for long-term change analysis and access to commercial data for high-resolution needs
Time interval between data collection	• Appropriate time gap: The interval between data acquisitions should allow for significant changes to be detected without too much external variation • Seasonal variability: Changes due to seasons (e.g., vegetation or water levels) must be considered to avoid confounding results
Environmental conditions	• Weather/atmospheric effects: Clouds (Fig. 15.4b), haze, and fog can obscure optical imagery. Radar (SAR) and lidar are useful in cloudy or night-time conditions • Terrain effects: Rugged terrain may cause misinterpretation, especially in optical and radar data due to shadowing or foreshortening
Preprocessing requirements	• Geometric corrections: Ensures alignment of data from different times for accurate comparison • Radiometric calibration: Adjusts for sensor variations over time to ensure consistent brightness values • Cloud masking and shadow removal: Eliminates cloud cover and shadows that can obscure true surface features
Change detection methodology	• Pixel-based methods (e.g., image differencing, ratioing) are useful for spectral changes but may suffer from noise and misalignments. Change Vector Analysis (CVA) captures magnitude and direction of change, and is good for detecting subtle change. Principal Component Analysis (PCA) reduces dimensionality and highlights changes, and is useful for large datasets • Classification-based methods (e.g., post-classification comparison) provide categorical change detection but depend on classification accuracy • Object-based methods (e.g., OBIA) reduce misclassification by considering spatial and contextual information. • Machine learning and AI approaches improve automation and accuracy but require extensive training data • Time-series analysis: Ideal for gradual or seasonal changes, computationally intensive
Data fusion and integration	• Combining data types: Combining data from optical, radar, and lidar sensors enhances change detection by providing complementary information • Data Fusion techniques: Integrating multisource data can improve results, especially for complex environments like urban areas
Temporal dynamics of	• Rate and type of change: The speed and nature of the change (e.g., rapid changes after a disaster vs. slow urban

change	growth) dictate the choice of data and methods • Reversibility of changes: Understanding whether changes are temporary or permanent is crucial for interpreting results (e.g., seasonal changes vs. deforestation)
Applications and decision-making	• Objective of study: Clear study goals (e.g., environmental monitoring, resource management, disaster response) will guide data selection and methodology • Decision support: The results should inform decision-making processes, such as policy development or conservation strategies
Cost and availability of data	• Data accessibility: Freely available satellite data (e.g., Landsat, Sentinel-2) may be sufficient for many studies, while commercial data (e.g., WorldView) offers higher resolution but at a cost • Budget Constraints: Cost limitations may influence the choice of data (e.g., opting for open-access data versus expensive commercial imagery)
Accuracy assessment	• Ground truthing: Field validation or ground-based data ensures change detection results match reality • Accuracy metrics: Use of metrics like kappa coefficient, confusion matrix, and overall accuracy to quantify change detection reliability • Error sources: Errors may arise from misregistration, misclassification, or sensor-related issues, requiring minimisation



(a)



(b)

Fig. 15.4: a) Mangrove and inland vegetation areas in 432 and 543 band combinations of LISS III images showing the importance of selection of appropriate bands suitable for mapping the features of interest; and b) Pre (left) and post tsunami (right panel) images of an island showing how presence of cloud cover can affect the interpretation/classification of the underlying features;. (Source: Prof. Benidhar Deshmukh)

These considerations are to be taken care of while performing change detection.

According to Lu et al., 2004, accuracies of change detection results depend on many factors, including:

- precise geometric registration between multi-temporal images,
- calibration or normalisation between multi-temporal images,
- availability of quality ground truth data,
- the complexity of landscape and environments of the study area,
- change detection methods or algorithms used,
- classification and change detection schemes,
- analyst's skills and experience,
- knowledge and familiarity of the study area, and
- time and cost restrictions.

Spend 5 minutes to check your progress.

SAQ II

a) List the classification based change detection approaches.

b) What is multi-date PCA?

c) What is change vector?

d) What is GIS based change detection method?

Let us now learn about the recent trends in the field of change detection studies.

15.6 RECENT TRENDS

In this section, you will learn about recent trends in the area of change detection.

Change detection studies face several challenges; some of them are listed here:

- **Variations in image quality**: Despite availability of several types of remote sensing data, at times suitable data is not available particularly in coastal areas due to cloud cover and difference in tidal conditions. And differences in resolution, illumination condition due to time of day, season or weather, and sensor quality can affect the accuracy of change detection.
- **Noise and registration errors**: Noise in the data and errors in aligning images taken at different times can lead to incorrect change detection.
- **Complex landscapes**: Heterogeneous landscapes with diverse land cover types can complicate the detection process.
- **Spatial heterogeneity**: Differences in spatial characteristics across the study area can make it difficult to detect changes consistently.

Recent trends and developments in change detection studies include:

- **Multi-sensor data integration**: Combining data from different sensors (e.g., optical, synthetic aperture radar) enhances accuracy and robustness.
- **Artificial intelligence and deep learning techniques**: AI-based methods are increasingly being adopted for their superior performance over traditional techniques. The use of deep learning has become prevalent, improving feature extraction and addressing challenges like image quality variations and complex landscapes.
- **Unsupervised and semi-supervised learning**: These methods are gaining traction as they require less labelled data and can handle large datasets more efficiently.
- **Foundation models**: These models offer multi-task adaptability and are being explored for their potential in change detection.

Recent developments in change detection studies include development of new advanced algorithms to improve the accuracy and efficiency of change detection. Ongoing research is focusing on enhancing unsupervised learning, self-supervised learning, and multimodal data integration. These advancements and trends are driving the field forward, making change detection more accurate and applicable to a wider range of scenarios.

15.7 TERMINAL QUESTIONS

1. What are the variables offered by satellite data for land use land cover change?
2. Discuss the object based change detection methods.
3. Describe the spectral index based change detection methods?
4. What are the recent trends and development in the realm of change detection?

15.8 SUMMARY

Let us summarise what we have learnt in this unit. We have learnt that:

- Identifying, describing, and quantifying variations between images of the same scene taken at different times or under various circumstances are the goal of change detection analysis.
- Analysing changes in remote sensing images collected at two different times is a process called change detection. Different methods can be used to calculate the changes in these multi-temporal satellite images.
- The major steps in a change detection study include: image acquisition and selection, image preprocessing, selection of change detection method, change analysis and interpretation, and accuracy assessment and validation.
- Change detection methods can be categorised under pixel based, object based, classification based, spectral index based, ML and AI based, and GIS based.

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- The pixel based change detection methods include: image differencing, post-classification comparison, change vector analysis (CVA), principal component analysis (PCA), thresholding, vegetation index differencing, image ratioing and multivariate statistical techniques.
- Image differencing, Image ratioing, Image regression, change vector analysis, Vegetation index differencing, Multi date principal component analysis, Post classification techniques and on-screen digitisation are some of the techniques of change detection.
- Multi-date Principal Component Analysis is analysis where two images from the same location taken at different times are superimposed and analysed as a single image. The local alterations are revealed by the minor component images, while the major component images display the albedo (reflectance) and radiometric variances (minor changes).
- Vector data based change detection approaches are an example of the GIS based change detection method.
- There are several factors that need to be considered and carefully taken care of while carrying out a remote sensing data based change detection study.
- Recent developments in change detection studies include development of new advanced algorithms to improve the accuracy and efficiency of change detection.

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15.11 ANSWERS

SAQ I

a) Identifying, describing, and quantifying variations between images of the same scene taken at different times or under various circumstances are the objectives of change detection.

b) The major steps in a change detection study include: image acquisition and selection, image preprocessing, selection of change detection method, change analysis and interpretation, and accuracy assessment and validation.

c) The pixel based change detection methods are: image differencing, post-classification comparison, change vector analysis (CVA), principal component analysis (PCA), thresholding, vegetation index differencing, image ratioing and multivariate statistical methods.

SAQ II

a) Your answer should list the approaches discussed in section 15.4.2.

b) Multi-date Principal Component Analysis is analysis where two images from the same location taken at different times are superimposed and analysed as a single image. The local alterations are revealed by the minor component images, while the major component images display the albedo (reflectance) and radiometric variances (minor changes).

c) A change vector of a pixel is the vector difference between the multi-band digital vector of the pixel on two different dates.

d) Vector data based change detection approaches are generally covered under the GIS based change detection method.

Terminal Questions

1. It covers an inventory level of data indicating the location, nature, and extent of change is provided by the satellite land cover change information
2. You answer should cover the methods covered in section 15.4.3.
3. You answer should cover the methods covered in subsection 15.4.4.
4. You answer should cover the methods covered in section 15.6.

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