QUICK REFERENCE GUIDE
on
Digital Image Processing

Regional Remote Sensing Centre-North
National Remote Sensing Centre, ISRO

Quick Reference Guide

On

Digital Image Processing

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National Remote Sensing Centre

Indian Space Research Organisation

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Foreword

National Remote Sensing Centre (NRSC) is one of the primary centres of Indian Space Research Organisation (ISRO), Department of Space (DOS) for developing remote sensing applications, establishing ground stations for receiving satellite data and generating high-quality satellite data and aerial data products. Regional Remote Sensing Centres (RRSC) are part of NRSC supporting various remote sensing tasks specific to their regions at the national level.

At present, satellite data usage has increased many folds in multiple domains. Digital image processing (DIP) techniques enable processing of satellite data in an efficient manner. It involves the manipulation of satellite data to enhance the image quality, remove noise and other artifacts, and extract useful information from the data. Advance DIP techniques help in obtaining data for multi-dimensional representation like Data Cubes. The Analysis ready data (ARD) required for development of Data Cube is very much required for real time applications.

The quick reference guide on Digital Image Processing prepared by RRSC-North, conveys in-depth knowledge of image processing techniques in a comprehensive manner with clear explanations and conceptual illustrations used throughout to enhance student learning. I hope that this quick reference guide will be useful for all the students and researchers who are venturing into satellite data processing domain.

September 17, 2024 **(Prakash Chauhan)**

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From The Chief General Manager's Desk

National Remote Sensing Centre (NRSC) has five Regional Remote Sensing Centres (RRSCs) spread across the country. These centres are involved in addressing the local and regional issues using space and geospatial technology and also actively participate in capacity building as well as outreach activities in their respective regions. RRSC-North, located at New Delhi, caters to the needs of users in the Northern states of India viz. Delhi, Himachal Pradesh, Jammu & Kashmir, Uttar Pradesh and Uttarakhand. RRSC-North also organises training programmes and workshops on topics related to remote sensing, geographic information systems, digital image processing and their applications for government officials, academia and students.

I am extremely happy that RRSC-North has prepared a "Quick Reference Guide on Digital Image Processing." Basic concepts of Digital Image Processing (DIP) are covered in a crisp and lucid manner in this compilation. I am sure that this reference guide will be quite helpful for the beginners to get familiar with the concepts of DIP in a short time.

एस. के. श्रीवास्तव

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About The Book

Digital image processing of satellite remote sensing data is a preliminary step to learn remote sensing technology. It involves combination of techniques such as image pre-processing, image enhancement, image classification and image accuracy. An effort in the form of Quick reference guide on Digital Image Processing covering various aspects of DIP will help readers in understanding the image processing techniques in an accessible and comprehensive manner with clear explanations and conceptual illustrations used throughout to enhance student learning. It consists of seven chapters. The first chapter covers basics of Remote Sensing, GIS and DIP. The image processing techniques like filtering, rectification, geometric correction etc. are explained in chapter 2. Detailed discussion of Image enhancement techniques on remote sensing satellite data is discussed in chapter 3. Image classification section in chapter 4 successfully brought the concepts of supervised and unsupervised classification techniques with example. Importance of automation for information extraction using remote sensing satellite data is attempted in chapter 5. Applications of DIP techniques in the field of SAR & hyperspectral data processing is showcased with examples in chapter 6 & 7.

The study material will be helpful for understanding the DIP techniques in an easier and lucid manner for the benefit of the beginners in the field of satellite remote sensing.

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Chapter 1

Basics of Digital Image Processing

1.1 Overview of Remote Sensing

Remote sensing is the science of measuring, detecting, and monitoring of physical properties of a target object/area without coming in direct contact with the target, usually by measuring the reflected or emitted radiation at a distance.

Remote sensing can be classified as active and passive (Figure 1.1). Active remote sensing transmits and measures the electromagnetic radiation emitted and reflected, while passive remote sensing only measures the reflected radiation from the target.

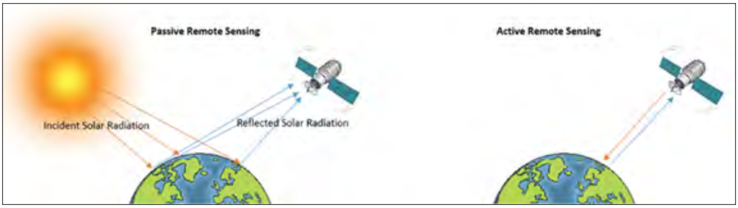


Figure 1.1: a. Passive remote sensing b. Active remote sensing

Based on the number of bands available in the sensor, the data may be classified as multispectral or hyperspectral. While multispectral remote sensing gathers data from a few discrete spectral bands that are broad and cover a wide range of wavelengths or frequencies.

Hyperspectral remote sensing, on the other hand, collects data from hundreds or even thousands of narrow and adjacent spectral bands.

Quality and nature of remote sensing data can be assessed on the basis of 4 types on resolution:

1. *Radiometric Resolution*: Radiometric resolution refers to the sensitivity of the sensor towards incoming electromagnetic radiation. It is equal to the number of bits in which the recorded energy can be divided.
2. *Spatial Resolution*: Spatial resolution refers to size of the smallest object on the ground that can be resolved by the sensor. It is usually represented

by a single value which is equal to length of square on the ground that the pixel represents.

3. *Spectral Resolution*: Spectral resolution is the number and the size of bands in the electromagnetic spectrum that a remote sensing system is able to capture.
4. *Temporal Resolution*: Temporal resolution refers to how often the satellite/sensor acquires the image of a particular target on the ground.

1.2 Digital Image

With the invention of modern computers, researchers quickly realised the benefits of storing data in a digitized format for processing. Digital, means any representation of signal/data/information in quantized form or in terms of digits. Digital image is pictorial representation of an object or a scene by a group of divided cells (pixels) organised in a definite grid and having quantized values or values in terms of digits of average intensity of the target object or a scene.

1.2.1 Pixel

These individual cells that make up a digital image are called picture elements or pixel for short (Figure 1.2). The smallest unit that can be displayed on a digital display device in a digital image or graphic is called pixels.

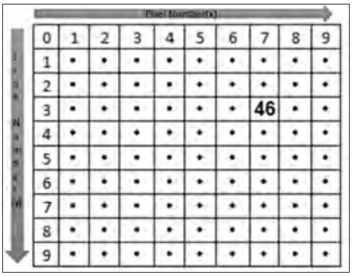


Figure 1.2: Image grid

1.2.2 Grid

The regular grid in which pixels combines to form the digital image is called the image grid (Figure 1.3). In the case of remote sensing images or other forms of geospatial imagery, these image grids have location information appended with them, hence each pixel represents some specific region on the Earth that it is tied to.

249	231	231	287	247	207	436	442	365	251	464	532	569	294	402	372	500	501
237	212	225	237	248	199	301	399	354	250	303	331	422	282	345	394	471	507
222	229	237	253	247	175	216	379	443	299	293	447	551	375	317	432	420	525
272	256	238	212	208	198	227	362	457	337	284	423	548	392	276	405	454	509
289	241	245	246	254	220	224	280	416	350	251	321	349	301	242	473	550	403
249	192	172	252	259	242	214	310	462	420	294	266	315	327	271	391	451	371
301	236	270	307	346	372	379	393	464	472	355	341	386	339	357	370	341	409
382	372	345	338	386	416	453	421	398	415	366	341	358	372	436	399	413	450
394	372	325	270	271	295	378	421	351	315	280	264	311	399	474	467	424	426
396	402	346	276	305	349	414	427	333	307	305	235	277	369	406	444	429	395
345	328	297	253	258	275	453	381	306	303	374	332	333	413	436	455	450	438
331	309	310	288	228	229	420	338	317	408	432	433	430	464	462	452	408	397
464	444	433	439	411	323	360	364	375	410	377	406	393	359	336	302	253	231
263	290	304	308	240	251	272	251	227	214	217	277	244	200	210	192	173	172
110	100	109	117	88	149	141	86	111	112	115	158	179	192	202	177	172	180
105	88	81	77	67	87	91	84	95	91	90	88	102	120	141	138	122	130
86	65	72	82	81	71	58	73	86	85	79	70	85	91	100	107	104	94
70	73	72	71	66	67	64	69	78	80	68	61	73	79	89	87	88	90

Figure 1.3: Remote sensing image and its respective pixel values in the image grid

Each pixel in the image grid is represented by a number. These digital numbers are almost always stored in binary format. Higher pixel value represents higher intensity of that pixel in the image and lower pixel value is represented by lower intensity of that pixel in the image grid.

1.3 Digital Image Processing

The use of a digital computer to process digital images, specifically remote sensing images in our context, through an algorithm or series of algorithms to achieve a desired outcome is known as digital image processing (Figure 1.4).

Figure 1.4: Process flow of capturing data to digital image processing to derivation of meaningful outcomes

As the name suggests, these algorithms are specifically designed to work on digital images. Remote sensing images are captured from different platforms (satellite, aerial etc.) and by various sensors (multi spectral sensors, digital cameras, Synthetic Aperture Radars (SAR), etc.) stored in a digital format. These image datasets are processed using a digital computer by running various algorithms to derive meaningful information from them.

1.4 Remote Sensing Data formats

Remote sensing image datasets usually consist of more than one band (multi-band images). In such datasets location of each pixel in the image grid is defined as their row number, column number and also by their band number information. Most commonly used formats are discussed in this section and briefed in table 1.

Table 1: Commonly used Remote Sensing data formats

S. No.	Format	Description
1	Flat Binary	1. Data is stored in binary files 2. Can be BSQ, BIL and BIP 3. Meta data is stored in separate file
2	Geotiff	1. Extension of regular tiff 2. Uses small set of reserved TIFF tags to stored georeferencing information
3	HDF	1. Is used to store images, tables, texts and data arrays 2. It is self-describing in nature
4	NetCDF	1. An interface for array-oriented data access. 2. Mostly used for atmospheric models, marine Geophysics data etc.

Flat binary multi-band formats

It is the most basic form of storing raster data. It is usually accompanied by metadata file (ASCII or XML). Multi band image datasets are classified on the basis of data format in the following 3 types (Figure 1.5):

1. *BSQ format* (Band Sequential)

In BSQ format image data for each band is stored separately, one after the other.

2. *BIL format* (Band interleaved by line)
   In BIL format the line data is arranged in the order of band number and repeated with respect to line number.
3. *BIP format* (Band interleaved by pixel)
   In BIP format bands change with respect to every pixel, which are spatially arranged by pixel element number and line number are stored.

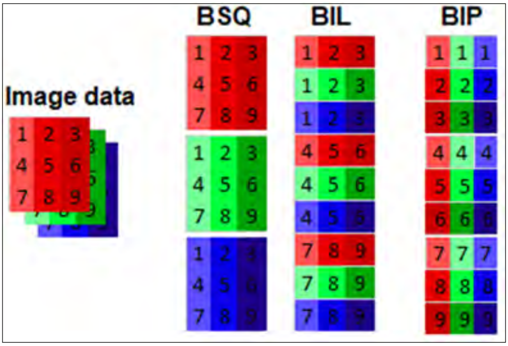


Figure 1.5: Illustration of multi band raster image with nine pixels and three bands arranged in the three different types of formats.

GeoTiff format

TIFF stands for Tag Image File Format and it is a very popular format to store raster image data. They are a high bit rate lossless data format, which means that it can store high quality images with any information being lost. So many users started embedding georeferencing information with the satellite imagery in tiff format, which later evolved in GeoTiff format (Figure 1.6).

GeoTIFF format fully complies with the TIFF 6.0 specifications, and its extensions. It uses a small set of reserved TIFF tags to store a broad range of georeferencing information, catering to geographic as well as projected coordinate system's needs. Numerical codes are used in GeoTIFF format to describe projection types, coordinate systems, datums, ellipsoids, etc. The projection, datums and ellipsoid codes are derived from the EPSG (European

Petroleum Survey Group) list compiled by the Petrotechnical Open Software Corporation (POSC). Images in GeoTiff format can be easily viewed using remote sensing and GIS softwares like QGIS, ArcGIS, ERDAS IMAGINE etc.

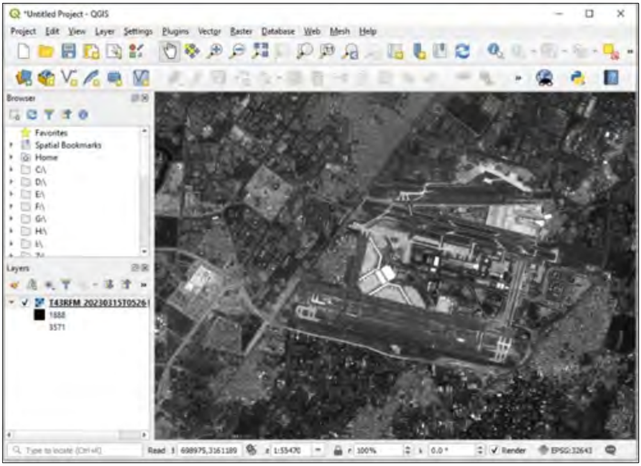


Figure 1.6: Satellite image of Delhi airport in GeoTIFF format being displayed in QGIS software

HDF format

The National Centre for Supercomputing Applications (NCSA) designed the Hierarchical Data Format (HDF) as a data file format to aid users in storing and manipulating scientific data on different operating systems and machines. HDF is capable of supporting various data types, such as scientific data arrays, tables, and text annotations, as well as different types of raster images and their associated color palettes. There are two types of HDF, HDF (version 4 and earlier) and HDF5.

HDF offers a range of features, including the ability for programs to retrieve data information from the data file instead of an external source. It also standardizes the format and descriptions of frequently used data sets, such as scientific data and raster images. Additionally, HDF is platform-independent, meaning it can be utilized on a variety of computers, regardless of the operating system. Both the HDF development team and users can add new data models to HDF.

NetCDF format

NetCDF (Network Common Data Form) comprises machine-independent data formats and software libraries that facilitate the creation, access, and sharing of array-oriented scientific data. It is a recognized community standard for sharing scientific data. The netCDF programming interfaces for C, C++, Java, and Fortran are supported and maintained by the Unidata Program Center, while interfaces for Python, IDL, MATLAB, R, Ruby, and Perl are also available. Data in netCDF format is self-describing and contains information about the data it includes. It is portable and accessible to computers that store integers, characters, and floating-point numbers differently. NetCDF interfaces enable efficient access to small subsets of large datasets in various formats, even from remote servers. Additionally, data can be appended to a correctly structured netCDF file without copying the dataset or redefining its structure. Multiple readers can simultaneously access the same netCDF file, and one writer can also access it. Opensource software like Panoply can be used to read the NetCDF file (Figure 1.7).

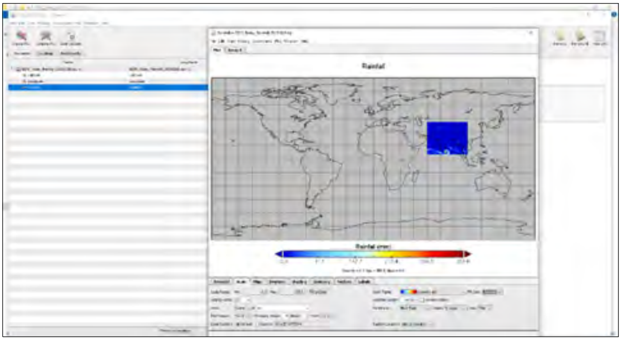


Figure 1.7: Rainfall data (GEFS) over India as on 26/10/2015 visualised using Panoply

1.5 Digital image display

To display digital image currently 3 major technologies are in use (Figure 1.8):

1. Cathode Ray Tubes (CRTs)
2. Liquid Crystal Displays (LCDs)
3. Light Emitting Diodes (LEDs)

4. Organic light-emitting diode (OLED) displays
5. Plasma displays.

Figure 1.8: The 3 major types of digital image display technologies

a. Cathode Ray Tube b. Liquid Crystal Displays c. Light Emitting Diodes

The digital image displays consist of a grid of individuals display units, each of which capable of producing colours individually. Each The display unit is then assigned to produce a specific colour based on the zoom level of the digital image chosen to be display.

1.6 Human Vision

The colours produced by the digital image display is observed by the human eye (Figure 1.9). Retina presents in the human eye have two types of photoreceptor cells:

1. *Rod cells*: Rod cells work better in dim light and are responsible for the scotopic vision.

2. *Cone cell:* Cone cells work better in bright light and are responsible for the photopic vision.

Cone cells are mainly responsible for perception of colour. There are three types of cone cells present in the retina and each one is sensitive to different parts of the electromagnetic spectrum:

1. L(Rho): sensitivity peaks between 564–580 nm.

2. M(Gamma): sensitivity peaks between 534–545 nm.

3. S(Beta): sensitivity peaks between 420–440 nm.

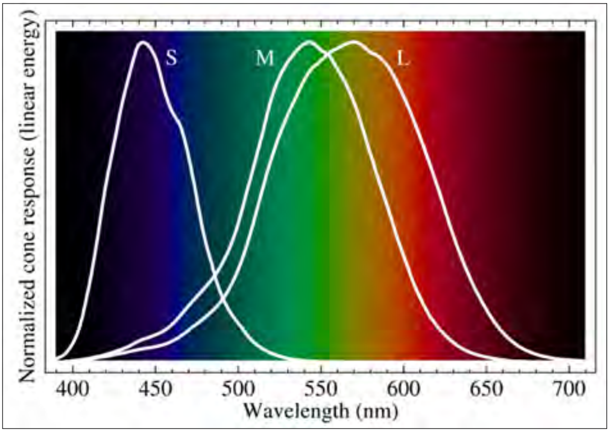


Figure 1.9: Sensitivity of different cone cells to different parts of the EM spectrum (The Stockman and Sharpe (2000)).

Our perception of colours is based on the complex response and sensitivity of these 3 types of cells. The range of colour perceptions are quantified by CIE to provide the standardization and is called chromaticity diagram (Figure 1.10). Since the chromaticity diagrams spans the entire colour spectrum possible to be perceived by the human eye, all of the digital image displays try to cover the entire span of the diagram but are limited in practice.

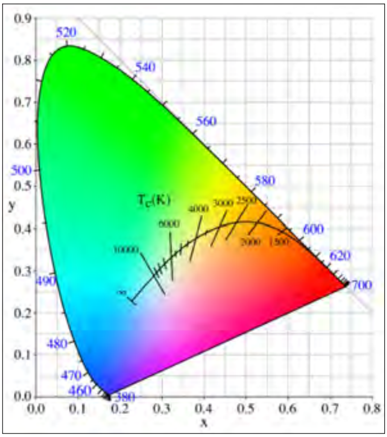


Figure 1.10: CIE 1931 Chromaticity Diagram

1.7 Look up table

In an image being displayed, each individual display unit is linked with a look up table in the graphics adapter for the colour generation. It has 3 channels corresponding to the 3 different primary colors used for formation. Values for each channel is scaled using the Look Up Table to generate the required colour by the pixel (Figure 1.11).

Red				Green				Blue		
R	G	B		R	G	B		R	G	B
255	0	0		0	255	0		0	0	255

Figure 1.11: RGB look up table

1.8 Colour space

Perception of colour in our eyes comes from 3 different types of cells, hence the colour space defined by them is 3 dimensional in nature. It can be visualised as a cube with origin as black (all three types have zero response) and the three axes representing the response from the 3 types of cells. Hence corner opposite to black will be white where all the type of cells is producing their maximum response. This cube is also standardised by the CIE (Figure 1.12).

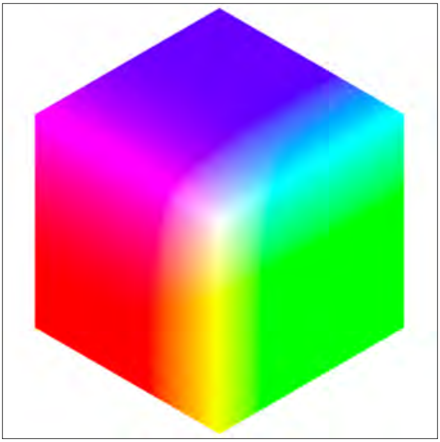


Figure 1.12: CIE RGB colour cube

1.9 Access to remote sensing datasets

Remote sensing datasets are provided by different space agencies around the world through their own portals. Various remote sensing datasets and value-added product are also available through different websites that aggregate these products.

The most common one in use are as follows:

Indian Portals:

1. Bhoonidhi portal
   - Boonidhi portal is primary data provider of Indian remote sensing satellites (https://bhoonidhi.nrsc.gov.in/).
2. MOSDAC (Meteorological & Oceanographic Satellite Data Archival Centre)
   - MOSDAC is the satellite data repository of ISROs satellite missions dealing with meteorology, oceanography and tropical water cycles. (https://www.mosdac.gov.in/).

Global Portals:

1. USGS Earthexplorer
   - USGS Earthexplorer is the primary data provider for the remote sensing missions conducted by NASA (https://earthexplorer.usgs.gov/).
2. Copernicus Open Access Hub
   - Copernicus Open Access Hub is the primary data provider for remote sensing missions conducted by ESA (https://scihub.copernicus.eu/).
3. AppEEARS
   - The Application for Extracting and Exploring Analysis Ready Samples (AppEEARS) is an American service that provides a straightforward and effective approach to obtaining and converting geospatial data from several federal data archives (https://appeears.earthdatacloud.nasa.gov/).

4. Google Earth Engine
   - With planetary-scale analysis capabilities, Google Earth Engine merges a multi-petabyte catalog of satellite imagery and geospatial datasets (https://code.earthengine.google.com/).

Remote sensing satellite imagery from these websites comes in different files formats and it corresponds to different bands present in that particular sensor of that particular satellite. The images can be easily view in a remote sensing and GIS software. Examples of some of the different land cover features as captured by remote sensing satellite are shown in figure 1.13. Sometimes one particular pass of the satellite may not be able to cover the entire target region and for these multiple images are mosaicked to cover the entire area. Multiple bands can also be stacked together and 3 band can be scaled to generated RGB colour composite of your choice (Figure 1.14).

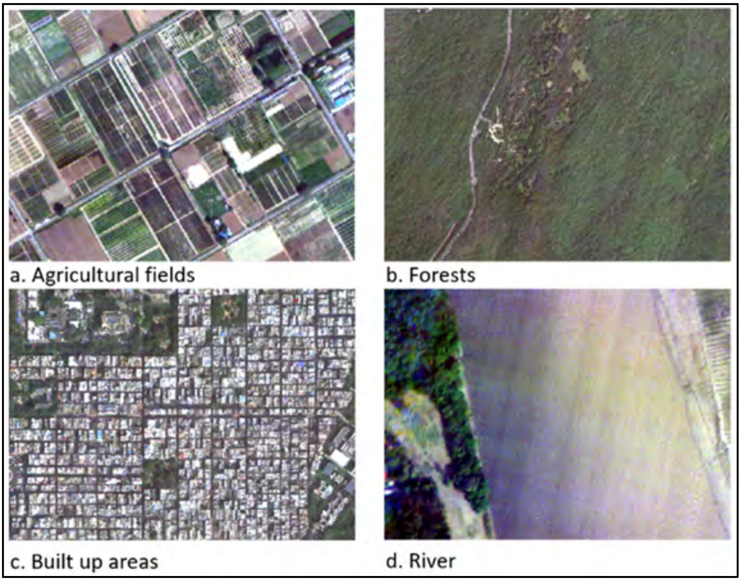


Figure 1.13: Cartosat-3 Satellite image of a. Agricultural fields b. Forests c. Built up areas d. River.

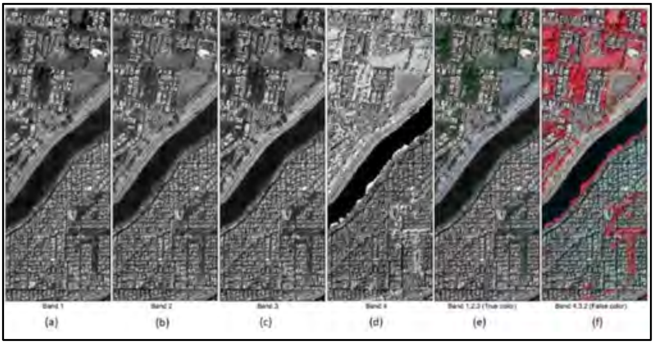


Figure 1.14: Cartosat-3 Satellite data of a part of Delhi. (a) Band 1, (b) Band 2, (c) Band 3, (d) Band 4, (e) True color composite and (f) False color composite

Summary

Concepts of remote sensing data and digital image processing are explained in this chapter. Different remote sensing satellite data sources and their formats are discussed in detail with examples. Band combination of Indian remote sensing and foreign satellite datasets were showcased by implementing basic digital image processing. An overall introduction of digital image processing is successfully showcased in this chapter.

Chapter 2

Digital Image Processing Techniques

2.1 Introduction

Digital Image processing is the class of methods that deal with manipulating digital images through the use of various algorithms. It is an essential pre-processing step in many applications, specifically remote sensing images in our context. (Jain, 1989; Kenneth, 1996; Rafael, 2001). Image processing techniques are used to manipulate, analyse and enhance the information from digital images. Image processing has become an essential field due to the availability of vast digital data and images. So, there was a need to use efficient and effective processing techniques for analysing digital images (Wayne, 1985).

The basic details of the image acquired with overview of remote sensing are covered in Chapter 1 with the majorly used types of the data formats, image display technologies, coloured images, and various sources for image downloading with the applications of digital image in remote sensing.

This chapter will highlight the majorly used processing techniques after the image acquisition. Multi-temporal remote sensing images can provide the vast information depending upon the applications which is essential for interpretation and timely management. Image processing techniques have vast application areas in remote sensing, including agricultural applications, forestry, hydrology, urban, disaster management, etc. Remote Sensing images acquired need to pre-processed including steps such as band selection, radiometric correction, image rectification & geometric correction, image enhancement, image filtering, image thresholding. The flow chart of the major steps in digital image processing in remote sensing is shown in Figure 2.1.

The detailed description of various image enhancement techniques is provided in Chapter 3. The various steps of pre-processing of microwave data in remote sensing are covered in Chapter 6. After pre-processing of the images, the image may be interpreted with the relevant information as per the requirement. The feature can be extracted based upon the spectral signatures or backscatter values in case of optical and microwave data respectively. After the segmentation and feature extraction, the images can be classified into the relevant information using various methods. The several methods for image classification including unsupervised and supervised classification are briefed in Chapter 4.

In the recent years, satellite images are available after the radiometric correction, atmospheric correction and orthorectified. In this chapter, the basic details of image rectification and geometric correction, image filtering, image thresholding, image segmentation, feature extraction, and resampling techniques are discussed in a brief manner as follows:

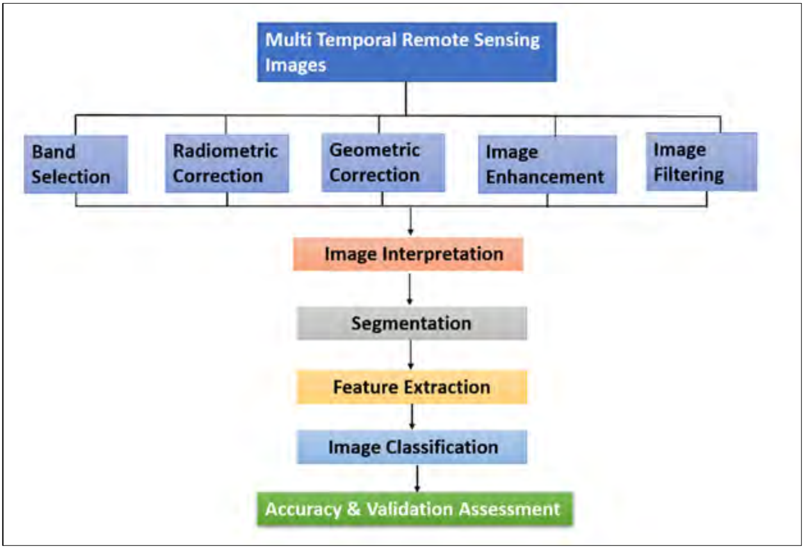


Figure 2.1: Flow chart of the major steps involved in remote sensing data

2.2 Image Rectification and Geometric Correction

Image rectification transforms an image to align with a reference coordinate system, such as a map projection. This is typically done by identifying and matching control points between the image and the reference system and then applying a geometric transformation to the image. The objective is to ensure the two images have the same image coordinate and lie on the same horizontal line. Image rectification is essential to improve the accuracy of feature extraction, tracking algorithm, and matching the objects.

Apart from image rectification, Geometric correction is the process of removing geometric distortions from an image or map. This is done to correct for distortions caused by the camera angle, lens distortion, or other factors. The goal of geometric correction is to represent the scene's geometry or location accurately. Geometric correction is essential in remote sensing, aerial photography, and satellite imagery, where accurate spatial information is required for analysis and interpretation.

The most common geometric corrections include:

2.2.1 Orthorectification: Orthorectification is an image processing technique used to remove geometric distortions and project an image onto a planar surface or a map. The process involves correcting for the effects of terrain relief, sensor orientation, and atmospheric conditions to produce an accurate and georeferenced image that can be used for mapping, analysis, and visualization purposes.

Orthorectification is particularly important in remote sensing applications, where images are often acquired from a high-altitude platform, such as an aircraft or satellite, and have a distorted perspective due to the sensor position, terrain relief, and atmospheric conditions. Orthorectification corrects these distortions and makes the image usable for quantitative analysis and geospatial applications.

The orthorectification process involves several steps, including:

2.2.1.1 Sensor model creation: A sensor model describes the geometric relationship between the sensor and the Earth's surface. This model includes information about the sensor's position, orientation, and field of view.

2.2.1.2 Terrain correction: A digital elevation model (DEM) is used to correct the effects of terrain relief on the image (Figure 2.2). The DEM provides information about the elevation of the terrain, which is used to calculate the ground position of each pixel in the image.

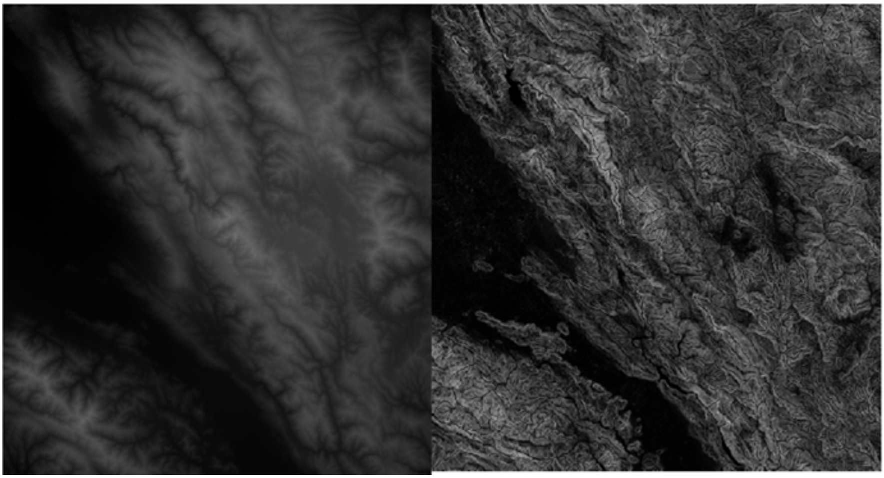


Figure 2.2: Shuttle Radar Topography Mission (SRTM) digital elevation dataset, DEM (left) and Slope (right) over the regions of San Francisco, USA

*2.2.1.3 Atmospheric correction***:** Atmospheric effects, such as scattering and absorption, can cause image distortions. Atmospheric correction algorithms are used to remove these effects and produce a more accurate image.

2.2.1.4 Image projection: The corrected image is projected onto a planar surface or a map using a cartographic projection. The projection method depends on the image's intended use and the area being mapped. Map projections are used to represent the curved surface of the Earth on a flat map. Geometric correction techniques convert satellite images and aerial photographs to a map projection, which is then used for spatial analysis and mapping (Figure 2.3).

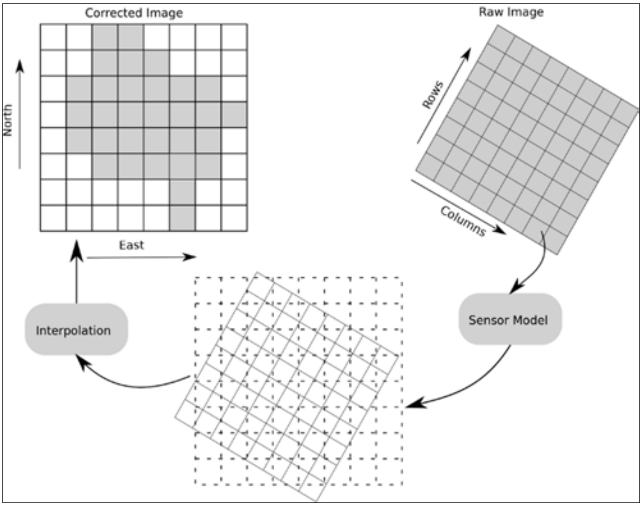


Figure 2.3: Example of Geometric Correction

*Source:*http://wiki.awf.forst.unigoettingen.de/wiki/index.php/File:Geometric_correction.png

Orthorectification is a complex and computationally intensive process that requires accurate sensor and terrain data and advanced image processing techniques. However, the resulting orthorectified image provides a valuable tool for geospatial analysis, mapping, and visualization.

2.2.2 Georeferencing: Georeferencing is the process of assigning spatial coordinates to an image or a map. Georeferencing aims to align the image or map with a geographic coordinate system, allowing it to be accurately located and integrated with other spatial data.

Georeferencing is critical in many geospatial applications, such as mapping, remote sensing, and geographic information systems (GIS). The process involves several steps, including:

2.2.2.1 Selecting a coordinate system: The first step in georeferencing is selecting a coordinate system that defines the geographic reference system for the image or map. This system can be based on various global or local coordinate systems, such as latitude/longitude or Universal Transverse Mercator (UTM).

2.2.2.2 Identifying control points: Control points are known points on the image or map that can be identified on both the image and the reference data, such as ground control points (GCPs) or features readily identifiable in both the image and the reference data.

2.2.2.3 Assigning spatial coordinates: The spatial coordinates for each control point are assigned by matching the locations of the control points on the image to their known locations in the reference data. This process is typically performed using software that allows the user to select the control points and assign their coordinates.

2.2.2.4 Transforming the image: Once the spatial coordinates for the control points have been assigned, the image is transformed to align with the coordinate system of the reference data. The transformation is based on a mathematical model that relates the coordinates of the control points in the image to their coordinates in the reference data.

2.2.2.5 Checking accuracy: The accuracy of the georeferenced image is checked by comparing the locations of additional control points in the image to their known locations in the reference data. Any discrepancies are corrected by adjusting the transformation model or selecting additional control points.

Georeferencing is a critical step in many geospatial applications, and the accuracy of the georeferencing process is essential for ensuring the accuracy of subsequent analyses and visualizations.

Geometric corrections are essential in remote sensing, cartography, and GIS applications. Accurate spatial information is necessary for making informed decisions in environmental monitoring, land use planning, and resource management.

2.3 Image Filtering

Filtering is a technique used in image processing to enhance or modify an image. It involves the use of a mathematical operation known as a filter to transform an image. Filters can be used for various purposes, such as noise reduction, image smoothing, edge detection, and feature extraction.

The most commonly used filters in image processing are:

2.3.1 Gaussian filter: A Gaussian filter, also known as a Gaussian smoothing filter, is a commonly used image processing technique for reducing noise and smoothing an image. It is based on the Gaussian distribution, a bell-shaped probability density function.

The Gaussian filter works by convolving an image with a Gaussian kernel. The Gaussian kernel is a two-dimensional array of numbers that defines the shape of the filter. The values in the kernel are calculated using the Gaussian function, which gives more weight to the central pixels and less weight to the pixels farther away from the center.

The amount of smoothing applied to the image is determined by the standard deviation of the Gaussian function and the size of the Gaussian kernel. A larger kernel size and a higher standard deviation result in more smoothing, while a smaller kernel size and a lower standard deviation result in less smoothing.

The Gaussian filter is widely used in image processing for edge detection, feature extraction, and image segmentation applications. It is also commonly used as a pre-processing step for other image-processing techniques.

However, it is essential to note that the Gaussian filter can also blur important image details, especially if the kernel size and standard deviation are too high. Therefore, the selection of the appropriate filter parameters should be carefully considered depending on the specific application and image characteristics.

2.3.2 Median filter: A median filter is a nonlinear image processing technique used to remove noise from an image (Figure 2.1). Unlike linear filters, such as the Gaussian filter, which perform a weighted average of pixel values in a local neighbourhood, the median filter replaces each pixel value with the median value of its neighbouring pixels.

The median filter works by sliding a window over the image, and for each pixel within the window, it sorts the neighbouring pixel values and replaces the pixel value with the median value. The size of the window determines the size of the neighbourhood used to calculate the median value. Removing impulse noise, such as salt-and-pepper noise, which randomly changes the pixel values to the maximum or minimum possible intensity values, is particularly achievable with the median filter.

Figure 2.4: True Color Image (left) and after median filtering image (right) using Landsat 8 OLI February 2020, over the regions of San Francisco, USA

Compared to linear filters, the median filter can better preserve edges and other sharp details in an image since it does not blur the pixel values in the same way as a weighted average. However, the median filter can also introduce some blurring if the window size is too large, and it may need to be more effective in removing other types of noise, such as Gaussian noise.

The median filter is commonly used in various image-processing applications, including medical imaging, satellite imagery, and digital photography. It is a simple and effective method for removing impulse noise, and it can be easily implemented on digital platforms with low computational requirements.

2.3.3 Sobel filter: A Sobel filter is an image processing filter that is used for edge detection in images. It is a spatial filter that calculates the gradient of the image intensity values in the horizontal and vertical directions separately.

The Sobel filter works by convolving the image with two separate 3x3 kernels, one for the horizontal gradient and one for the vertical gradient. The kernels are designed to approximate the first derivative of the image intensity concerning the spatial coordinates. The filtered image is obtained by combining the horizontal and vertical gradient images using the square root of the sum of their squared values.

The Sobel filter is a commonly used edge detection filter due to its simplicity and effectiveness. It can detect edges in an image with high accuracy and low computational cost. It is also robust to noise, as the filter has a smoothing effect due to the averaging of neighbouring pixels in the convolution process.

In addition to edge detection, the Sobel filter is often used for other image processing tasks such as feature extraction, image segmentation, and object recognition. It is a fundamental tool in computer vision and is widely used in various applications such as autonomous driving, robotics, and medical imaging.

2.3.4 Laplacian filter: A Laplacian filter is an image processing filter for edge detection and image sharpening. It is a second-order derivative filter, which calculates the second derivative of the image intensity concerning the spatial coordinates.

The Laplacian filter works by convolving an image with a kernel that approximates the second derivative of the image intensity. The kernel is a 3x3 or 5x5 matrix, and the filter operation involves subtracting the sum of the surrounding pixels from the value of the central pixel. This process highlights the regions in the image where the intensity changes rapidly, which typically correspond to the edges or boundaries between different objects or regions in the image.

The Laplacian filter can be used for edge detection by thresholding the output image to identify regions with high second derivative values corresponding to firm edges. It can also be used for image sharpening by adding the filtered image to the original image, which enhances the contrast and detail in the edges of the image.

However, the Laplacian filter is sensitive to noise in the image and can amplify the noise if the noise is not removed before applying the filter. Therefore, it is often used in conjunction with other image processing techniques, such as smoothing filters or noise reduction methods.

Overall, the Laplacian filter is a powerful tool for detecting edges and enhancing the detail in an image. It has a wide range of applications in image processing, computer vision, and machine learning.

2.3.5 Canny filter: The Canny filter, also known as the Canny edge detection algorithm, is an image processing technique used for edge detection. It was developed by John F. Canny in 1986 and is considered one of the most accurate and widely used edge detection filters.

The Canny filter works by first smoothing the image using a Gaussian filter to remove noise. Then, it calculates the image intensity gradient using a Sobel filter, which gives the direction and strength of the edge at each pixel. Next, it applies non-maximum suppression to thin the edges by only keeping the pixels with the highest gradient value in the direction of the edge. Finally, it applies hysteresis thresholding to determine the final edge map by selecting only those edges above a high threshold and connecting to edges above a lower threshold.

The Canny filter is known for its ability to detect edges while also accurately minimizing false positives and negatives. It is robust to noise and can detect edges with low contrast and variable lighting conditions. Additionally, the parameters used in the Canny filter can be adjusted to fine-tune the sensitivity and specificity of edge detection.

The Canny filter is widely used in various applications such as object recognition, tracking, and segmentation in computer vision and image processing. It is a powerful tool for detecting edges in images and plays a fundamental role in many algorithms and applications.

In image processing, filters can be applied in the spatial or frequency domain. Spatial filtering involves applying the filter directly to the image pixels, while frequency filtering involves converting the image to its Fourier transform and applying the filter in the frequency domain.

2.4 Image Thresholding

Thresholding is a common technique used in image processing to convert a grayscale or color image into a binary image. The process involves selecting a threshold value, which is used to segment the image into two categories: foreground and background. Pixels with intensity values above the threshold are classified as foreground, while those below the threshold are classified as background.

Thresholding is helpful in many applications, such as image segmentation, edge detection, and object recognition. There are several types of thresholding techniques, including:

2.4.1 Global thresholding: Global thresholding is a simple technique for image segmentation that separates an image into foreground and background regions based on a single threshold value. The threshold value is chosen based on the image's histogram, which shows the distribution of pixel intensities.

The global thresholding technique works by comparing each pixel in the image to the threshold value. If the pixel intensity is greater than or equal to the threshold value, it is assigned to the foreground region; otherwise, it is assigned to the background region.

Global thresholding can be performed using different methods, such as Otsu's method, which automatically calculates the optimal threshold value by maximizing the between-class variance of the image intensity distribution. Another method is the triangle method, which selects the threshold value at the peak of the histogram divided by the line connecting the histogram's edge and the highest point of the histogram.

Global thresholding is a simple and efficient technique for image segmentation, and it works well for images with a bimodal intensity distribution, where there are apparent intensity differences between foreground and background regions. However, it may not be suitable for images with complex or uneven intensity distributions, where multiple threshold values may be required for accurate segmentation. More advanced segmentation techniques such as clustering, region growing, or deep learning methods may be necessary in such cases.

2.4.2 Adaptive thresholding: Adaptive thresholding is an image processing technique used for image segmentation that allows for more accurate segmentation of images with non-uniform illumination or varying contrast. Unlike global thresholding, where a single threshold value is applied to the entire image, adaptive thresholding calculates the threshold value for each pixel based on its local neighbourhood.

Adaptive thresholding works by dividing the image into small, overlapping regions and calculating the threshold value for each region based on its local statistics, such as the mean or median intensity. Each pixel within the region is subjected to the threshold value to determine whether it belongs to the foreground or background region. Adaptive thresholding is a powerful technique for image segmentation, especially in cases where the illumination or contrast varies across the image. It is widely used in various applications such as document image analysis, medical imaging, and computer vision.

2.4.3 Multi-thresholding: multi-thresholding, also known as multiple thresholding, is an image processing technique used for image segmentation, where an image is divided into multiple segments based on several threshold values. It is a more advanced technology than global thresholding, where only one threshold value is used to segment the image.

Multi-thresholding works by dividing the image into multiple intensity intervals, where each interval corresponds to a specific segment or region of the image. A threshold value is selected for each interval to separate it from the adjacent intervals. The threshold values can be determined using various methods, such as histogram-based, clustering, or optimization techniques.

One popular method for multi-thresholding is Otsu's method, which selects threshold values to maximize the between-class variance of the image. Another method is the k-means clustering algorithm, which groups pixels into clusters based on their intensity values, and the number of clusters corresponds to the number of segments desired.

Multi-thresholding is particularly useful in cases where the image has more than two regions with different intensity levels or when the objects of interest have different shades or colors. It has numerous applications in various fields, such as medical imaging, remote sensing, and industrial inspection.

However, multi-thresholding may not be suitable for images with complex or overlapping regions, where more advanced segmentation techniques such as region growing or deep learning methods may be necessary.

Thresholding can be performed using mathematical operations, such as logical operations, histogram analysis, or statistical methods. The choice of the thresholding technique depends on the image characteristics and the application requirements.

2.5 Image Segmentation

The process of dividing an image into multiple segments or regions, with each segment representing a meaningful object or part of an object in the image, is known as image segmentation (Michael, et al, 2000). The purpose of image segmentation is to simplify the representation of an image and make it more meaningful and easier to analyse. It can be performed using various techniques, including thresholding, clustering, edge detection, region growing, and more advanced methods such as deep learning. Each of these techniques has its strengths and weaknesses, and the choice of method depends on the specific application and image characteristics. Standard techniques used for image segmentation include thresholding, edge detection, and feature extraction.

2.6 Feature Extraction

Feature extraction is the process of selecting and transforming relevant features from raw data to improve the performance of a machine-learning model. The goal is to reduce the dimensionality of the data and to highlight the most critical aspects of the input data that are relevant to the problem at hand.

Feature extraction can be done manually or automatically. In manual feature extraction, domain experts select the relevant features based on their knowledge of the problem domain. In automatic feature extraction, machine learning algorithms identify the most informative features.

Examples of feature extraction techniques include principal component analysis (PCA), linear discriminant analysis (LDA), and wavelet transforms. PCA is a technique for reducing the dimensionality of data by projecting it onto a lower-dimensional space while preserving the most critical information. LDA is a technique for finding the linear combinations of features that best separate different classes in the data. Wavelet transforms used to decompose signals into different frequency bands and to extract features representative of different aspects of the signal.

Feature extraction is a critical step in many image processing applications, and the choice of feature extraction method depends on the specific task and the characteristics of the image data. Once features have been extracted, they can be used for subsequent analysis and processing, such as classification, object recognition, or detection.

2.7 Resampling Techniques

Resampling techniques refer to methods used in digital image processing to change an image's spatial resolution or size. The most common resampling techniques include the following:

2.7.1 Nearest Neighbor: Nearest Neighbor is a simple algorithm used in many data analysis fields, including image processing, machine learning, and data mining. In image processing, the nearest neighbour algorithm is often used for tasks such as image classification, image registration, and image segmentation.

The nearest neighbour algorithm works by finding the closest data point in a training dataset to a given input data point. This is done using a distance metric such as Euclidean distance or Manhattan distance. Once the closest data point is found, the algorithm assigns the class label of that data point to the input data point.

In image processing, the nearest neighbour algorithm can be used for tasks such as image classification, where the algorithm assigns a class label to an input image based on the closest training image. It can also be used for image registration, where the algorithm finds the closest match between two images based on the pixel values. Finally, it can be used for image segmentation, where the algorithm assigns each pixel in an image to a class based on the closest training data point.

While the nearest neighbor algorithm is simple and easy to implement, it has several limitations (Figure 2.5). For example, it can be sensitive to noise in the input data, and it may not be suitable for high-dimensional datasets with many features. Additionally, it may only perform well if the training dataset is representative of the data distribution. As a result, more advanced algorithms such as decision trees, random forests, and deep learning networks are often used in image processing applications.

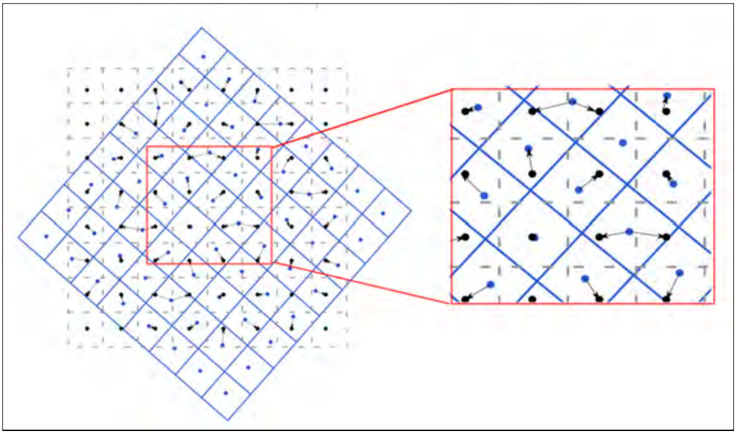


Figure 2.5: Example of Nearest Neighbor Interpolation in Image Resampling

Image Source: http://wiki.awf.forst.unigoettingen.de/wiki/index.php/File:Interpolation_NN.png

2.7.2 Bilinear Interpolation: Bilinear interpolation is a method of estimating the value of a function at a point within a rectangular grid based on the values of the function at the four nearest grid points. Bilinear interpolation is commonly used in image processing and computer graphics to resize or rescale images.

When an image is rescaled, the original pixels are moved to new locations, resulting in gaps between the original pixels. Bilinear interpolation fills in these gaps by computing the weighted average of the four nearest pixel values. Specifically, the value at a new pixel location is computed as a weighted average of the pixel values at the four closest grid points, with the weights determined by the distance between the new pixel location and each of the four grid points.

2.7.3 Bicubic Interpolation: Bicubic interpolation involves using a weighted average of a more significant number of neighbouring pixels to assign a value to the new pixel in the resized image. This technique is more computationally intensive than bilinear interpolation but produces smoother results with less loss of image detail.

Bilinear interpolation is preferred over other interpolation methods, such as nearest neighbor interpolation and bicubic interpolation, because it provides a good balance between computation time and image quality. Nearest neighbor interpolation is the fastest method, but it can result in pixelated images, while bicubic interpolation provides smoother images but requires more computation time.

One drawback of bilinear interpolation is that it can result in image artifacts such as blurring and aliasing if the image is scaled too much or if the interpolation is performed multiple times. More advanced interpolation methods, such as Lanczos interpolation or spline interpolation, can be used to avoid these artifacts, but these methods are more computationally intensive.

Resampling techniques are used in various applications, including image scaling, image registration, and image mosaicking. Choosing the appropriate resampling technique depends on the specific application and the desired level of image quality.

2.8 Commonly used Vegetation Indices

Vegetation indices are mathematical formulas that use spectral bands from remote sensing data to estimate vegetation health, vigor, and productivity. To maximize the sensitivity of the vegetation characteristics while minimizing factors such as atmospheric and soil reflectance effects, various vegetation indices are utilized. Some commonly used vegetation indices are listed below:

2.8.1 Normalized Difference Vegetation Index (NDVI): NDVI is a widely used vegetation index that measures the difference between the reflectance of near-infrared (NIR) and visible red (VIS) light. NDVI values range from -1 to +1, with higher values indicating healthier vegetation.

$$NDVI\ \rho = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}}$$

ρ_{NIR} and ρ_{RED} represent the spectral reflectance in NIR and Red regions, respectively.

NDVI is the most commonly used vegetation index mainly used for assessing the vegetation cover, vegetation monitoring over time, estimation of crop acreage, productivity, and plant stress or disease in agricultural applications.

2.8.2 Enhanced Vegetation Index (EVI): EVI is another popular vegetation index that is more sensitive to changes in vegetation cover than NDVI. EVI takes into account the blue band and corrects for atmospheric influences. EVI is used for optimizing the vegetation signal with improved sensitivity in regions of high biomass

$$EVI\ \rho = G\ \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + C_1\ \times \rho_{RED} - C_2\ \times \rho_{BLUE} + X}$$

The surface reflectance at the blue band, denoted by ρ_BLUE, the coefficients of the aerosol resistance term represented by C1 and C2, and the Canopy background adjustment factor given as X, are the components used to calculate the gain factor G.

2.8.3 Soil Adjusted Vegetation Index (SAVI): SAVI is similar to NDVI, but it also considers the amount of soil cover in the area. SAVI can be helpful in areas with sparse vegetation cover.

$$SAVI\ \rho = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}} + C$$

The spectral reflectance in NIR and Red regions is denoted by ρ_NIR and ρ_RED, respectively, with the constant C introduced to reduce the impact of soil brightness. The variation of SAVI from zero to infinity is dependent on the canopy density. SAVI is equivalent to NDVI if C=0

2.8.4 Leaf Area Index (LAI): LAI measures the area's vegetation. It is calculated as the total surface area of leaves per unit of the ground area covered by vegetation. LAI is typically expressed as a dimensionless ratio or as a unit of area (e.g., m2 leaf area per m2 ground area). LAI can be measured using various techniques, including direct measurements of leaf area, indirect methods such as optical sensors, and remote sensing techniques such as satellite or airborne imagery.

$$LAI = \frac{Leaf\ Area\ (m^2)}{Ground\ Area\ (m^2)}$$

LAI values can vary widely depending on factors such as vegetation type, plant density, and environmental conditions. LAI is an essential parameter in many applications, such as crop growth modeling, carbon cycle studies, and climate change research. It provides a measure of the amount of photosynthetic surface area available for plant growth and can be used to estimate plant productivity and water use efficiency.

2.8.5 Normalized Difference Water Index (NDWI): NDWI is the spectral index commonly used to estimate the presence and quantity of water in vegetation or soil. It measures the difference between the reflectance of NIR and shortwave infrared (SWIR) light.

$$NDWI\,\rho = \frac{\rho_{NIR} - \rho_{SWIR}}{\rho_{NIR} + \rho_{SWIR}}$$

Where ρ_{NIR} and ρ_{SWIR} represent the spectral reflectance in NIR and SWIR regions, respectively, the NIR band is sensitive to vegetation, while the SWIR band is sensitive to water. So, by comparing the two bands, NDWI can distinguish between water and vegetation, and its values range between -1 to +1, with higher values representing the higher presence of water.

This Vegetation index is used in many applications in environmental science, including hydrology, agriculture, and forestry. NDWI may be used to detect water stress in plants, which can help farmers optimize irrigation practices. It can also use to monitor water bodies, such as lakes and rivers, and to estimate water content in crops and soil.

2.8.6 Chlorophyll Index (CI): CI is a spectral index used to estimate the amount of chlorophyll in plants. Chlorophyll is the green pigment responsible for photosynthesis, and its concentration in leaves is an essential indicator of plant health and productivity. It is calculated as the difference between the reflectance of NIR and red edge (RE).

$$CI\,\rho = \frac{\rho_{NIR} - \rho_{RE}}{\rho_{NIR} + \rho_{RE}}$$

The NIR band is sensitive to leaf structure, and the RE band is sensitive to chlorophyll absorption. Chlorophyll Index can estimate the chlorophyll concentration in plant leaves by comparing the difference between these two bands. CI values range from -1 to 1, with higher values indicating a greater chlorophyll concentration. Chlorophyll Index has many applications in agriculture, forestry, and environmental science. It can monitor plant health and productivity, estimate crop yields, and detect plant stress caused by nutrient deficiencies or water scarcity.

These are just a few examples of the many vegetation indices available for remote sensing analysis. The choice of index depends on the specific research question, data availability, and the characteristics of the study area.

Summary

In this chapter, firstly the overview of multi-temporal remote sensing data processing after the image acquisition to image classification is provided. Secondly, widely used image processing techniques including image rectification and geometric correction, image filtering, image thresholding, image segmentation, edge detection, feature extraction, and resampling techniques are discussed in a brief manner. The details of the image acquisition including satellite data products, formats, widely famous data sources are also provided in Chapter1. The pre-processing steps of microwave data is discussed in Chapter 6. The widely used classification techniques in remote sensing field are discussed in Chapter 4. This chapter basically focuses only the image processing techniques in remote sensing.

Chapter 3

Image Enhancement

3.1 Introduction

The process of Image Enhancement is a method of accentuating image characteristics such as image contrast, and brightness by applying various technologies to improve the visual quality of an image. Image enhancement is a tool rendering clearer and more informative images for better visual interpretation and analysis. Remote sensing involves collection of data in the form of stored images from sensors mounted on aerial vehicles or satellites. These images supply a wealth of knowledge regarding the types of vegetation, surface water and land use patterns on Earth's surface. Images captured by remote sensing sensors are often affected by various types of noise and distortion that reduce the clarity and usefulness of the data. For more accurate identification and interpretation of the Earth's features there is a constant need of enhancement of data quality. Applying image enhancement to remote sensing has many practical advantages. For example, enhanced images are applied in detection and monitoring changes in land use patterns, such as deforestation or urbanization. They can also be used to identify and map land cover, which is essential for monitoring agricultural productivity and forest health (Jain 1989). The enhanced imagery can also be used to identify and map water bodies, which is important for water resource management and monitoring changes in hydrological systems. Needs and benefits of improving remote sensing imagery are: Remote sensing imagery captured by satellites or aircraft are often affected by atmospheric and environmental conditions such as haze, cloud cover and lighting conditions. These conditions can affect the quality and accuracy of the images which make them difficult to interpret. Therefore, image enhancement in remote sensing is necessary to improve image quality and enhance its visual appearance. The benefits of enhanced remote sensing imagery are:

3.1.1 Improved Image Quality:

Using enhancement techniques such as removing noise, distortions and other artifacts the quality of the image improves drastically. This improves the visual appearance of the images and makes them easier to interpret.

3.1.2 Better Feature Extraction:

Image enhancement techniques helps to accurately extract features and details from the data regarding Land Use Land Cover. Which is essential in various fields, such as agriculture, land management, and urban planning.

3.1.3 Increased Accuracy:

Image enhancement in remote sensing helps to increase the accuracy of image interpretation by providing clearer and more detailed images. This accuracy is critical in fields such as environmental management, where accurate measurements are necessary for decision making.

3.2 Techniques of Image Enhancement

The various techniques of image enhancement are given in below (Li et al., 2019; Jensen 2016; Lillesand et al.,2014):

3.2.1 Contrast Stretching

Contrast stretching is a technique used to enhance the contrast of an image. This technique involves adjusting the brightness and contrast of an image to make it more attractive and sharper. It increases the range of brightness values for efficient display in an image. The ratio of the maximum intensity to the minimum intensity of an image defines contrast stretching. The contrast ratio (CR) is valuable for comprehending the resolution and edge of an image. Greater the ratio, easier the interpretation. Contrast difference (CD) is used to visualize the difference between the maximum grey level (I_{max}) and the minimum grey level (I_{min}) of an image. Contrast index (CI) is a useful tool in assessing the contrast level of the image.

$$CD = I_{max} – I_{min}$$

$$CR = \frac{I_{max}}{I_{min}}$$

$$CI = \left(\frac{I_{max} - I_{min}}{I_{max} + I_{min}} \right)$$

Where, I_{max} is the maximum grey level of the image and I_{min} is the minimum grey level of the image

There are two types of Contrast stretching: Linear and Non – Linear.

3.2.2 Linear Stretching

Linear stretching is a type of contrast stretching that involves adjusting the brightness and contrast of an image in a linear way. This means that the same number of adjustments is applied to all parts of the image, regardless of their original brightness or contrast.

3.2.2.1 Min-Max Linear Stretch

Linear min-max stretching is a type of linear stretching used in image processing to improve image contrast (Khan et al., 2018). To adjust the contrast and brightness of an image, so that the minimum and maximum pixel values of the image match the minimum and maximum values of the display range this technique is employed. In simple terms, the min-max linear stretching technique involves scaling the pixel values of an image so that the darkest pixel is the darkest possible hue in the display range and the pixel the lighter is the lightest shade possible as shown in Figure 3.1. This results in images with improved contrast and enhanced visual appeal. This technique is particularly useful for low contrast images, where the range of pixel values is compressed and appears dull.

Figure 3.1: Min-Max Linear Stretch using Cartosat-3 data of a Part of Delhi

3.2.3 Non - Linear Stretching

Nonlinear stretching, on the other hand (Figure 3.2), involves adjusting the brightness and contrast of an image in a nonlinear way (Chan et al., 2020; Wei et al., 2020). This means applying different amounts of adjustments to different parts of the image, depending on their original brightness or contrast. It helps bring out more details in an image and creates a more visually appealing end product. It has been more preferable for enhancing the colour contrast between various nearly-classes and subclasses.

Square root: In square root stretch, it transforms the pixel values of an image by taking the square root of each value. This type of stretching is useful for increasing contrast in low dynamic range images.

Square: In square stretching, pixel values are transformed by squaring each value. This type of stretching is useful for increasing contrast in high dynamic range images.

Logarithmic: In logarithmic stretching, pixel values are transformed using a logarithmic function. This type of stretching is useful for improving contrast in unevenly lit or high dynamic range images.

Exponential: In exponential stretching, pixel values are transformed using an exponential function. This type of stretching is useful for increasing contrast in low dynamic range images.

Histogram equalization: In the process histogram equalization, the pixel values of an image are transformed to evenly distribute the pixel values. This type of stretching is useful for increasing contrast in images with low dynamic range or uneven lighting.

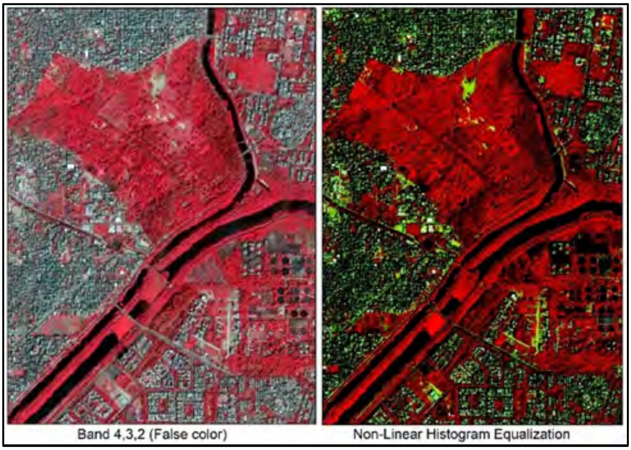


Figure 3.2: Non-Linear Histogram equalization using Cartosat-3 data of a Part of Delhi

3.3 Spatial Filtering

Spatial frequency is another element of an image. For any given part of the image, it is the per unit distance changes in the number of brightness values. Few changes in brightness value are called low frequency and dramatic changes over short distance is called high frequency. The spatial filtering process involves dividing the image into its constituent spatial frequencies and selectively modifying certain spatial frequencies to accentuate particular features. Spatial filtering is also a process where an image is modified by applying a filter or a mathematical operation to it. The filter is a matrix of numerical values that is placed over the image, and each pixel in the image is replaced with a new value that is a function of the values in the corresponding positions in the filter.

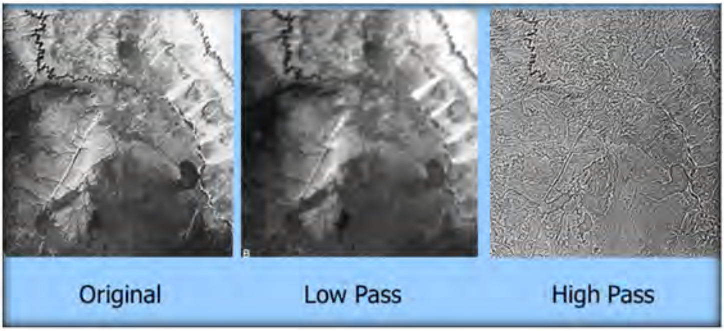


Figure 3.3: Type of Spatial Filtering

There are two main types of spatial filtering: low pass and high pass as shown in Figure 3.3.

3.3.1 Low Pass Filtering

Low pass filtering is a type of spatial filtering that removes high frequency information from an image, leaving only low frequency components. Low-frequency components are parts of an image that change slowly, such as the overall brightness or contrast of an image as shown in Figure 3.4. It can be useful for smooth images, reduce noise, or blur images.

Figure 3.4: Low pass filtered image of Cartosat-3 data

3.3.2 High Pass Filtering

High-pass filtering, on the other hand, is a type of spatial filtering that removes low-frequency information from an image, leaving only the high-frequency components as shown in Figure 3.5.

Figure 3.5: High pass filtered image of Cartosat-3 data

High-frequency components refer to parts of the image that change rapidly, such as edges or image detail. High pass filtering can be used to sharpen images or detect edges and boundaries.

3.4 Image Fusion

Image fusion, also known as data fusion, is a process that combines information from multiple satellite images or different sensor bands to create a composite image that contains more detailed and comprehensive information than any individual image. The goal of image fusion is to exploit the complementary strengths of different data sources to improve the interpretation, analysis, and understanding of the scene being observed.

There are several methods commonly used for satellite image fusion:

Pan-Sharpening: Pan-sharpening combines high-resolution panchromatic imagery with lower-resolution multispectral imagery (which provides images with lower spatial resolution but more spectral information). By fusing these two sources, a single image is created that has both high spatial and spectral resolution.

Brovey Transform: The Brovey transform is a simple ratio-based fusion method. It assigns more weight to the panchromatic band than to the multispectral bands, preserving the spectral information while enhancing the spatial details.

Intensity-Hue-Saturation (IHS) Transform: The IHS transform separates the intensity (or brightness), hue, and saturation components of an image. It fuses the high-resolution panchromatic image with the intensity component of the multispectral image and then transforms the fused image back to the RGB color space.

Principal Component Analysis (PCA): PCA is a statistical technique that transforms the original multispectral bands into a new set of uncorrelated variables called principal components. The high-resolution panchromatic image is then combined with selected principal components to create a fused image.

Wavelet Transform: The wavelet transform decomposes an image into different frequency components. In image fusion, the high-resolution panchromatic image is combined with the low-frequency components of the multispectral image, while the high-frequency components are preserved from the multispectral image.

Sparse Representation-based Methods: Sparse representation-based methods aim to represent the multispectral image using a linear combination of atoms from a dictionary that is learned from the panchromatic image. This allows for the extraction of high-frequency details from the panchromatic image and their fusion with the multispectral image.

These methods are just a few examples of satellite image fusion techniques. The choice of fusion method depends on factors such as the characteristics of the satellite data, the level of detail required, and the specific application or analysis being conducted. Each method has its strengths and limitations, and researchers continue to explore new approaches to improve the quality and accuracy of fused satellite images.

3.5 Band Math

Band math is a technique used in remote sensing to extract useful information from satellite images. It involves combining two or more spectral bands, which are different wavelengths of light, to create a new image. This new image can reveal features that may not be easily visible in the original image and can be used for various purposes such as vegetation monitoring, land use mapping, and environmental monitoring.

The basic concept of band math is to combine bands in a way that enhances the information content of the image. For example, combining the near-infrared and red bands can highlight vegetation, as plants reflect more strongly in the near-infrared range than other objects. Similarly, combining the blue and green bands can help to identify water bodies, as water absorbs strongly in these wavelengths.

There are several techniques for band math, including addition, subtraction, multiplication, and division (Zhou et al.,2019). The choice of technique depends on the specific application and the desired outcome. For example, adding two bands together can help to enhance the contrast between different features, while subtracting two bands can help to isolate specific features such as urban areas or vegetation.

Band math requires knowledge of the characteristics of different spectral bands and their interactions with the objects and surfaces being observed. It also requires careful calibration and validation to ensure accurate results. The results obtained through band math should always be interpreted in conjunction with ground truth data and other sources of information, to ensure that they are meaningful and useful for the intended purpose.

3.6 Indices

Indices in remote sensing are mathematical formulas that use combinations of spectral bands to calculate specific properties of objects or surfaces. These indices can provide valuable information about vegetation, water bodies, urban areas, and other features in an image.

The NDVI (Normalized Difference Vegetation Index) is used for monitoring vegetation health and productivity (Figure 3.6). A simple formula is used, that subtracts of the reflectance value of red band from NIR band upon the sum of the two (Gonzalez et al., 2008). NDVI values lies between -1 to +1, with positive value indicating healthier vegetation as shown in Figure 3.6. NDVI image can further be classified in different classes based on NDVI values as shown in Figure 3.7.

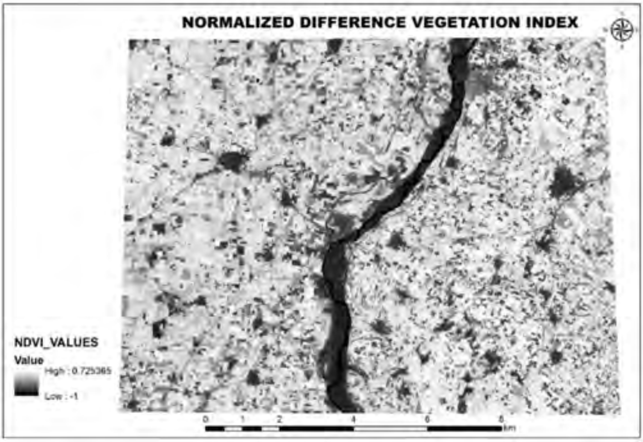


Figure 3.6: NDVI Image

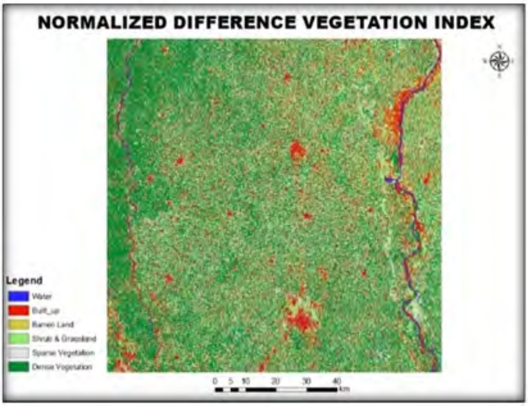


Figure 3.7: Classified NDVI Image

The NDBI (Normalized Difference Built-Up Index) is an index used to detect urban areas and the built environment. A simple formula is used to subtract the reflectance of SWIR band from the reflectance of NIR band, upon the sum of these two bands. NDBI values lies between -1 to +1; +1 being densely built-up area and -1 indicating water bodies as shown in Figure 3.8.

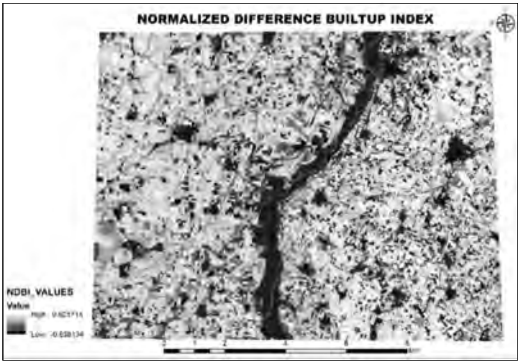


Figure 3.8: NDBI Image

NDSI (Normalized Difference Snow Index) is an index used to track snow and ice cover. It has different various but the most used on subtracts the reflectance value of SWIR band from the green band, upon the sum of these two bands. NDSI values lies between -1 to +1, with values above 0.4 indicating snow or ice.

NDWI (Normalized Difference Water Index) is an indicator used to locate bodies of water. A simple formula is used that includes subtraction of the near infrared band from the green or blue bands and, upon the sum of these two bands. NDWI values lies between -1 to +1, with higher values indicating higher humidity percentage. As shown in Figure 3.9.

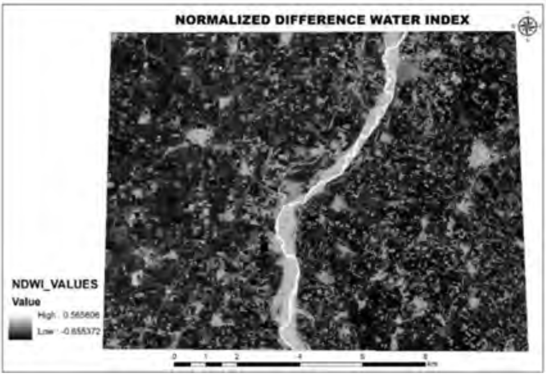


Figure 3.9: NDWI Image

Summary

Image enhancement techniques play a critical role in remote sensing applications, as they improve the quality of images acquired by remote sensors. The application of these techniques has become increasingly important due to the wide range of remote sensing applications, including environmental monitoring, agriculture, and urban planning.

There are various techniques available for image enhancement in remote sensing, including filtering, contrast stretching, and image fusion. These techniques can be applied to different types of remote sensing data, including optical, radar, and thermal images, to enhance their spatial, spectral, and radiometric properties.

However, it is imperative to note that the choice of technique should be made based on the specific requirements of the remote sensing application. For example, filtering techniques such as low-pass filtering are effective in reducing noise and enhancing edge details in optical images, while image fusion techniques such as principal component analysis and wavelet-based fusion are useful for combining different types of remote sensing data to produce a more informative image.

Moreover, it is essential to ensure that the image enhancement techniques used do not result in the loss of important information in the remote sensing data.

Over-enhancement can lead to the distortion of the image and the loss of important details, making the remote sensing data less useful.

In addition, there are advanced image enhancement techniques, such as machine learning-based approaches, which are becoming increasingly popular in remote sensing applications. These techniques have shown promising results in various applications, including land cover classification and change detection. However, it is important to note that the use of these advanced techniques requires a significant number of computational resources, which may not be readily available to everyone. As such, simpler techniques such as contrast stretching and filtering remain relevant and useful for basic image enhancement needs in remote sensing applications.

Image enhancement techniques are essential tools for improving the quality of remote sensing data. The choice of technique is dependent on the specific requirements of the exercise, and care should be taken to avoid over-enhancement that can result in the loss of important information. While advanced techniques such as machine learning-based approaches are promising, simpler techniques remain relevant and useful for basic image enhancement needs in remote sensing applications. For most display purposes, linear stretch is a preferred method; Non-linear enhancements always enhance pixels at the cost of others – for example, logarithmic stretch enhances dark pixels at the cost of brighter pixels Histogram equalization gives a sharp output but gives rise to the problem of reduction in number of classes. In summary, Contrast stretching, spatial filters, band math, and indices are all important image processing techniques that can be used to enhance and analyse satellite or aerial imagery., and we must keep in mind the end and process the data accordingly.

Chapter 4

Image Classification

4.1 Introduction

Remote sensing satellite data refers to the data acquired by sensors onboard satellites that orbit the Earth, which can be used to study and monitor the Earth's surface and atmosphere. There are several types of remote sensing satellite data, including:

- **Optical data**: This type of data is acquired by sensors that detect visible and near-infrared light, such as the Cartosat, Landsat and Sentinel satellites. Optical data can be used to map land cover and vegetation, monitor changes in land use, and detect natural disasters.
- **Radar data**: This type of data is acquired by sensors that emit and receive microwave radiation, such as the Synthetic Aperture Radar (SAR) on EOS-4(RISAT), Sentinel-1 and the Advanced Land Observing Satellite (ALOS) PALSAR. Radar data can penetrate clouds and vegetation, allowing for the detection of changes in topography, soil moisture, and land cover.
- **Thermal data:** This type of data is acquired by sensors that detect the amount of thermal radiation emitted by the Earth's surface, such as the VNIR sensor on IMS-1 and Thermal Infrared Sensor (TIRS) on Landsat 8. Thermal data can be used to study urban heat islands, monitor volcanic activity, and detect wildfires.
- **LiDAR data:** This type of data is acquired by sensors that emit laser pulses to the source and measure the return time of pulse (To sensor). LiDAR data can be used to generate high-resolution topographic maps and measure forest structure and biomass.

Remote sensing satellite data can be used for a wide range of applications, such as natural resource management, planning of land use, environment monitoring, and disaster management activities. The availability and accessibility of remote sensing data have greatly increased in recent years, allowing for more efficient and effective monitoring of the Earth's surface and atmosphere.

4.2 Remote Sensing Image Classification

To extract meaningful information from the vast amounts of data generated by remote sensing sensors, remote sensing satellite data needs to be classified into different categories. Some of the main reasons why remote sensing image classification is necessary include:

- **Land cover mapping**: Remote sensing image classification can be used in identification and land cover mapping, such as forests, crops, water bodies, and urban areas. This information is essential for land use planning, resource management, and environmental monitoring.
- **Change detection**: Remote sensing image classification can be used to detect changes in land cover over time, like deforestation, urbanization, and natural disasters. This information is crucial for assessing the impacts of human activities on the environment and for developing strategies to mitigate these impacts.
- **Environmental monitoring**: Remote sensing image classification is being to monitor environmental parameters such as water quality, air pollution, and soil moisture. This information is essential for assessing the health of ecosystems and for identifying potential environmental risks.
- **Disaster management**: Remote sensing image classification can be used to assess the impacts of natural disasters, such as floods, wildfires, and earthquakes. This information is crucial for developing effective response strategies and for planning for future events.

Overall, remote sensing image classification is a powerful tool for studying and monitoring the Earth's surface and atmosphere, and it is essential for different applications in environmental science, natural resource management, and disaster management.

Remote sensing satellite image classification is the process of giving land cover categories to different pixels or groups of pixels in an image acquired by remote sensing sensors, such as satellite or airborne sensors. Its goal is to find meaningful information from the input image, which can be further used for different applications, like land use planning, natural resource management, and environmental monitoring. Figure 4.1 shows image classification process.

The classified map shows classes A and B depecting different land features of the input surface.

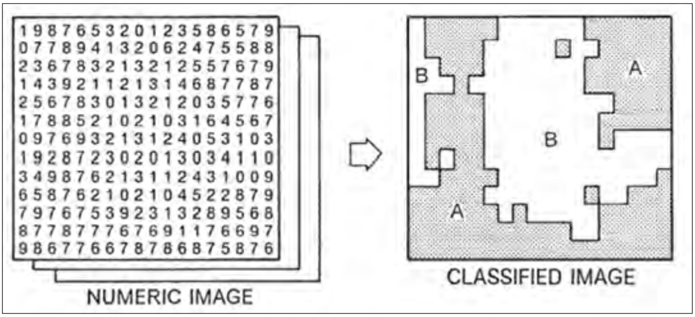


Figure 4.1: Digital image and classified image representation

(***Source***: Canada, Natural Resources. Image Classification and Analysis. 29 Jan. 2008, https://natural-resources.canada.ca)

4.3 Remote sensing image classification procedure

Remote sensing satellite image classification is used to determine the land use and land cover. Land cover in LULC means type of material present on the input landscape such as, crops, water, crops, wetland, forest, man-made materials. Land use in LULC refers to how humans utilize the land surface, such as for agriculture, commerce, settlement.

The various steps involved in extracting thematic land-cover information from remote sensing satellite data (Gong and Howarth 1990) include:

a. Scheme of image classification: It includes information classes such as urban, agriculture, forest areas, etc. field survey data and other ancillary data of the study area.
b. Pre-processing of the input satellite image, (Corrections of atmospheric, radiometric, atmospheric, topographic & geometric, image enhancement, & clustering of initial image.
c. Representative area selection of the input image and its analyze, involves initial clustering results or generation of training signs.
d. Running of Image classification techniques & algorithms.

e. Post-processing step: Geometric correction, filtering and classification on pre-processed image.
f. Accuracy assessment: It includes comparison of classification results with field studies.

4.3.1 Image classification scheme

The first step for the analyst is to identify the ROI (geographic region of interest) to conduct hypothesis testing. Next, a classification scheme is carefully developed to define the specific classes of interest for examination. Depending on the classes chosen, the analyst may opt for producing hard or fuzzy output products and decide whether to use per-pixel or object-oriented classification logic. It is crucial to meticulously select and define all classes of interest to successfully classify remotely sensed data for land-use, land-cover information. This involves using a classification scheme with accurately defined classes, organized based on logical criteria. For a hard (crisp) classification, the classification system should ideally have mutually exclusive, and hierarchical classes. While fuzzy classification systems are more flexible, they may not be easily transferable to different environments; hence, hard classification schemas are typically preferred for classification purposes.

4.3.2 Acquire appropriate remote sensing, initial ground reference data and pre-processing.

Afterward, the analyst acquires the suitable digital remote sensor data, considering both the sensor system's capabilities and environmental limitations. Whenever possible, ground reference information is collected simultaneously with the remote sensing data acquisition. Subsequently, the remote sensor data undergoes radiometric and geometric corrections to prepare it for further analysis.

4.3.3 Training data generation

Training data is one of the deciding factors in supervised classification. Preparation of the training data depends on various factors and the key characteristics of training in classification of remote sensing images are:

- **Spectral bands**: Remote sensing images usually have multiple spectral bands, which provide information about the reflectance of different wavelengths of electromagnetic radiation. The choice of spectral bands is critical to the performance of the algorithm, as they determine the information available to distinguish between different land cover types.
- **Spatial resolution**: Remote sensing images can have varying spatial resolutions, which affects the size of the smallest feature that can be detected. Higher spatial resolution images provide more detailed information but can be computationally intensive to process.
- **Training sample selection**: The selection of training samples is critical to the accuracy of the classification algorithm. Training samples should be representative of the land cover classes present in the image and should be spread throughout the image.
- **Class imbalance**: Remote sensing images often have imbalanced class distributions, where some land cover classes are much more common than others. This can affect the performance of the classification algorithm, as it may not be able to accurately predict the less common classes.

Overall, data requirement for classification of remote sensing images requires careful consideration of the spectral bands, spatial resolution, training sample selection, class imbalance to achieve accurate land cover classification. In addition of the above parameters, shape, location, number, placement and uniformity factors also needs to be taken care while preparing the training datasets for remote sensing image classification.

Shape: When preparing the training data, it is essential to consider shapes that minimize the number of vertices, such as rectangles or polygons.

Location: The training areas should be strategically positioned to facilitate accurate and easy transfer of their outlines from maps to the digital image.

Number: The ideal number of training areas depends on the number of classes to be categorized. Usually, representing each class with 5-10 training areas ensures the adequate representation of spectral properties for each category.

Placement: The placement of training areas within the image is crucial, allowing for precise location with respect to distinct features and boundaries between different features on the image.

Uniformity: Within each training area, the data should demonstrate a unimodal frequency distribution for every spectral band to be utilized.

4.4 Image classification techniques

A variety of classification methods have been developed and extensively employed to create land cover maps (Figure 4.2). These methods differ in their logic, including supervised and unsupervised, parametric and nonparametric, or hard and soft (fuzzy) classification, as well as per-pixel, sub-pixel, and prefield approaches. In the processing of remote sensing images, two primary types of classification procedures are commonly utilized: supervised classification and unsupervised classification. Although they can be used as independent approaches, they are often combined into hybrid methodologies, leveraging multiple methods simultaneously.

Methods	Examples
Parametric	Maximum Likelihood classification and Unsupervised classification etc.
Non-Parametric	Nearest-neighbor classification, Fuzzy classification, Neural networks and support Vector machines etc.
Non-metric	Rule-based Decision tree classification
Supervised	Maximum Likelihood, Minimum Distance, and Parallelepiped classification etc.
Unsupervised	ISODATA and K-means etc.
Hard (parametric)	Supervised and Unsupervised classifications
Soft (non-Parametric)	Fuzzy Set Classification logic
Pre-Pixel	
Object-oriented	
Hybrid Approaches	

Figure 4.2: Remote sensing image classification techniques (Mehmood et al. 2022)

4.4.1 Supervised Classification

Supervised classification is a type of machine learning algorithm which involves training a model, on a labelled dataset to predict the class of new, unlabelled data. In supervised classification, the algorithm is given a set of training data consisting of input features and its corresponding output labels. The algorithm then learns to map the input features to their correct output labels by minimizing a loss function, such as cross-entropy or mean squared error.

The trained model can then be used to predict the class of new, unlabelled data based on its input features. Supervised classification is widely used in various fields such as image recognition, natural language processing, and fraud detection. Common supervised classification algorithms include logistic regression, decision trees, random forests, and support vector machines.

The basic steps involved in supervised classification are:

a. **Data collection and pre-processing**: The first step is to collect and pre-process the dataset. This may involve cleaning and filtering the data, removing outliers, and converting the data into a suitable format for the algorithm.
b. **Data splitting**: The dataset is divided into distinct subsets, the training set and the testing set. The training set is utilized to train the algorithm, whereas the testing set is applied to assess the performance of the trained model.
c. **Feature extraction**: Features are extracted from the data that can be used to train the classification algorithm. Feature extraction involves selecting the most relevant attributes of the data and transforming them into a suitable format.
d. **Model training**: In the training set, the algorithm is utilized to predict the output label using the input features. By minimizing a loss function, the algorithm learns to accurately map the input features to their corresponding output labels.
e. **Model evaluation**: The performance of the trained model is evaluated using the testing set. The evaluation metrics used may vary depending on the application, but commonly used metrics include accuracy, precision, recall, and F1-score.

f. **Model deployment**: The model can be deployed in a real-world application to predict the class of new, unlabelled data after training and evaluation.

Overall, supervised classification involves the iterative process of selecting and pre-processing the dataset, extracting relevant features, training the model, evaluating its performance, and its deployment in a real-world application.

There are several supervised classification algorithms available for assigning an unknown pixel to one of the possible classes (m). The selection of a specific classifier or decision rule depends on the characteristics of the input data and the desired output, making it a crucial decision. Parametric classification algos assume that the measured vectors (Xc) for each class in each spectral band during the training phase of supervised classification follow a Gaussian or normal distribution (Schowengerdt, 2007). In contrast, nonparametric classification algorithms do not make such assumptions (Lu and Weng, 2007).

Some examples of nonparametric classification algorithms are:

- Parallelepiped
- Minimum distance
- Nearest-neighbour
- Neural network and expert system analysis

Among the widely used parametric classification algorithms is the maximum likelihood algorithm.

4.4.1.1 Parallelepiped Classifier:

The parallelepiped classification approach is computationally simple approach. For instance, two bands' digital number (DN) values are plotted in a scatter diagram, similar to the minimum distance to mean classifier. In this method, a rectangular box is created for each class. It is defined by the maximum and minimum values (of each band), as depicted in Figure 4.3. The classification of pixels is determined based on whether they fall inside any rectangular box called as parallelepiped decision region or not. If a pixel falls within a parallelepiped, it is assigned to that class. However, if a pixel falls within the boundaries of more than one class, it is labelled as the overlap class. If the pixel doesn't fit into any parallelepiped, it is assigned to the null class.

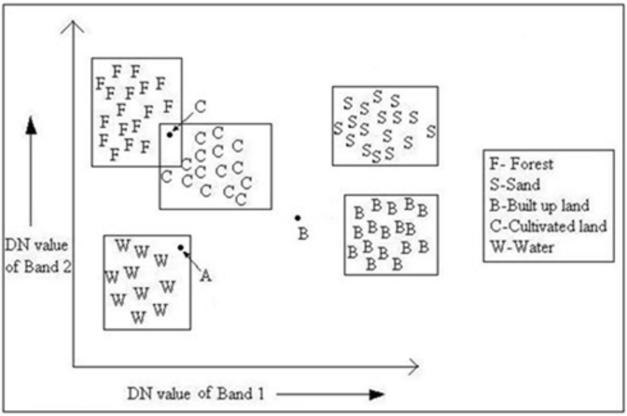


Figure 4.3: Parallelepiped classification strategy

(Source: RS&GA: Lesson 12 Image Classification. http://ecoursesonline.iasri.res.in/mod/page/view.php?id=2065. Accessed 15 June 2023)

In below mentioned example, three unknown pixels (A, B, and C) are considered. Pixel A will be classified as the water class since it falls within the parallelepiped of the water class. However, pixel B will be labelled as an unknown class, and pixel C will be labelled as the overlap class. Overlapping occurs due to high correlation or covariance between bands. Covariance refers to the tendency of spectral values to vary similarly in other bands. This method is less effective because spectral response patterns are often highly correlated, resulting in significant covariance.

4.4.1.2 Minimum Distance to Mean Classifier:

The minimum distance to mean classifier is simple one and commonly used classifier. It involves plotting of DN values of the training sets in a scattergram (Figure 4.4).

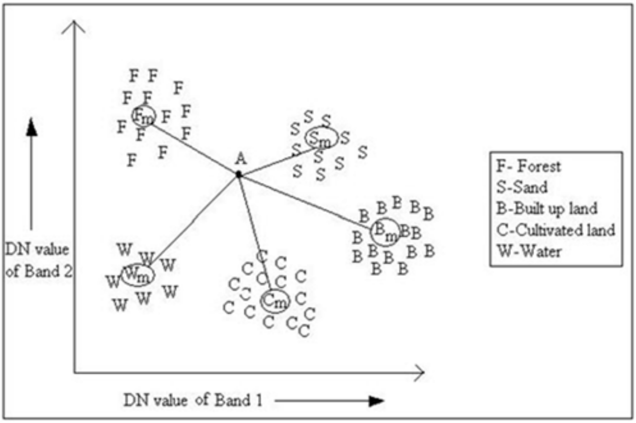


Figure 4.4: Minimum distance to means classification strategy

(Source: RS&GA: Lesson 12 Image Classification. http://ecoursesonline.iasri.res.in/mod/page/view.php?id=2065. Accessed 15 June 2023)

The process involves plotting DN (Digital Number) values of various training sets for different classes and calculating their means. When dealing with an unknown pixel A, it is classified or assigned to a specific class by computing the distance between the mean of each class and pixel A. Pixel A is then assigned to the class whose mean value is closest to it. In Figure 4.4, for instance, the unknown pixel A would be assigned to the sand class. This process is applied to all pixels in the image, resulting in the classification of various land use and land cover classes. For an n-Dimensional multispectral data, an n-D scatter diagram is plotted and the mean of every class is determined, and finally the image is classified based on the class with the shortest distance. Euclidean distance is a commonly used method for calculating the distance.

4.4.1.3 Nearest neighbor classifiers

Nearest neighbor classifiers, K-nearest neighbor (KNN) classifiers, and K-nearest neighbor distance-weighted classifiers are all related algorithms that rely on finding the nearest neighbors of a given data point in the training set to make predictions. Nearest neighbor classifiers make predictions by finding the single nearest neighbor to a given data point in the training set and using its label to predict the label of the new data point.

K-nearest neighbor classifiers find the k nearest neighbors to a given data point (in the training set) and use a majority vote of their labels to predict the label of the new data point. The value of k is a hyperparameter. It can be tuned to optimize performance.

K-nearest neighbor distance-weighted classifiers are similar to KNN classifiers, but they give more weight to the labels of the nearest neighbors that are closer to the new data point. This means that the algorithm considers the distances between the new data point and its nearest neighbors when making predictions.

The main advantage of these algorithms is their simplicity and ease of implementation, as they don't require a training phase or any assumptions about the underlying data distribution. However, they can be computationally expensive, it may also be suffering from the curse of dimensionality, if the features are large. In addition, they may not perform well on imbalanced datasets or datasets with noisy or irrelevant features.

4.4.1.4 Maximum likelihood classification

In maximum likelihood classification, it is assumed that the statistics for each and every input class in each band follow a normal distribution. The algo calculates the probability that a particular pixel belongs to a specific class. By default, all pixels are classified until the user sets a probability threshold. Each pixel is then assigned to the class with the highest probability. It is known as the max. likelihood classification. If the highest probability is lower than the threshold, the pixel remains unclassified.

$$g_i(x) = 1\mathrm{n}\, p(\omega_i) - {}^1\!/_2\, 1\mathrm{n}\, |\Sigma_i| - {}^1\!/_2 (x - m_i)^T \Sigma_i^{-1} (x - m_i)$$

Where:

i = indicated class

x = *n*-dimensional data

$p(\omega_i)$ = probability that class ω_i occurs in the image and it is same for all classes

$|\Sigma_i|$ = covariance matrix of the data in class ω_i

Σ_i^{-1} = inverse matrix

m_i = mean vector

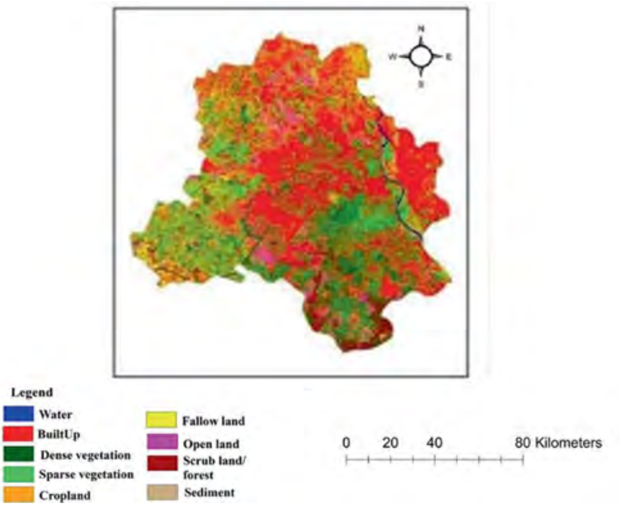


Figure 4.5 : LISS 4 data (2016) over Delhi (LULC classification using Maximum Likelihood Classification over Delhi)
(Source: Balha and Chander Kumar Singh, 2023)

The maximum likelihood method offers advantages from a probability theory perspective, but certain considerations should be taken into account:

(1) Ground truth data must be sampled to estimate the mean vector and variance-covariance matrix of the population.

(2) In cases of high correlation between two bands or the ground truth data is highly homogeneous, the inverse matrix of the variance-covariance matrix may become unstable. In such situations, it is advisable to reduce the number of bands using principal component analysis.

(3) The maximum likelihood method is not applicable when the population distribution deviates from the normal distribution.

Figure 4.5 illustrates the application of the Maximum Likelihood classification to the LISS 4 data over Delhi.

4.4.1.5 Feature Selection

After systematically gathering the training statistics from each band for the classes of interest, the next step is to decide which bands are most effective in distinguishing each class from the others. This procedure is known as feature selection and can be accomplished using graphical or statistical methods.

Graphical methods of feature selection in remote sensing satellite data involve visualizing the relationship between different spectral bands and the target variable to identify the most informative bands. Here are some common graphical methods of feature selection in remote sensing:

- Spectral signature plots: Spectral signature plots are used to visualize the spectral response of different land cover types in a particular scene. A spectral signature plot of each band can be used to identify the bands that show the strongest response for different land cover types, indicating that the band is informative for classification.
- Scatter plots: Scatter plots may be used view the relationship between 2 continuous variables. A scatter plot of each band against the target variable can be used to identify the bands that show the strongest correlation with the target variable.
- Histograms: Histograms are used to visualize the distribution of a continuous variable. Histograms of each band for each class of the target variable can be used to identify bands that show significant differences between classes, indicating that the band is informative for classification.
- Color composites: Color composites are used to visualize multiple bands as a single RGB image. Color composites can be used to identify bands that show the strongest contrast between different land cover types, indicating that the band is informative for classification.

Statistical methods of feature selection in remote sensing satellite data involve evaluating the statistical significance of each band and selecting the most informative bands based on a statistical criterion. Here are some common statistical methods of feature selection in remote sensing:

- Correlation analysis: Correlation analysis is used to evaluate the strength of the linear relationship between two variables. A correlation matrix can be computed between each spectral band and the target variable, and bands with high correlation coefficients can be selected as informative.
- Mutual information: It is a statistical measure that evaluates the amount of information that one variable provides for another variable. Mutual information can be used to evaluate the information gain of each spectral band with respect to the target variable. Bands with high mutual information can be selected as informative.
- Principal Component Analysis (PCA) is a widely employed statistical technique for feature selection and for reducing the dimensionality. It works by transforming the original features into a new set of uncorrelated variables called principal components, which capture the maximum variance in the data. The first principal component accounts for the most variance, then the second principal component, and so on. PCA can be utilized for feature selection by identifying the principal components that explain the most variance in the data. For instance, if the initial principal components account for a significant portion of the total variance, the left ones can be discarded, as they may contain relatively less essential information.

4.4.1.6 Logistic regression technique for image classification

Logistic regression is a supervised algo which can be used for image classification tasks. In image classification using logistic regression, the input image is represented as a vector of pixel values. The logistic regression model then applies a linear transformation to this vector and applies the sigmoid function to obtain a probability score for each category. The category with the maximum probability is chosen as the predicted label for the image.

The model parameters, including the weights and biases, are learned from a labelled training dataset using a loss function such as binary cross-entropy or categorical cross-entropy. The optimization process involves updating the parameters using gradient descent to minimize the loss function.

One disadvantage of logistic regression for image classification is that it may not be able to record complex nonlinear relationships in between the input features and the output labels. In such cases, more complex models such as neural networks may be more suitable. However, logistic regression can be a good starting point for simple image classification tasks, and it is relatively easy to interpret and implement.

4.4.1.7 Decision tree for image classification

In a decision tree for remote sensing image classification, each pixel in the image is represented as a vector of spectral values, such as the intensity values for different bands of the image. The decision tree algorithm then applies a sequence of binary decisions based on thresholds to classify each pixel into one of the predefined categories.

The decision tree algorithm constructs the tree by recursively splitting the training data based on the input feature which provides the maximum information gain. It measures the entropy reduction or uncertainty when a feature is used to split the data. The splitting process continues until a stopping criterion is reached.

One advantage of decision trees for remote sensing image classification is that they can handle non-linear relationships in between the input features and the output labels. They can also handle mixed data types, such as categorical and continuous features. Decision trees are also relatively easy to interpret and can provide insights into the decision-making process.

However, decision trees can be subjected to overfitting if the tree is too deep/if the training data is biased/noisy. Ensemble methods, like random forests or boosting, can help to mitigate the reported issues and improve the accuracy of the classification.

4.4.1.8 Support Vector Machine for classification

Support Vector Machines are a popular machine learning algorithm that can be used for land use land cover classification tasks. SVMs are a type of binary classifier that can be extended to handle multi-class classification problems.

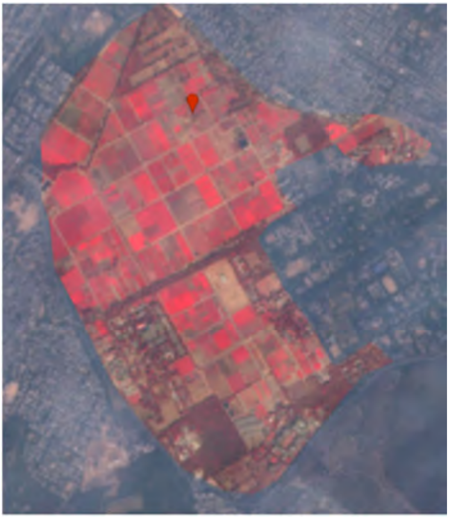
In SVMs for land use land cover classification, each pixel in a satellite or aerial image is represented as a vector of spectral values, such as the intensity values for different bands of the image.

The SVM algorithm learns the optimal hyperplane by solving a quadratic programming problem. The algorithm also uses regularization to minimise overfitting and ensuring of generalization to new data.

One advantage of SVMs for land use land cover classification is their ability to handle high dimensional data and nonlinear relationships between the input features and the output labels. SVMs are also less prone to overfitting compared to decision trees.

However, SVMs can be computationally expensive, mainly for huge datasets, and may require careful tuning of hyperparameters to achieve optimal performance (Neetu, and S. S. Ray, 2019). SVMs can also be sensitive to the kernel function choosen and regularization parameters (Figure 4.6).

(a)



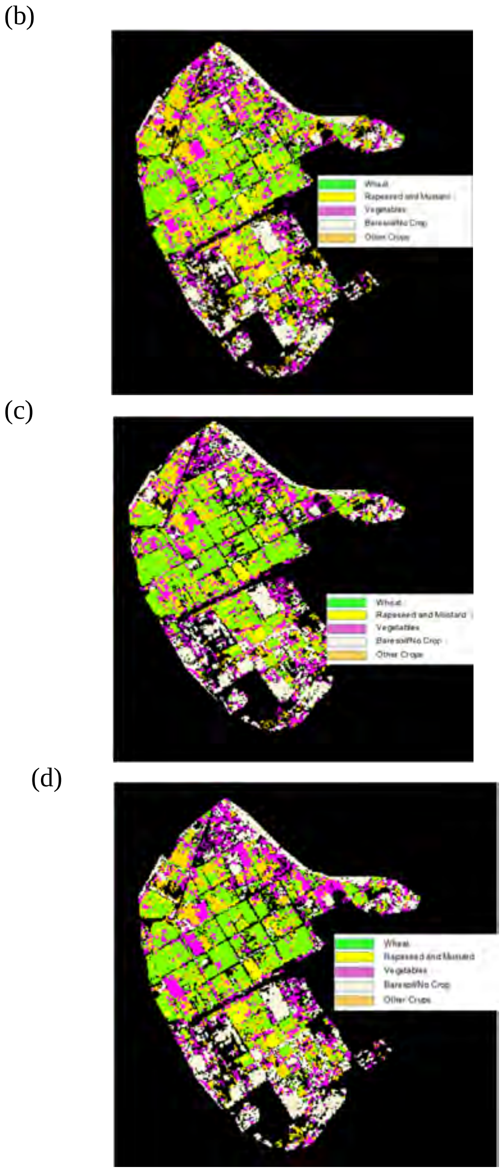


Figure 4.6: Sentinel 2 (Feb 2019) derived False Color Composite Image (a) and crop classification done using (b) CART, (c) Random Forest, and (d) SVM of IARI Farm New Delhi, India (Source: Neetu and Ray, 2019)

4.4.2 Unsupervised Classification

This method involves clustering similar pixels into groups based on their spectral properties without any prior knowledge of the land cover classes. The user then assigns these clusters to land cover classes based on their spectral characteristics.

4.4.2.1 Unsupervised classification using chain method

The chain method is a widely used unsupervised classification technique for remote sensing data analysis. It is an iterative approach that combines several unsupervised classification algorithms to produce a more accurate and reliable classification result.

The chain method typically involves the following steps:

1. **Initial clustering**: This step is to perform initial clustering to pre-processed satellite data, using one of the unsupervised classification algorithms such as K-means, ISODATA, or hierarchical clustering. This step produces an initial classification result, which serves as the starting point for the subsequent iterations.
2. **Feature selection**: The next step is to select the relevant features for classification based on the initial clustering results. This step involves analyzing the spectral characteristics of the clusters and selecting the features that can discriminate between the different land cover classes.
3. **Refinement**: The third step involves refining the initial clustering result using one or more unsupervised classification algorithms such as fuzzy C-means, neural networks, or Markov random fields. This step helps to improve the classification accuracy by incorporating spatial information and reducing the effects of mixed pixels.
4. **Validation**: The final step is to validate the classification result using ground truth data and statistical metrics (Like overall accuracy, kappa coefficient, etc.).

The chain method is a powerful technique for unsupervised classification of remote sensing data, as it combines the strengths of different algorithms to produce a more accurate and reliable result. However, it can also be time-consuming and computationally intensive, particularly for large datasets.

4.4.2.2 ISO Data clustering algorithm

ISO cluster algorithm can be used for image classification by assigning a label to each cluster based on the characteristics of the pixels in the cluster. Here are the steps to use the ISO cluster algorithm for image classification:

1. Convert the image to a grayscale image if it is a color image.
2. Define the number of clusters you want to create. This is the only parameter you need to set for the algorithm.
3. Randomly select initial cluster centers (Figure 4.7 & 4.8).
4. Calculate the distance between each pixel and each cluster center using a distance metric such as Euclidean distance.
5. Assign each pixel to the cluster with is closest to the center.
6. Recalculate the cluster centers based on the pixels assigned to them.

Repeat steps 4-6 until the algorithm converges, which means that the cluster centers no longer move or move less than a predefined threshold (Figure 4.8 a & b).

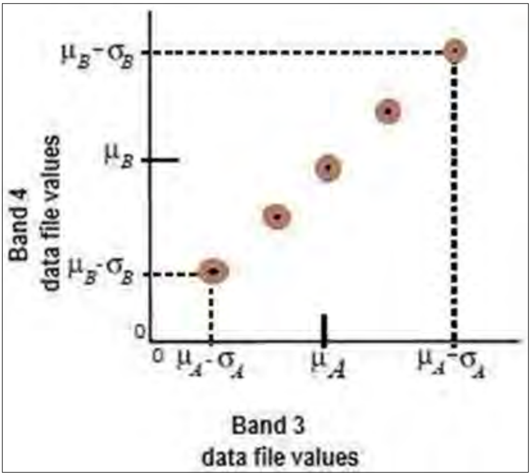
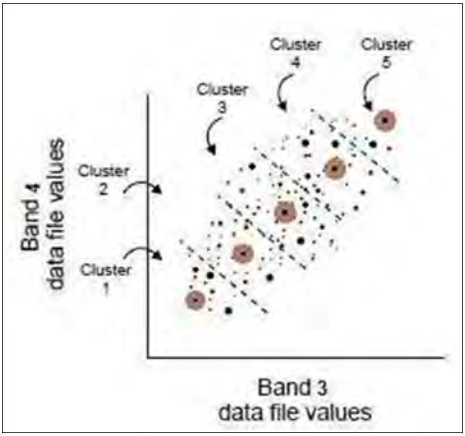


Figure 4.7: ISO data arbitrary clusters

(Source: GISRSSTUDY. "What Is ISODATA - ISODATA Clustering Method." GISRSStudy, 14 June 2022, https://gisrsstudy.com/isodata/.)

a)



b)

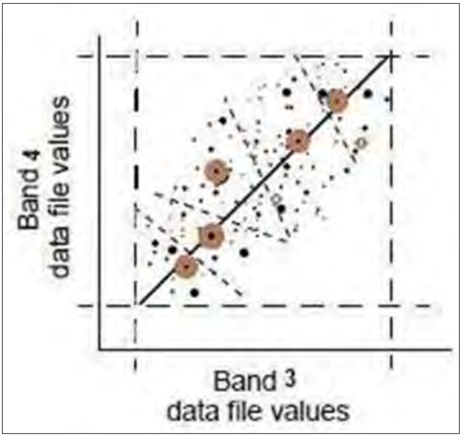


Figure 4.8 a: ISO data first pass, b. ISO data second pass
(Source: GISRSSTUDY. "What Is ISODATA – ISODATA Clustering Method." GISRSStudy, 14 June 2022, https://gisrsstudy.com/isodata/.)

Once the algorithm converges, the clusters can be used for image classification. Each cluster represents a group of pixels that are similar to each other. User can assign a label to each cluster based on the characteristics of the pixels in the cluster. For example, for classifying satellite images, it can assign labels such as "forest", "water", or "urban" to each cluster.

To classify a new image, the same clustering algorithm cab be used and the labels assigned to each cluster can be used to classify the new image. User can assign the label of the cluster that the majority of the pixels in the new image belong to as the label of the new image.

It's important to note that the ISO cluster algorithm is a basic clustering algorithm and may not perform as well as more advanced algorithms for image classification. User may need to experiment with different parameters and distance metrics to achieve the desired results.

4.4.2.3 K-means unsupervised classification

The K-Means algorithm is a type of unsupervised classification used to partition data into distinct clusters. It begins by initializing class means that are evenly distributed inside the data space. The pixels are then iteratively assigned to the nearest class based on a minimum distance technique. After each iteration, the class means are recalculated, and pixels are reclassified accordingly. Generally, all pixels are assigned to the nearest class unless specific criteria, such as a standard deviation / distance threshold, are specified. In such cases, some pixels might remain unclassified if they fail to meet the given criteria. The algorithm continues iterating until the number of pixels in each class changes by less than the designated pixel change threshold /the maximum number of iterations is reached (refer to Figure 4.9).

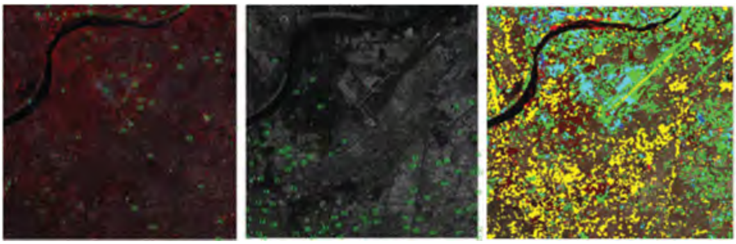


Figure 4.9 Multispectral images of Ahmedabad city (Resourcesat , 2015) (a) Image differencing (b) Image ratio (c) watershed segmentation (d) K-mean clustering (Yellow colour - changes) (Source: Mewada et al. 2020)

It is important to note that the performance of the algorithm depends on the initial values of the centroids, and the algorithm may converge to a local minimum instead of the global minimum. Therefore, multiple initializations with different centroid values are recommended to improve the robustness of the algorithm.

4.4.3 Pixel based or object-based classification

Pixel-based and the object-based classification, are the two approaches for classification of remote sensing images. The main differences between the two approaches are in the scale of the analysis and the features used for classification.

Pixel-Based Classification:

Pixel-based classification is the traditional approach for classification of remote sensing images. In pixel-based classification, every pixel in the image is assigned to a land cover class based on its spectral values. The spectral values are derived from the spectral bands of the image, and the classification algorithm makes a decision based on the spectral values of each pixel. Pixel-based classification assumes that the spectral characteristics of a given land cover class are homogeneous and can be characterized by the pixel's spectral values.

Object-Based Classification:

Object-based classification takes into account the spatial context of the pixels by grouping them into objects or image segments. Image segments are created by grouping pixels with similar spectral values and spatial proximity. Object-based classification considers the spectral values, texture, shape, and context of each object to make a classification decision. Object-based classification assumes that land cover classes are not characterized solely by spectral values but also by the spatial context of the objects.

The advantages of pixel-based classification include simplicity, speed, and the ability to handle large datasets. However, it can be affected by mixed pixels, noise, and variability in the spectral characteristics of land cover classes. Object-based classification, on the other hand, can provide more accurate classification results by taking into account the spatial context of the objects. It can also reduce the effect of mixed pixels and improve the classification of heterogeneous land cover classes. However, it can be computationally intensive and require more data pre-processing and feature extraction.

Overall, the choice of the classification approach depends on the specific requirements of the remote sensing application, such as the spatial and spectral resolution of the image, the complexity of the land cover classes, and the available computational resources.

4.4.4 Hybrid methods for image classification

Hybrid methods for image classification combine multiple approaches, including supervised and unsupervised methods, to improve the accuracy and efficiency of image classification. Some of the commonly used hybrid methods for image classification include:

- Decision tree-based classification: Decision trees can be used to combine supervised and unsupervised classification methods by first applying an unsupervised classification method to the data and then using a decision tree to assign class labels to the resulting clusters. This method can be more efficient than pure supervised classification as it reduces the number of training samples required.
- Ensemble classification: Ensemble classification combines multiple classification models to produce a more accurate classification result. This method involves training multiple classifiers, and then combining their predictions using methods such as majority voting or stacking.
- Deep learning-based classification: Deep learning-based classification combines deep neural networks with supervised or unsupervised methods to perform image classification. This approach can be used for both pixel-based and object-based classification and has been shown to achieve high accuracy on large-scale datasets.
- Hybrid clustering: Hybrid clustering combines the strengths of different clustering algorithms to improve the clustering results. This approach involves first applying an unsupervised clustering algorithm, such as K-means or hierarchical clustering, and then refining the results using a supervised clustering algorithm, such as fuzzy clustering or self-organizing maps.

Overall, hybrid methods for image classification can improve the accuracy and efficiency of image classification by combining the strengths of different approaches. However, the selection and combination of methods should be based on the specific characteristics of the data and the classification objectives.

4.5 Image fusion techniques

The process of combining multiple images of the same scene to create a single image that contains more information than any of the individual images is known as image fusion techniques. There are several types of image fusion techniques (Prasad et al., 2001), including multi-sensor image fusion, Multi-resolution image fusion, multi-focus image fusion, Principal component analysis (PCA) based image fusion and Wavelet-based image fusion.

4.6 Accuracy Assessment

Accuracy assessment holds great significance in remote sensing image classification as it plays a pivotal role in evaluating the dependability and effectiveness of classification outcomes. This process entails the comparison of the classified image with a reference dataset to ascertain the level of accuracy achieved. Through accuracy assessment, valuable insights can be obtained regarding the quality of the classification, identification of errors, and potential enhancements in algorithms and parameters.

Accuracy assessment commonly employs the confusion matrix, which serves as a valuable tool. This matrix measures the level of agreement and discrepancies between the classified image and the reference dataset. It comprises four components: true positives, false positives, true negatives, & false negatives. True positives (TP) are the count of pixels or instances accurately classified as positive or belonging to a particular class. True negatives (TN) denote the number of pixels or instances correctly classified as negative or not belonging to a specific class. False positives (FP) correspond to the tally of pixels or instances inaccurately classified as positive or belonging to a particular class when they should not belong to that class. False negatives (FN) indicate the quantity of pixels or instances inaccurately classified as negative or not belonging to a specific class when they should belong to that class. These components represent pixels that are correctly classified, correctly unclassified, misclassified, and missed, respectively. The confusion matrix enables the calculation of various accuracy metrics, including overall, producer's, and user's accuracy. Overall accuracy shows the proportion of pixels correctly classified out of the total pixels. Confusion matrix can be explained with the below mentioned example:

	Forest	Water	Urban
Forest	9000	200	100
Water	150	9500	1000
Urban	50	300	8500

For instance, in this scenario where the total number of pixels is 30,000 and the correctly classified pixels amount to 26,450, the overall accuracy is 88.2%. Producer's accuracy indicates the classification's reliability for each class by measuring the correct identification of each class. To illustrate, for the "forest" class, the producer's accuracy is computed as TP (9000) divided by the sum of TP (9000) and FN (150), resulting in 98.4%. On the other hand, user's accuracy reflects the likelihood of a pixel being correctly classified for each class. For instance, considering the "water" class, the user's accuracy is calculated as TP (9500) divided by the sum of TP (9500) and FP (200), yielding 97.5%. By evaluating these accuracy metrics, users can assess classification algorithm performance, identify error sources, and refine the classification process to enhance accuracy and reliability in subsequent analyses.

Summary

Remote sensing image classification methods are explained in this chapter. Supervised & unsupervised classification techniques are explained with the help of examples. Mixed approach i.e., hybrid method of applying both supervised and unsupervised classification techniques is illustrated. The classification methods can be used to classify the satellite images into different classes.

Chapter 5
Automatic Information Extraction

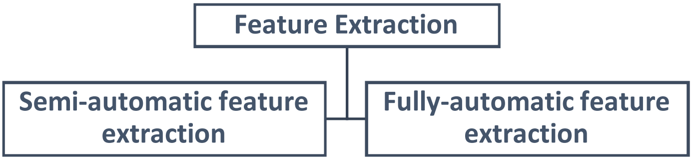
5.1 Introduction

Remote sensing has revolutionized the way we observe and understand the Earth's surface. It has become a crucial tool for various applications such as land use/cover mapping, disaster management, and natural resource management. However, interpreting and analyzing the vast amount of data generated by remote sensing platforms is a challenging task. The need for automatic information extraction in remote sensing arises from the sheer volume and complexity of the data that is collected through remote sensing technologies. Remote sensing data can cover vast areas and provide a wealth of information that is critical for various applications, such as environmental monitoring, disaster response, and resource management. Manual analysis of this data is time-consuming, expensive, and prone to errors. Automated methods of information extraction can quickly process large amounts of data and extract relevant information, providing real-time or near-real-time analysis with greater accuracy and precision. Automated methods are also cost-effective, consistent, and can handle the complexity of remote sensing data more efficiently than manual methods. Automatic information extraction in remote sensing is crucial for timely, accurate, and cost-effective analysis of large and complex datasets.

5.2 Feature Extraction

Feature extraction in remote sensing involves identifying and extracting meaningful information or features from remotely sensed images or data collected through satellites, aircraft, UAV or other platforms. Remote sensing data can be in the form of images, such as satellite images or aerial photographs, or as digital data that represents the reflectance or emission of electromagnetic radiation from the Earth's surface. The data collected can include a wide range of information, such as the location, shape, size, and spectral characteristics of different features on the Earth's surface.

Feature extraction in remote sensing involves using image processing techniques to identify and extract relevant features from the raw data. These



features can include natural features such as forests, rivers, and mountains, as well as man-made features such as buildings, roads, and agricultural fields. There are two main approaches to feature extraction: semi-automatic and fully automatic.

Figure 5.1 Two main approaches to feature extraction techniques

1. **Semi-automatic feature** extraction involves a combination of manual and automated methods. In this approach, an analyst or expert first identifies features of interest in the image, such as buildings, roads, or vegetation, using their knowledge and expertise. Then, they use specialized software tools to automatically extract these features from the image. Semi-automatic feature extraction can be more accurate and efficient than manual methods alone, while still allowing for human oversight and input.

2. **Fully automatic feature extraction**, uses entirely automated methods to identify and extract meaningful information from satellite or aerial imagery without human intervention. This approach typically involves the use of advanced algorithms and machine learning algorithms, such as neural networks or decision trees, that have been trained on large datasets of annotated images. Once trained, these algorithms can automatically identify and extract features of interest from new images, without the need for human input. Fully automatic feature extraction can be faster and more scalable than semi-automatic methods, but may be less accurate in some cases.

Both semi-automatic and fully automatic feature extraction methods have their advantages and disadvantages, and the choice of approach will depend on the specific application and requirements of the analysis.

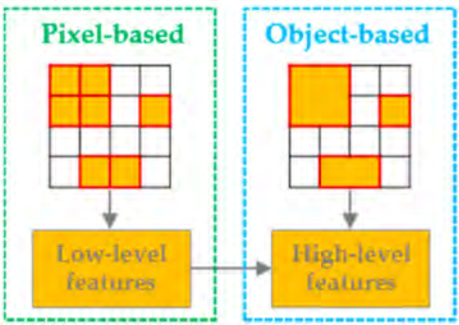


Figure 5.2: Automatic Feature extraction methods

There are several approaches to **automatic** feature extraction in remote sensing, which are mainly divided in to pixel-based and object-based methods (Figure 5.2), while object-based methods involve grouping pixels together to form objects and then analysing those objects to extract features.

Pixel-based Methods: Pixel-based methods involve analyzing individual pixels in a remotely sensed image to extract information about the features on the ground. For example, in a multispectral image, each pixel represents a different combination of reflectance values across multiple spectral bands (Figure 5.3). By examining the spectral values of each pixel, we can identify and classify different features on the ground, such as land cover types, vegetation density, and water bodies. These methods include spectral indices, principal component analysis, and machine learning algorithms such as decision trees and random forests. Pixel-based methods are commonly used in remote sensing applications such as land cover mapping, environmental monitoring, and urban planning.

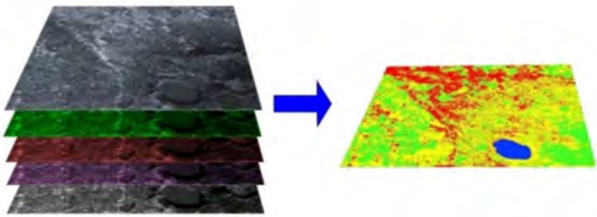


Figure 5.3 A multispectral Landsat image processed to produce a land cover classification

Object-based Methods: Object-based feature extraction methods involve the segmentation of an image into homogeneous regions, followed by the extraction of features from these regions to represent their spectral, spatial, and contextual properties. The process involves the classification of pixels by considering their spectral characteristics, shape, texture, and spatial relationship with nearby pixels. Object-based classification methods have been developed more recently in comparison to traditional pixel-based classification techniques. While pixel-based classification relies solely on the spectral information of individual pixels, object-based classification utilizes information from a group of similar pixels known as objects or image objects. Image objects or features are clusters of pixels that share similarities in spectral properties (such as color), size, shape, texture, and context within their neighbouring area. This classification approach aims to replicate the type of analysis performed by humans during visual interpretation.

Object-based feature extraction methods segments an image by grouping pixels. It doesn't create single pixels. Instead, it generates objects with different geometries. If you have the right image, objects can be so meaningful that it does the digitizing for you. For example, the segmentation results shown in Figure 5.4 shows roads, buildings and vegetation.

Figure 5.4: Left: Original satellite image. Right: Semantic segmentation of roads, building and vegetation (source: Ng, Virginia & Hofmann, Daniel. (2018). Scalable Feature Extraction with Aerial and Satellite Imagery. 145-151. 10.25080/Majora-4af1f417-015.)

These methods typically involve the following steps:

1. **Image segmentation**: This is the process of dividing an image into regions based on their spectral and spatial properties. Various segmentation algorithms can be used such as watershed, region growing, and mean shift.
2. **Object classification**: Once the objects have been defined, they are classified into different categories based on their spectral and contextual properties. Classification can be performed using supervised or unsupervised methods.
3. **Feature extraction**: Features are extracted from each object to represent its spectral, spatial, and contextual properties. These features can include texture, shape, size, context, and spectral values.
4. **Feature selection**: This step involves selecting the most relevant features for the analysis. Feature selection can be performed using various techniques such as correlation analysis and principal component analysis.
5. **Object-based analysis**: The extracted and selected features are used to perform various analyses such as change detection, object recognition, and object tracking.

Object-based feature extraction methods offer several advantages over pixel-based methods, including the ability to incorporate contextual information, improved accuracy, and reduced noise. However, they can be computationally intensive and may require significant expertise to implement effectively. Object-based feature extraction methods are commonly used for applications such as land cover mapping, urban growth analysis, and vegetation monitoring.

5.2 Techniques used for feature extraction

There are several techniques used for feature extraction in remote sensing, which can be broadly classified into three categories: spectral, spatial, and temporal.

5.2.1 ***Spectral feature extraction***: Spectral feature extraction involves the use of spectral bands to extract information about the properties of the target. Each spectral band represents a range of wavelengths that corresponds to a specific region of the electromagnetic spectrum. The most commonly used spectral bands in remote sensing are the visible, near-infrared, and thermal infrared bands. Spectral feature extraction techniques include:

a) **Principal component analysis** (PCA): PCA is a widely used technique that reduces the dimensionality of the data by transforming the original bands into a set of uncorrelated principal components. These principal components are ordered in such a way that the first principal component accounts for the maximum variance in the data, the second principal component accounts for the maximum remaining variance, and so on. The first few principal components often contain the most relevant information about the target.

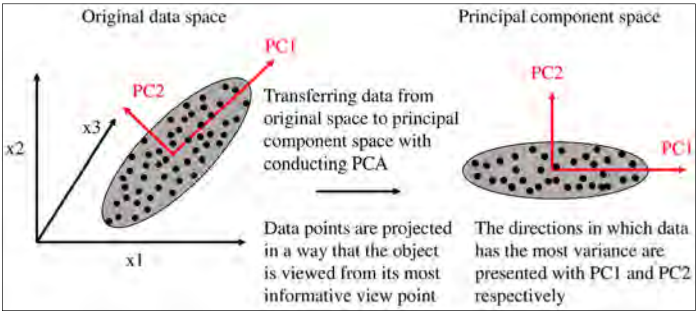


***Figure** 5.5 Schematic of PCA transformation. Original data space presented on the left with 3 (input) variables transformed to a component space with lower dimension and pc1 and pc2 being the axes of the coordinate (source: Ghasemi, P.; Aslani, M.; Rollins, D.K.; Williams, R.C. Principal Component Neural Networks for Modeling, Prediction, and Optimization of Hot Mix Asphalt Dynamics Modulus. Infrastructures 2019, 4, 53. https://doi.org/10.3390/infrastructures4030053)*

b) Spectral indices: Spectral indices are mathematical formulas that combine the values of two or more spectral bands to extract specific information about the target. Examples of spectral indices include the normalized difference vegetation index (NDVI) and the soil-adjusted vegetation index (SAVI) (Figure 5.6), which are used to estimate vegetation cover and health.

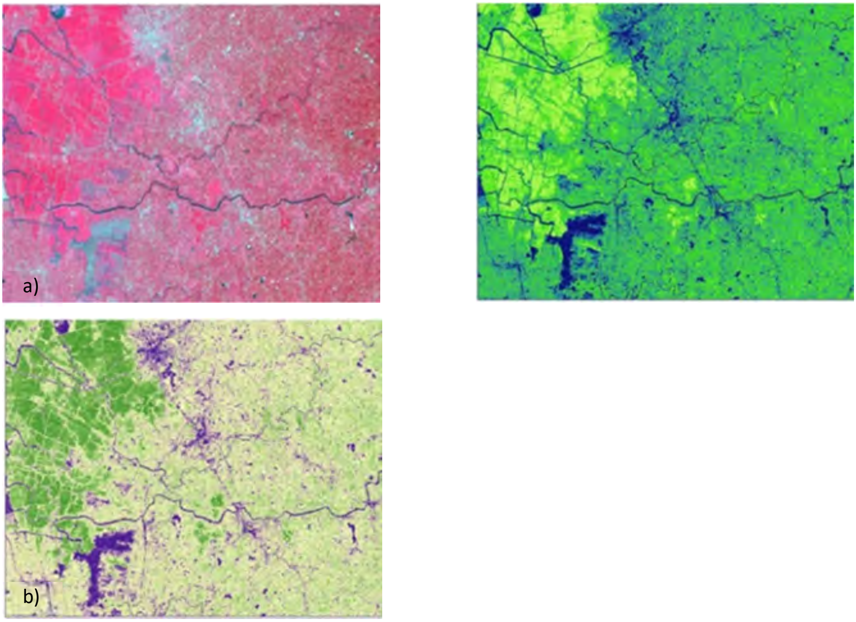


Figure 5.6 Generation of Spectral Indices on Landsat Image to estimate vegetation cover and health a) Landsat Image b) NDVI c) SAVI (source: https://grindgis.com/blog/vegetation-indices-arcgis)

c) Endmember extraction: Endmember extraction involves the identification of pure spectral signatures of the target, which can be used to classify the target into different categories. Endmembers can be extracted using various techniques, such as linear spectral unmixing and vertex component analysis.

5.2.2 *Spatial feature extraction*: Spatial feature extraction involves the analysis of the spatial distribution of the target. Spatial features can provide information about the size, shape, texture, and pattern of the target. Spatial feature extraction techniques include:

a) Texture analysis: Texture refers to the spatial arrangement of pixels in an image. Texture analysis involves analyzing the patterns and variations in pixel values to identify and classify features. This can be done using techniques such as grey-level co-occurrence matrices (GLCM), wavelet transforms, and fractal analysis. Texture analysis can be used to distinguish between different land cover types, such as forests, grasslands, and agricultural fields.

b) Object-based image analysis (OBIA): OBIA involves the segmentation of the image into objects based on their spectral and spatial properties. Objects can be classified based on their size, shape, texture, and other attributes. OBIA can be used as a semi-automatic or fully automatic method, depending on whether the object selection and classification are done manually or automatically. OBIA can be used to extract features such as roads, buildings, and water bodies.

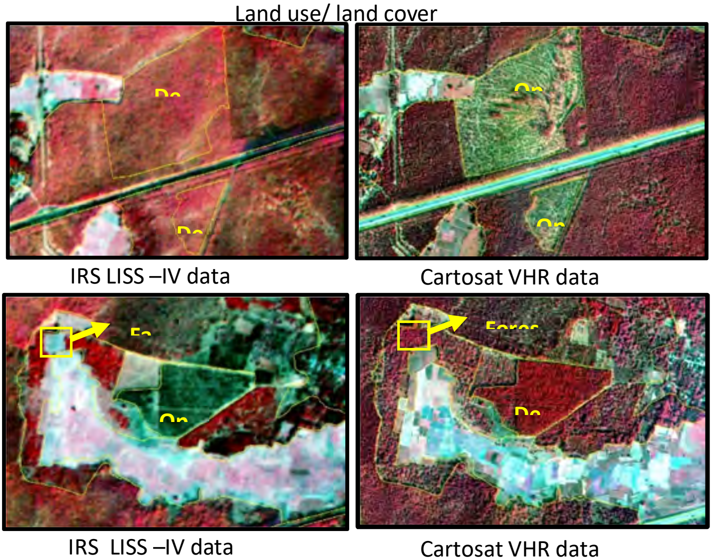


Figure 5.7 Temporal Change Analysis for Aguiboni GP, West Bengal

5.2.3 Temporal feature extraction: Temporal feature extraction involves the analysis of the temporal changes in the target over time. Temporal features can provide information about the dynamics of the target, such as growth, decay, and disturbance. Temporal feature extraction techniques include:

a) Change detection: Change detection involves the identification of changes in the target between two or more images taken at different times. Change detection can be done using various techniques, such as image differencing, image ratioing, and vegetation indices.

b) Time series analysis: Time series analysis involves the analysis of a sequence of images taken at regular intervals over time. Time series analysis can be used to extract information about the seasonal patterns of vegetation, the growth and development of crops, and the dynamics of land cover changes.

Feature extraction in remote sensing involves the identification and extraction of relevant information from the raw data. Spectral, spatial, and temporal feature extraction techniques are commonly used in remote sensing analysis and can be used in combination to extract comprehensive information about the target.

Machine learning techniques: In addition to above, recently machine learning techniques has gained popularity for extracting information from remote sensing data. Machine learning techniques can be used for feature extraction in remote sensing to automatically identify and extract relevant information from images. Here are some common machine learning techniques used for feature extraction in remote sensing:

1. **Convolutional neural networks (CNNs):** CNNs are a type of deep learning algorithm that have proven to be highly effective for feature extraction in remote sensing. CNNs learn to identify patterns in the data by passing the image through a series of convolutional layers, which apply filters to the image to identify features such as edges, textures, and shapes. The output of the convolutional layers is then passed through one or more fully connected layers to perform classification or regression tasks. CNNs can be trained using labeled data to learn to recognize specific features or classes in the image.

2. **Random forests:** Random forests are an ensemble learning algorithm that can be used for feature extraction in remote sensing. Random forests consist of a collection of decision trees, where each tree is trained on a random subset of the data. The trees then vote on the final classification or regression output. Random forests can be used to identify the most important features in the image based on their contribution to the classification or regression task.

3. **Support vector machines (SVMs):** SVMs are a type of supervised learning algorithm that can be used for feature extraction in remote sensing. SVMs work by finding the hyperplane that maximally separates the different classes in the data. SVMs can be used for both classification and regression tasks, and can handle high-dimensional data of remote sensing images.

4. **Autoencoders**: Autoencoders are a type of neural network that can be used for unsupervised feature extraction in remote sensing. Autoencoders consist of an encoder network that learns to compress the input image into a lower-dimensional representation, and a decoder network that learns to reconstruct the original image from the compressed representation. The compressed representation can be used as a feature vector for downstream tasks such as classification or clustering.

5. **Transfer learning**: Transfer learning involves using a pre-trained machine learning model, such as a CNN, on a related task to extract features from remote sensing images. The pre-trained model is fine-tuned on the remote sensing data by retraining the final layers of the network for the specific classification or regression task. Transfer learning can be effective for tasks where there is limited labeled data available, as it can leverage the features learned on a related task to improve performance.

Machine learning techniques can be powerful tools for feature extraction in remote sensing, as they can learn to identify complex patterns in the data and extract relevant information automatically.

Summary:

Automatic feature extraction plays a crucial role in remote sensing by enabling efficient and accurate analysis of large amounts of complex data. With the growing availability of high-resolution satellite and aerial imagery, the need for automated feature extraction has become increasingly important. Manual feature extraction can be time-consuming, subjective, and error-prone, making it impractical for analysing large datasets. Automated feature extraction algorithms can quickly and objectively identify features of interest, such as land cover types, objects of interest, and changes over time. This can provide valuable information for a range of applications, including environmental monitoring, urban planning, and disaster response. The accuracy and consistency of automated feature extraction can help to improve the reliability and efficiency of remote sensing analysis. It has the potential to significantly reduce the time and cost involved in analysing satellite or aerial imagery, making it an increasingly important area of research and development in the field of remote sensing.

Chapter 6

SAR Image Processing

6.1 Introduction

Microwave remote sensing utilizes electromagnetic radiation in the microwaves range, which has a wavelength between 1 cm and 1 m. These microwaves possess the ability to penetrate through clouds, fog, and other obstructing substances such as ash or powder coverages (e.g., during a volcanic eruption or building collapse). This unique characteristic enables microwave remote sensing to operate effectively in any weather condition or environment.

Microwave remote sensing systems can be categorized into two groups: passive and active. Passive systems capture naturally emitted radiation from the observed surface, although the amount of energy emitted at microwave frequencies is usually minimal. These systems generally have lower spatial resolutions.

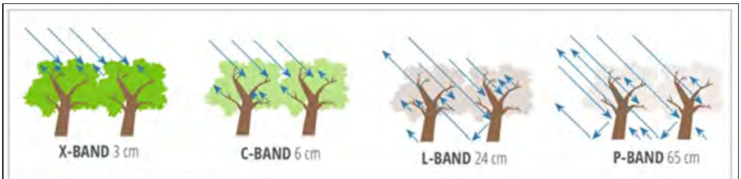
On the other hand, active systems feature their own source (transmitter) that illuminates the observed scene, allowing their operation during both day and night, regardless of sunlight availability. The sensor transmits a radio signal within the microwave spectrum and records the portion of the signal that is backscattered by the target and returned to the sensor. By analyzing the power and timing of the backscattered signal, different targets within the scene can be distinguished, and the distance to the target can be measured. This operational principle is known as RADAR (short for RAdio Detection and Ranging), and it enables the acquisition of microwave images of the observed scene.

The most commonly employed microwave imaging sensor is Synthetic Aperture Radar (SAR), a radar system that provides high-resolution microwave images. SAR images have distinct characteristics compared to conventional optical images acquired in the visible or infrared bands. Consequently, radar and optical data can complement each other, offering different informative contributions.

Synthetic Aperture Radar (SAR) employs different frequency bands for remote sensing, each with distinct characteristics and applications (Figure 6.1). The X-band (9.6 GHz) offers high-resolution imaging suitable for land cover classification, coastal monitoring, and infrastructure analysis. The C-band (5.3 GHz) excels in urban monitoring, agriculture, and soil moisture detection due to its ability to penetrate vegetation. The S-band (3.1 GHz) is effective for forest mapping, biomass estimation, and flood monitoring. The L-band (1.25 GHz) penetrates vegetation and soil well, making it useful for land deformation monitoring, subsurface imaging, and forest structure analysis. Additionally, the P-band (0.3-0.7 GHz) has great potential for soil moisture estimation, subsurface imaging, and ice monitoring due to its longer wavelength (Figure 6.2). The choice of SAR band depends on the specific objectives and environmental characteristics of the remote sensing application.

Band	Frequency	Wavelength	Typical Application
Ka	27 – 40 GHz	1.1 – 0.8 cm	Rarely used for SAR (airport surveillance)
K	18 – 27 GHz	1.7 – 1.1 cm	rarely used (H_2O absorption)
Ku	12 – 18 GHz	2.4 – 1.7 cm	rarely used for SAR (satellite altimetry)
X	8 – 12 GHz	3.8 – 2.4 cm	High resolution SAR (urban monitoring,; ice and snow, little penetration into vegetation cover; fast coherence decay in vegetated areas)
C	4 – 8 GHz	7.5 – 3.8 cm	SAR Workhorse (global mapping; change detection; monitoring of areas with low to moderate penetration; higher coherence); ice, ocean maritime navigation
S	2 – 4 GHz	15 – 7.5 cm	Little but increasing use for SAR-based Earth observation; agriculture monitoring (NISAR will carry an S-band channel; expends C-band applications to higher vegetation density)
L	1 – 2 GHz	30 – 15 cm	Medium resolution SAR (geophysical monitoring; biomass and vegetation mapping; high penetration, InSAR)
P	0.3 – 1 GHz	100 – 30 cm	Biomass. First p-band spaceborne SAR will be launched ~2020; vegetation mapping and assessment. Experimental SAR.

Figure 6.1: Utilisation of Different SAR Wavelength for various application



Sensitivity of SAR measurements to forest structure and penetration into the canopy at different wavelengths used for airborne or spaceborne remote sensing observations of the land surface. Credit: NASA SAR Handbook.

Figure 6.2: Penetration of different SAR wavelength (Source: NASA SAR Handbook.)

6.1.1 *Radar Equation*

A radar equation explains the physical dependences of the range of a radar to the characteristics of the transmitter, receiver, antenna, target, and distance between the radar and target.

$$R = \sqrt[4]{\frac{P_s G^2 \lambda^2 \sigma}{P_e (4\pi)^3}}$$

R= Range
P_s= Transmitted Power
G=Antenna Gain
λ= Wavelength
σ =Radar Cross Section
P_e = Reflected Power

Radar Cross Section is the ratio of the backscattered energy to the energy that the sensor would have received if the target was an ideal isotropic reflector.

6.2 SAR Data Processing:

Radiometric calibration of microwave satellite images involves the conversion of raw digital numbers (DNs) into physically meaningful units, such as backscatter coefficients or radar cross-section, that can be used for scientific and operational purposes. The following are some commonly used terms in radiometric calibration of microwave satellite images:

- Digital number (DN): The raw measurement of the satellite sensor, usually in the form of a digital number (DN), which represents the amplitude of the received signal.
- Sigma naught (σ0): The backscatter coefficient, or radar cross-section, normalized to the incidence angle, which is a measure of the radar reflectivity of the surface.
- Beta naught (β0): The backscatter coefficient, or radar cross-section, normalized to unit area, which is a measure of the radar reflectivity of the surface.
- Gamma naught (γ0): The backscatter coefficient, or radar cross-section, normalized to both the incidence angle and unit area, which is a measure of the radar reflectivity of the surface.
-

6.2.1 *Multi-Looking*

In microwave imaging, the spatial resolution is limited by the wavelength of the radar signal, and it is usually coarser than that of optical images. The speckle noise is caused by the interference of the electromagnetic waves reflected from the different surface elements of the target, which creates a grainy appearance in the image.

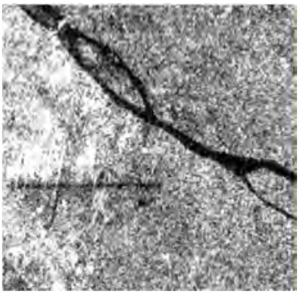
Multi-looking works by averaging the radar signal from adjacent pixels within a defined window or kernel, which reduces the speckle noise and increases the signal-to-noise ratio. The result is a smoother image with improved spatial resolution, but at the cost of reduced radiometric resolution due to averaging.

6.2.2 *Speckle*

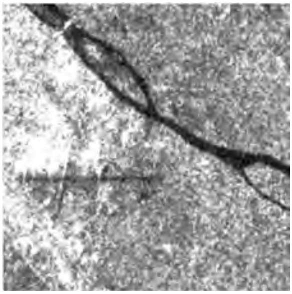
It is a type of noise that is commonly found in Synthetic Aperture Radar (SAR) images, which is caused by the interference of electromagnetic waves reflecting off of different surfaces. The presence of speckle in SAR images can make it difficult to extract useful information from the image. Therefore, various speckle suppression filters have been developed to reduce the noise and improve the overall quality of the image. Some of the most common types of speckle suppression filters used in SAR image processing are.

- **Median Filter**: Median filter is commonly used in Synthetic Aperture Radar (SAR) image processing to reduce speckle noise. By replacing each pixel's value with the median value of its neighboring pixels, the filter effectively preserves edges and fine details while smoothing the overall image. It improves SAR image quality and enhances interpretability
- **Lee Filter**: The Lee filter is a commonly used speckle reduction filter that applies a statistical approach to reduce speckle in SAR images. The filter works by using a sliding window technique to calculate the mean and variance of the image pixels. The filter then compares each pixel to the mean value of the surrounding pixels and replaces it with a filtered value based on this comparison. This filter is effective at reducing speckle while preserving the edges and details in the image (Figure 6.3).
- **Frost Filter**: The Frost filter works by assuming that the speckle in the image is a combination of a signal and additive white Gaussian noise. The filter then estimates the parameters of the noise model and removes the noise from the image. This filter is effective at reducing speckle in homogeneous regions of the image.

- **Gamma Map** Filter: The Gamma Map filter is a speckle reduction filter that works by modelling the statistical properties of the image. The filter calculates a gamma map for the image, which is used to weight the contribution of each pixel to the filtered image. The filter effectively reduces speckle while preserving image details and edges.
- **Kuan Filter**: The Kuan filter is a speckle reduction filter that uses a combination of adaptive filtering and non-linear diffusion to reduce speckle in SAR images. The filter works by dividing the image into small blocks and using the standard deviation of the pixel values within each block to determine the degree of filtering applied. This filter is effective at reducing speckle while preserving the sharpness of edges in the image.



EOS 4 on 28-Mar-2023, Kanpur(Sigma Naught)



EOS 4 on 28-Mar-2023 , Kanpur(Lee Filter)

Figure 6.3: EOS 4 image of 28 March 2023 over Kanpur

6.3 Types of Image Distortions

- **Layover** occurs when a tall object such as a building or a mountain is imaged, and its top appears closer to the radar than its bottom. This creates an illusion of compression, and the image appears as if the top of the object is leaning over the bottom.
- **Foreshortening**, on the other hand, occurs when an object is imaged from an oblique angle, and its apparent height appears shorter than its actual height. This distortion occurs because the radar signal takes a longer path when it hits the top of the object than when it hits the bottom.
- **Shadow** is a third distortion that occurs when an object blocks the radar signal, creating a dark area in the image. This can make it

difficult to interpret the image, and shadow detection algorithms are used to identify and remove or minimize the impact of shadows (Figure 6.4).

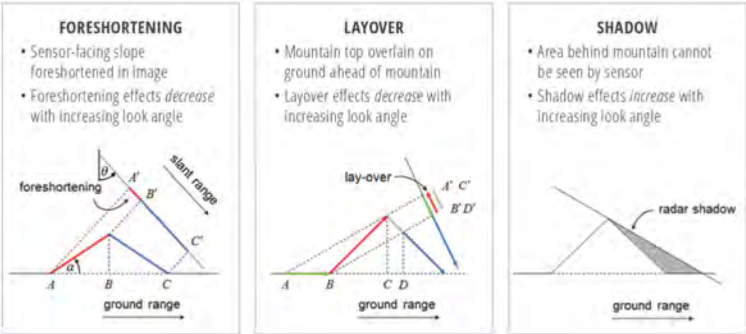


Figure 6.4: Image distortion observed in SAR

Geometric distortions such as foreshortening, layover, shadow and other problems related to special imaging geometry of radar systems, decrease reliability of radar imageries. Thus, radiometric and geometric corrections and calibrations must be applied to the radar images before using them.

6.4 Types of Correction

Terrain Correction: Range Doppler Correction, Range Terrain Flattening and Geocoding: Range Doppler Correction is a process that corrects the distortions in SAR images caused by the motion of the satellite and the rotation of the Earth. The motion of the satellite causes a shift in the frequency of the radar signal, known as the Doppler shift, which leads to range compression or expansion in the image. The rotation of the Earth causes a change in the direction of the radar beam, leading to azimuth distortions in the image.

Range Doppler Correction compensates for these distortions by applying a mathematical transformation to the radar signal. The transformation corrects for the Doppler shift and azimuth distortions, and produces an image that is free of motion-related distortions.

After the Range Doppler Correction, the RTF and Geocoding processing steps can be applied to further improve the quality of the image. RTF removes the effect of terrain on the radar signal and produces a terrain-flattened image, while Geocoding transforms the image coordinates to geographic coordinates for accurate positioning of the image in geographic space.

6.5 SAR Polarimetry and Decomposition

6.5.1 *SAR Polarimetry*

It is the science of acquiring, processing and analyzing the polarization state of an electromagnetic field including the magnitude and relative phase. SAR polarimetry is concerned with the utilization of polarimetry in radar applications (Table 6.1).

Table 6.1: SAR Polarimetry

		Received Polarization		
		H or V	H and V	**H and V and relative phase**
Transmitted Polarization	H or V	Single [1] Pol	Dual [2] Pol	**Dual Polarimetric**
	H and V	Dual [2] pol	Quad [4] Pol	**Fully Polarimetric**

In SAR (Synthetic Aperture Radar) remote sensing, the decomposition of the measured signal into different scattering mechanisms is an essential step for understanding the physical properties of the imaged scene. There are two main types of decomposition techniques: coherent decomposition and incoherent decomposition.

6.5.1.1 Coherent Decomposition

It is based on the eigenvalue analysis of the coherency matrix (Figure 6.5). The coherency matrix contains the second-order statistics of the backscattered electromagnetic waves and describes the polarimetric properties of the scattering medium. The eigenvalues and eigenvectors of the coherency matrix are used to decompose the scattering mechanisms into coherent scattering mechanisms. Coherent decomposition can be used to identify the different scattering mechanisms in a scene, such as surface scattering, double-bounce scattering, volume scattering, and helix scattering.

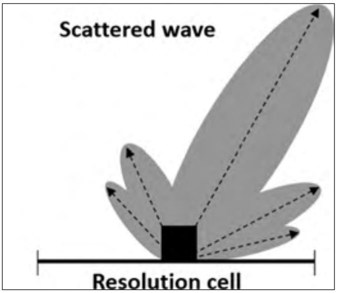


Figure 6.5: Coherent Scattering

6.5.1.2 Incoherent Decomposition

It also known as the decomposition of the covariance matrix, is a statistical approach that does not require the coherent phase information of the backscattered signals (Figure 6.6). The most commonly used incoherent decomposition technique is the Freeman-Durden decomposition, which is based on the assumption that the backscattered signals from a scene can be decomposed into three different scattering mechanisms: surface scattering, double-bounce scattering, and volume scattering.

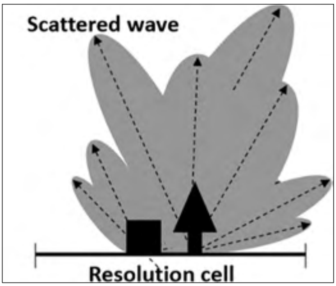


Figure 6.6: Incoherent Scattering

Both coherent and incoherent decomposition techniques have their advantages and limitations, and the choice of the decomposition technique depends on the specific application and the physical properties of the scene being imaged.

Coherent decomposition provides a more detailed and accurate decomposition of the scattering mechanisms, but it requires a high signal-to-noise ratio and a stable coherent phase of the backscattered signals. In contrast, incoherent decomposition is less sensitive to noise and phase errors but provides less detailed information on the scattering mechanisms

6.5.2 *SAR Decomposition Process*

This process of decomposition involves several steps, as outlined below:

6.5.2.1 Multi-looking: The SAR data is often multilooked to reduce speckle noise and improve the signal-to-noise ratio. Multilooking involves averaging the complex data over a certain number of looks in both the range and azimuth directions.

6.5.2.2 Scattering matrix: The fully polarimetric SAR data contains the complete scattering matrix for each pixel, which provides detailed information on the scattering properties of objects on the ground (Figure 6.7). The scattering matrix is a 2x2 matrix that describes the relationship between the transmitted and received electromagnetic waves. Scattering matrix is used to identify the scattering behaviour of objects after an interaction with electromagnetic wave. This matrix is represented by a systematic combination of horizontal and vertical polarization states of transmitted and received signals.

$$(S) = \begin{pmatrix} S_{VV} & S_{VH} \\ S_{HV} & S_{HH} \end{pmatrix}$$

Sometimes scattering mechanism which is not observable with linear basis can be enriched through transformation of basis from linear to Pauli for representation of scattering information. Pauli basis is defined by sum and difference of co-pol terms and twice the cross-pol term. The feature vector in Pauli basis is given by

$$K_L = \begin{bmatrix} S_{HH} \\ \sqrt{2}S_{HV} \\ S_{VV} \end{bmatrix}$$

$$K_P = \begin{bmatrix} S_{HH} + S_{VV} \\ S_{HH} - S_{VV} \\ 2S_{HV} \end{bmatrix}^{1/2}$$

6.5.2.3 Coherency matrix: The coherency matrix is derived from the scattering matrix and is a 2x2 matrix that contains the polarimetric information. It is given by:

T = $K_P . K_P$ ‘T

Where ‘T represents the Conjugate Transpose.

$$[T] = \frac{1}{2}\begin{bmatrix} S_{HH}+S_{VV} \\ S_{HH}-S_{VV} \\ 2S_{XX} \end{bmatrix}\begin{bmatrix} (S_{HH}+S_{VV})^* & (S_{HH}-S_{VV})^* & 2S^*_{xx} \end{bmatrix} = \begin{bmatrix} T_{11} & T_{12} & T_{13} \\ T_{12}^* & T_{22} & T_{23} \\ T_{13}^* & T_{23}^* & T_{33} \end{bmatrix}$$

where T11, T12, T21, and T22 are complex values. The coherency matrix can be used to calculate various polarimetric parameters, such as the polarimetric entropy, degree of polarization, and polarimetric coherence.

$$[T] = \frac{1}{2}\begin{bmatrix} |S_{HH}+S_{VV}|^2 & (S_{HH}+S_{VV})(S_{HH}-S_{VV})^* & 2(S_{HH}+S_{VV})S^*_{xx} \\ (S_{HH}+S_{VV})^*(S_{HH}-S_{VV}) & |S_{HH}-S_{VV}|^2 & 2(S_{HH}-S_{VV})S^*_{xx} \\ 2(S_{HH}+S_{VV})^*S_{XX} & 2(S_{HH}-S_{VV})^*S_{XX} & 4|S_{XX}|^2 \end{bmatrix}$$

6.5.2.4 Covariance matrix: The covariance matrix is another representation of the polarimetric data and is defined as the Hermitian transpose of the coherency matrix. It is given by:

C = $K_L . K_L$ ‘T

Where ‘T represents the Conjugate Transpose.

$$[C] = \begin{bmatrix} S_{HH} \\ \sqrt{2}S_{XX} \\ S_{VV} \end{bmatrix}\begin{bmatrix} S^*_{HH} & \sqrt{2}S^*_{XX} & S^*_{VV} \end{bmatrix} = \begin{bmatrix} C_{11} & C_{12} & C_{13} \\ C_{12}^* & C_{22} & C_{23} \\ C_{13}^* & C_{23}^* & C_{33} \end{bmatrix}$$

where C11, C12,C13 are the complex covariance values. The covariance matrix can be used to calculate various polarimetric parameters, such as the co-polarization ratio, cross-polarization ratio, and orientation angle.

$$[C]=\begin{bmatrix} |S_{HH}|^2 & \sqrt{2}S_{HH}S_{XX}^* & S_{HH}S_{VV}^* \\ \sqrt{2}S_{HH}^*S_{XX} & 2|S_{XX}|^2 & \sqrt{2}S_{XX}S_{VV}^* \\ S_{HH}^*S_{VV} & \sqrt{2}S_{XX}^*S_{VV} & |S_{VV}|^2 \end{bmatrix}$$

6.5.3 *Types of Polarimetric Decompositions*

The polarimetric decomposition is a mathematical process that separates the scattering mechanisms of the target into individual components, such as surface scattering, double-bounce scattering, and volume scattering. Different polarimetric decompositions can be used, such as the Freeman-Durden decomposition, Cloude-Pottier decomposition, and Touzi decomposition. These decompositions involve eigenvalue and eigenvector analysis of the coherency or covariance matrix.

6.5.3.1 Pauli Decomposition: This is the most basic and widely used polarimetric decomposition technique in SAR. It is a simple 3-channel decomposition that separates the total power, the power in the horizontal polarization, and the power in the vertical polarization. This technique is particularly useful for identifying and visualizing the orientation of scattering structures, such as vegetation, buildings, and ships.

6.5.3.2 Freeman-Durden Decomposition: This decomposition technique is used to distinguish between surface, double-bounce, and volume scattering mechanisms. It separates the scattering from the surface and the volume and provides information on the double-bounce scattering caused by the interaction of the radar signal with two different scatterers. The Freeman-Durden decomposition is often used for land cover classification, particularly in urban areas. The Freeman-Durden model assumes reflection symmetry hence T_{13} T_{23} and their Conjugates are assumed to be zero (Figure 6.7).

Total Scattering = Surface Scattering + Double-bounce + Volume Scattering

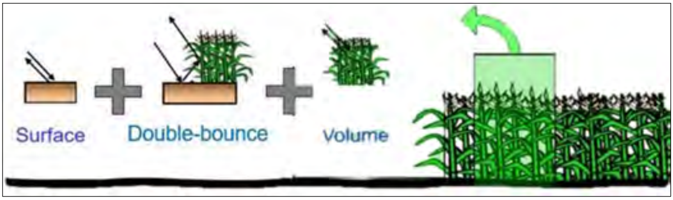


Figure 6.7: Types of Scaterring Mechanism

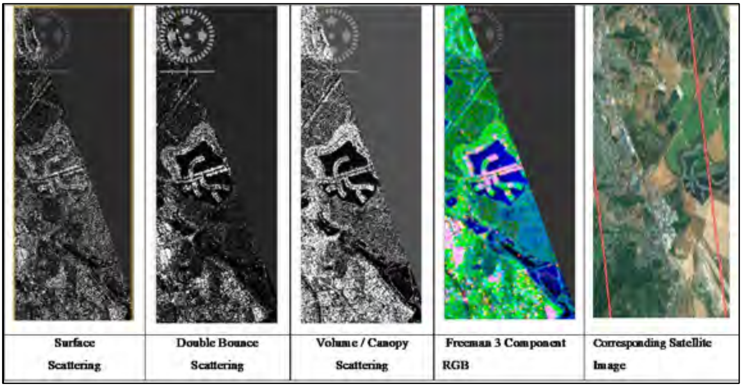


Figure 6.8: Decomposition of fully polarimetry data (Radarsat 2)

6.5.3.3 Cloude-Pottier Decomposition: This is a powerful technique that provides information on the dominant scattering mechanisms within a pixel. It decomposes the polarimetric data into a set of eigenvalues and eigenvectors that can be used to identify the scattering mechanism. The Cloude-Pottier decomposition is particularly useful for identifying and characterizing the scattering properties of man-made objects such as buildings and roads.

6.5.3.4 Yamaguchi Decomposition: This technique separates the polarimetric data into four scattering components: surface, double-bounce, volume, and helix scattering. The helix scattering is a unique feature of the Yamaguchi decomposition and is caused by the interaction of the radar signal with helical structures, such as tree branches or wires. The Yamaguchi decomposition is used for analyzing vegetation and forest structures, as well as for identifying man-made objects.

6.5.3.5 Touzi Decomposition: This technique is based on the coherent decomposition of the scattering matrix and provides a detailed analysis of the polarimetric scattering mechanisms. The Touzi decomposition separates the polarimetric data into four parameters: the surface scattering coefficient, the dihedral scattering coefficient, the volume scattering coefficient, and the helix scattering coefficient. This technique is particularly useful for analyzing complex scattering structures, such as forests and agricultural fields.

6.5.4 *Interpretation*:

The output of the polarimetric decomposition is a set of images that represent the different scattering mechanisms. These images can be interpreted to identify the different types of targets, such as vegetation, buildings, and water bodies.

6.6 Interferometric Synthetic Aperture Radar

InSAR (Interferometric Synthetic Aperture Radar) processing is a complex procedure (Figure 6.9) that involves several steps to extract valuable information about ground deformation and create accurate digital elevation models.

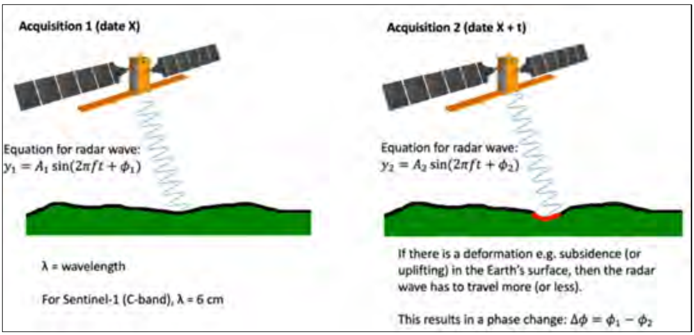


Figure 6.9: Working Principle of Interferometric SAR

6.6.1 *Data Acquisition:*

The first step in InSAR processing is to acquire pairs of SAR (Synthetic Aperture Radar) images. These images should be taken from slightly different positions in space and time, with a suitable time baseline between them. It is important to ensure that the images have similar acquisition geometries and are coregistered to sub-pixel accuracy.

6.6.2 *Calibration*:

Once the SAR images are acquired, they need to be calibrated to account for various system-induced artifacts. This involves correcting for sensor-specific effects such as antenna phase center variations, platform motion, and radiometric calibration.

6.6.3 *Coregistration*:

In order to compare the two SAR images accurately, they need to be coregistered. Coregistration involves aligning the images to sub-pixel accuracy, compensating for any geometric differences. This step is crucial for achieving precise interferometric measurements.

6.6.4 *Interferogram Formation*:

The next step is to generate an interferogram by combining the two coregistered SAR images (Figure 6.10). This is done by pixel-by-pixel differencing of the complex radar data. The resulting interferogram represents the phase difference between the two acquisitions and contains information about ground deformation.

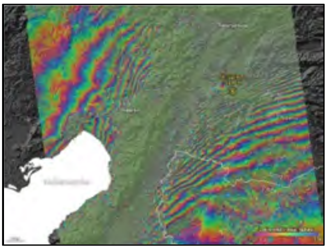


Figure 6.10: Interferogram of Turkey Earthquake using Sentinel
(Source :
https://www.esa.int/ESA_Multimedia/Images/2023/02/Tuerkiye_Syria_interferogram)

6.6.5 *Phase Correction*:

The interferometric phase contains not only the information about ground deformation but also atmospheric and other noise-related effects. These artifacts need to be corrected to obtain accurate deformation measurements. System-induced errors, such as topographic variations and antenna phase center variations, are also corrected during this stage.

6.6.6 *Phase Unwrapping*:

The interferometric phase is inherently wrapped within a limited range, causing phase discontinuities. To obtain a continuous phase field, phase unwrapping algorithms are applied (Figure 6.11). These algorithms reconstruct the unwrapped phase by adding multiples of 2π to the wrapped phase values, ensuring a smooth and continuous phase distribution.

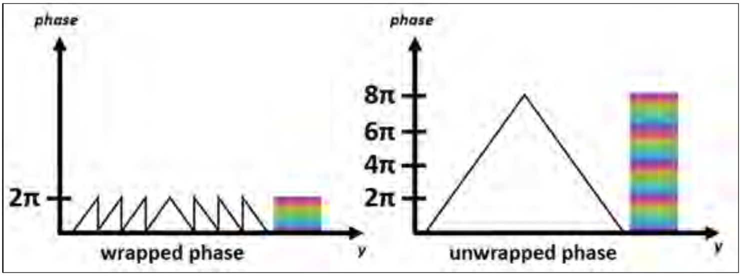


Figure 6.11: Wrapped Phase vs Unwrapped Phase

6.6.7 *Interferogram Filtering*:

Interferograms often contain noise and unwanted signals that can affect the accuracy of the deformation measurements. Filtering techniques are applied to suppress the noise and enhance the coherent deformation signal. Adaptive filtering, multi-looking, and spatial filtering methods are commonly employed to improve the signal-to-noise ratio and enhance the quality of the interferogram.

6.6.8 *Phase-to-Height Conversion*:

The next step is to convert the interferometric phase values into meaningful displacement measurements. This process, known as phase-to-height conversion, requires information about the radar wavelength and the baseline, which is the perpendicular distance between the satellite positions during image acquisition. By combining this information, it is possible to estimate the three-dimensional displacement of the Earth's surface.

6.6.9 *DEM Generation*:

InSAR processing also enables the creation of highly accurate Digital Elevation Models (DEMs). By comparing multiple interferograms acquired from different pairs of SAR images, it is possible to obtain a dense network of height measurements. These measurements are then combined and adjusted to create a detailed and precise representation of the topography.

6.6.10 *Interpretation and Analysis*:

Once the InSAR processing steps are completed, the resulting products can be interpreted and analyzed for specific applications. Ground deformation measurements can be used to monitor volcanic activity, landslides etc.

6.7 Applications of SAR:

- **Flood Monitoring and Mapping:** SAR is instrumental in monitoring and mapping flood events. By capturing images during and after floods, SAR can detect changes in water bodies, identify flood extent (Figure 6.12), and aid in flood management and response. SAR's ability to penetrate clouds and capture data day or night makes it particularly useful during disaster situations.

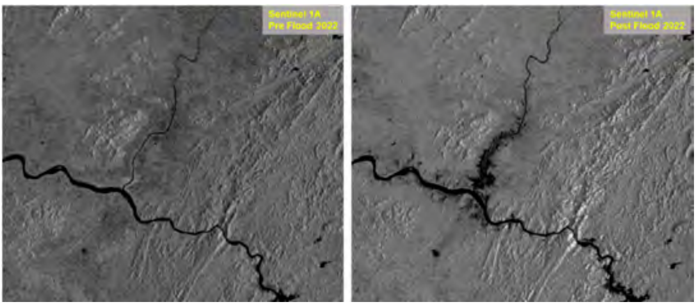


Figure 6.12: Pre Flood Vs Post Flood Using Sentinel SAR over Sabari River

- **Forestry:** SAR plays a crucial role in forest monitoring and management. It can provide information on forest structure, biomass estimation, and deforestation detection.

- **Geology and Geohazards:** SAR is widely used in geology and geohazard studies. It can detect and monitor ground deformation associated with earthquakes, volcanic activity, and landslides.

- **Oil Spill Detection:** SAR is highly effective in detecting and monitoring oil spills in marine environments. SAR's sensitivity to the roughness of the sea surface and its ability to detect changes in backscatter make it a valuable tool for oil slick monitoring and tracking (Figure 6.13).

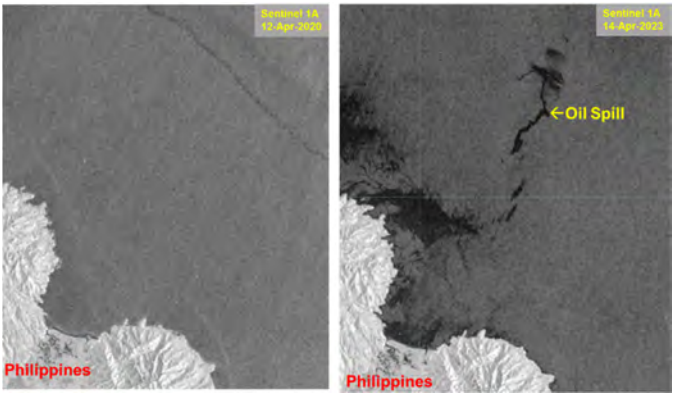


Figure 6.13: Oil spill from tanker Princess Empress off the coast of Philippines.

- **Agriculture and Crop Monitoring:** SAR is used in agriculture to monitor crop growth, estimate biomass etc. It can provide valuable information on soil moisture and vegetation characteristics. This data aids in optimizing irrigation practices, predicting crop yield, and supporting agricultural management decisions.

- **Glaciology and Cryosphere Studies:** SAR is extensively used in glaciology and polar studies to monitor ice sheets, glaciers, and polar regions. It can measure ice motion, detect changes in ice cover, and estimate ice thickness.

Summary

This chapter provides details of SAR image processing. Types of image distortion in SAR data is explained in detail. SAR Polarimetry & InSAR data processing and its applications in various fields are elaborated with example.

Chapter 7

Hyperspectral Image Analysis

7.1 Introduction

Hyperspectral remote sensing involves collecting and analyzing data from a range of electromagnetic wavelengths in order to extract information about objects on the Earth's surface or any other planetary surface (Camps-Valls et al., 2011; Goetz et al., 1985; Richard and Jia, 2006). Sensors typically collect this data on airborne or spaceborne platforms, which measure the radiance or energy reflected or emitted by the objects. By analyzing the unique spectral signatures of different objects, hyperspectral remote sensing is used to identify and map different types of vegetation, minerals, water bodies, and other features of interest. This technique is utilized in a variety of fields, such as agriculture, environmental monitoring, geology, food technology, and archaeology, among others.

Hyperspectral imaging, also called imaging spectroscopy, collects information in a spectral vector with hundreds or thousands of elements from every pixel in a given scene. This continuous information provides a continuous spectrum for each image cell. The result is hyperspectral image (HSI) or hyperspectral data cubes. It can be interpreted as a stack of images representing the radiance in each respective band or wavelength interval, as shown in the illustration below (Figure 7.1).

Multispectral remote sensors such as the Landsat, Thematic Mapper, IKONOS, IRS LISS II, LISS III, and Sentinel 2, SPOT XS, on the other hand, produce images with a few relatively broad wavelength bands. The primary drawback of multispectral data is that it gathers information within wide wavelength bands, consequently restricting the extent of available spectral information.

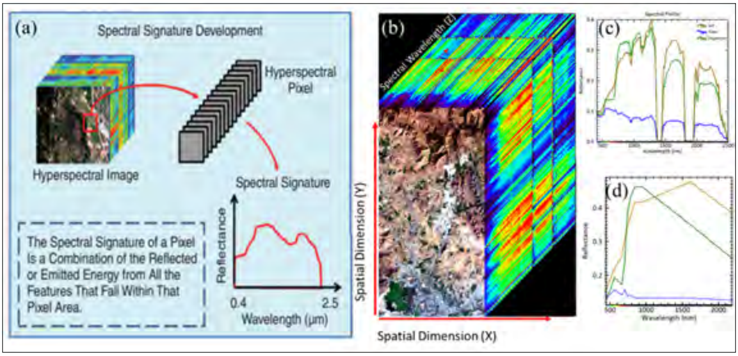


Figure 7.1a: Concept of hyperspectral image (Source- Bioucas-Dias et al., 2013) and spectral signature. b. EO-1 Hyperion 3D spectral cube of Udaipur in a natural color composite. c & d shows the spectral signatures of vegetation, soil, and water extracted to demonstrate their differences in spectral properties in hyperspectral and multispectral data (Sentinel-2).

7.2 Hyperspectral Datasets

NASA's Earth Observing-1 (EO-1) Hyperion instrument was the first ever space-borne hyperspectral instrument launched in year 2000. EO-1 provided continuous spectral information in terms of spectral profiles across the broad electromagnetic spectrum ranging from 400 nm to 2500 nm. Hyperion has a total of 242 spectral channels with 30 m spatial resolution. Examples of other hyperspectral sensors are listed in Table 7.1.

Interpreting the information captured by hyperspectral images requires a great understanding of the ground material's properties under measurement and their correlation to the actual measurements obtained by the hyperspectral sensor. Hyperspectral images require the removal of atmospheric and terrain effects before any interpretation, only after which the image spectra are comparable with field or laboratory reflectance spectra. Therefore, pre-processing is critical and an essential step before any scientific analysis.

Table 7.1: Hyperspectral sensors

PARAMETER	AVIRIS	HYDICE	CHRIS	PRISMA	HyspIRI	EnMAP	HYPERION
Altitude (km)	20	1.6	556	614	626	653	705
Spatial Resolution (m)	20	0.75	36	5-30	60	30	30
Spectral resolution (nm)	20	7-14	1.3–12	10	4-12	6.5–10	10
Spectral Coverage (µm)	0.4–2.5	0.4–2.5	0.4–2.5	0.4–2.5	0.38–2.5 & 7.5–12	0.4–2.5	0.4–2.5
Number of bands	224	210	63	238	217	228	220

7.3 Pre-processing of Hyperspectral Data

Hyperspectral sensors typically provide images in raw digital numbers (DN), representing the sensor's measured radiance values. Several corrections and calibrations must be applied to convert these raw digital numbers into surface reflectance. Firstly, radiometric calibration is performed to convert the raw digital numbers into at-sensor or top-of-atmosphere (TOA) radiance values, which account for the sensor characteristics. This involves using the sensor's characteristic gain and offset values to convert the raw digital numbers into radiance values.

Next, atmospheric correction is applied to scientifically measure the radiance at the Earth's surface, removing any unwanted spurious noise effects introduced by atmospheric interferences. As sunlight passes through the atmosphere, it gets partially absorbed and scattered, which can influence the spectral values measured by the sensor. Various atmospheric correction algorithms are applied to estimate atmospheric conditions and remove their influence on spectral values.

Finally, geometric and surface corrections need to be applied for the removal of illumination, viewing angle, and the surface's structural and optical properties effect. This involves correcting for things like shadows, topography, and surface orientation, as well as accounting for differences in reflectance due to the surface properties such as vegetation, water, and soil. These corrections and calibrations are necessary to convert the raw digital numbers into valid surface reflectance values for advanced information extraction techniques such as classification and feature extraction.

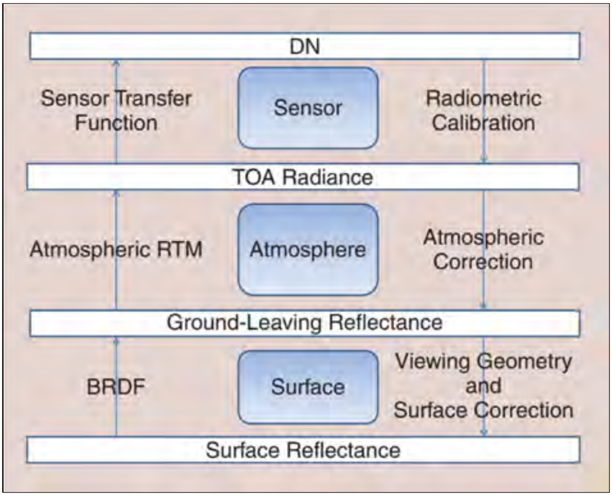


Figure 7.2: Steps of conversion of DN values to Surface Reflectance (Source: Bioucas-Dias et al., 2013*)*.

Step 1. Conversion of DN to spectral radiance

The DN to radiance conversion step is based on gain and bias information in each band of the sensor, which is provided by the calibration team (Figure 7.3). This transformation relies on a calibration curve of DN to radiance, which is measured pre-launch during the calibration of the sensor. As sensor accuracy changes over time, re-calibration of the sensor is carried out periodically, and gain and offset values are provided with the satellite data. The lower (Lmin) and upper (Lmax) limits of the post-calibration spectral radiance range define the gain and bias values.

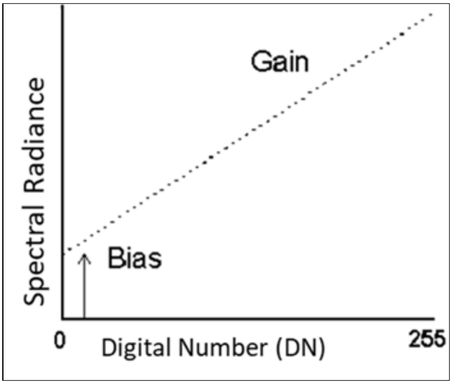


Figure 7.3: Calibration curve of Sensor. Gain represents the gradient and the spectral radiance of the sensor for a zero DN is Bias.

The formula to convert DN to radiance using gain and bias values is:

$$L_{\lambda} = gain * DN + bias$$

units: mW cm^{-2} $ster^{-1}$ μm^{-1}

Where:

L_{λ} is the cell value as radiance

DN is the cell value digital number

gain is the gain value for a specific band

bias is the bias value for a specific band

Gain can be calculated using the equation –

$$\text{Gain} = \frac{\text{Lmax} - \text{Lmin}}{255}$$

Step 2. Spectral radiance to reflectance conversion

The apparent reflectance, which is also termed Top of the atmospheric reflectance, ρ, defined as the ratio of measured radiance, L, to the solar irradiance incident at the top of the atmosphere and is expressed as a decimal fraction between 0 and 1.

$$\frac{\pi * L * d^2}{ESUN * \cos(SZ)}$$

ρ = unitless reflectance (ranges 0-1)

π = 3.141593

L = Spectral radiance at sensor aperture in mW cm^{-2} $ster^{-1}$ μm^{-1}

d^2 = the square of the Earth-Sun distance in astronomical units = (1 - 0.01674 cos(0.9856 (JD-4)))2 where JD is the Julian Day (day number of the year) of the image acquisition.

ESUN = Mean solar atmospheric irradiance in mW cm^{-2} μm^{-1}.

SZ = sun zenith angle in radians when the scene was recorded.

Step 3. Removal of atmospheric effects due to absorption and scattering

Atmospheric correction techniques are categorized into absolute (empirical) and relative atmospheric corrections (Van der Meer, 1999) and are explained in the next section.

7.4 Absolute Atmospheric Correction Techniques

In this method, a priori knowledge of the surface characteristics and atmospheric model is not required. This method corrects the image data for scattering and absorption of water vapor, mixed gases, and topographic effects (AIG, 2001). Radiative transfer codes (i.e., LOWTRAN - Low-resolution propagation model and MODTRAN (MODerate resolution atmospheric TRANsmission) utilize the scattering and transmission properties of the atmosphere to assess the variance between the radiation emitted by the Earth's surface and the radiation detected by the sensor. It can model the scattering effects in the atmosphere (Van der Meer, 1999). MODTRAN is coded in FORTRAN and is licensed to U.S. Air Force. It is designed for visible to far infrared region modeling with a spectral resolution of 100 µm. These codes are designed to model various types of atmospheric conditions and can be applied to a wide range of atmospheric scenarios. Their purpose is to calculate the atmospheric radiance spectrum on a pixel-by-pixel basis.

Different atmospheric correction modules are available –

- *Atmospheric CORrection (ACORN) (Goetz, et. al., 2002),*
- *ATmospheric CORrection (ATCOR2 and ATCOR 3),*
- *Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH))*

For Hyperion images, FLAASH is commonly used for atmospheric correction. FLAASH is developed by Air Force Research Laboratory, Space Vehicles Directorate (AFRL/VS) and is a physics-based algorithm from the MODTRAN4 radiative transfer code (Felde et. al., 2003). It is used to removed unwanted atmospheric effects caused by scattering and absorption by molecules and particulate matter from the sensor received radiance and provide reflectance image of the surface. FLAASH employs a standard equation of spectral radiance at a sensor pixel (L), specifically designed for the solar wavelength range and flat Lambertian materials. FLAASH is available in ENVI software and is widely used by scientific community for atmospheric corrections (ENVI Manual, 2005).

7.5 Relative Atmospheric Correction Techniques

Relative atmospheric correction method uses directly image brightness values and reflectance value of pixels are computed relatively to each other (Van der Meer, 1999). The priori knowledge of the surface characteristics and atmospheric model is not required in this method. Four different methods which are commonly used are:

- *Logarithmic residuals*
- *Flat field correction*
- *Internal Average Relative Reflectance Correction,*
- *Empirical Line Correction.*
- *QUick Atmospheric Correction- QUAC*

Logarithmic residuals, or shortly log residuals correction, account for the illumination, reflectance, and topographic factors. The method employs the logarithm on the resulting data obtained after dividing the radiance value of each wavelength by the geometric mean of all channels.

Flat Field Correction - The approach assumes that a particular area in the image exhibits spectrally neutral reflectance (minimal variation with wavelength). The mean reflectance curve of this "flat field" is then utilized to derive the relative reflectance spectra of all other image pixels.

IARR correction allows the calibration when no sensor information is available (Kruse, 1988). This technique involves using the average reference spectrum of an entire image to divide the radiance spectrum of each pixel in the image, resulting in the relative reflectance spectrum for each pixel. This method may introduce wrong data as spectral features (Van der Meer, 1999). The IAR approach and the "flat field" approach are Scene-Based Empirical Approaches and are independent of any field measurements of reflectance spectra.

The Empirical Line Method (ELM) requires two or more calibration targets (at least one bright and one dark target) with known reflectance values. A linear regression equation (i.e., the empirical line) is derived for each spectral band to derive the gain and offset curves (Karpouzli & Malthus, 2003). After obtaining the gain and offset curves, it is applied to the entire image to derive surface reflectance for the entire scene. The resulting reflectance spectra obtained after applying this approach resemble laboratory-based reflectance spectra.

Quick Atmospheric Correction (QUAC) derives the atmospheric compensation parameters directly using the pixel spectra of the scene (Figure 7.4). The approach is based on finding the mean spectrum of a diverse collection of material spectra, such as the end-member spectra in a scene, which remains essentially constant and unchanged from one image to another (Bernstein et al., 2005). It allows the retrieval of reasonably accurate reflectance spectra even without proper sensor radiometric or wavelength calibration or when the solar illumination intensity is unknown. This method works very faster than first-principles methods, making it potentially suitable for real-time applications.

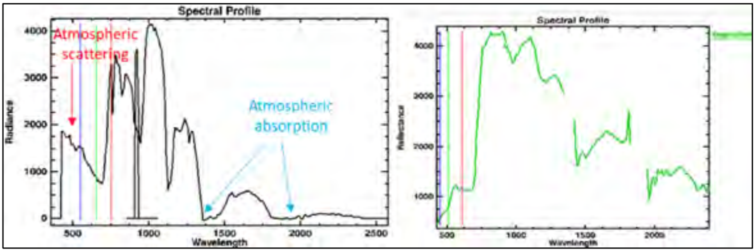


Figure 7.4: Example of Hyperion spectra showing effect of atmospheric correction. Note the difference between at-sensor pixel spectra (left) and atmospherically corrected surface reflectance spectra (right) using QUAC. At 1400 and 1900 nm regions due to water vapours and strong atmospheric attenuation, the effect cannot be removed.

Other important pre-processing steps involved in Hyperspectral image analysis involves - Bad band removal i.e., removing the bands with no information, and destriping.

7.6 Bad band removal

Different ground objects are characterized by different spectral characteristics forming the physical basis for target detection or mapping. Band combinations of hyperspectral data play an important role while detecting or separating one specific target. Choosing a specific band combination is quite tricky and depends upon the interpreter's knowledge. One band may be effective for a particular target, but when dealing with different targets, the informative band combinations may vary. Even for the same target, the informative band combination can alter by changing the background or environmental conditions. The choice of band combinations should be tailored to suit the specific characteristics of the target and its surroundings to ensure optimal results in different scenarios. However, certain bands in the datasets that provide little information to detect any target in the scene and have a low SNR value are considered Bad Bands. The number and locations of bad bands will change in different scenes and regions of study.

In the case of Hyperion, which has 242 bands, bands 1 to 7 and 225 to 242 have zero values and are not useful. Additionally, bands 58 to 76 fall in the overlap region of the two spectrometers and have higher noise levels, making them bad bands as well. Therefore, for the Hyperion dataset, only 196 bands out of 242 are considered good bands. The water vapor absorption bands 120 to 132 (1346 nm to 1467 nm), bands 165-182 (1800 to 1971 nm), and bands 221 (above 2356) and higher also need to be eliminated (Beck, 2003). An example of bad bands is shown in Figure 7.5. The list of bad bands of Hyperion data is listed in Table 7.2.

Table 7.2: List of bands which are eliminated from Hyperion data including the water absorption bands.

Bands	**Description**
1 to 7	Not Illuminated
58 to 78	Overlap Region
120 to 132	Water Vapour Absorption Band
165 to 182	Water Vapour Absorption Band
185 to 187	Identified by Hyperion Bad Band List
221 to 224	Water Vapour Absorption Band

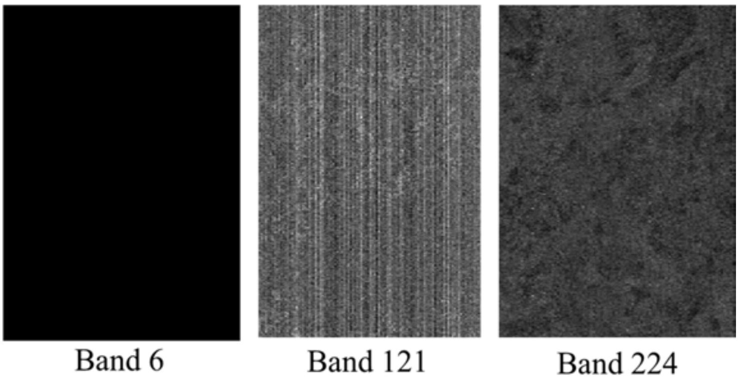


Figure 7.5: Example of bad bands in Hyperion data.

7.8 Destriping

Hyperspectral data sets are often affected by striping noise, i.e., intensity variations in either rows or columns of an image. Striping is resultant of sensor or viewing conditions and can affect the image along either the scan direction or the cross-track direction (Kruse, 1988). These stripes and the corrupted pixels are referred to as abnormal pixels. Along-track striping is frequently encountered and is primarily caused by either the drifting of the detector array element's radiometric responses or issues arising from the readout electronics. Vertical stripes occur due to the deviation of any detector from VNIR or SWIR arrays from its normal response or its neighbors (Figures 7.6 and 7.7). The impact of striping can be minimized or eliminated through "fine-tuning" the calibrations, and it varies for each detector array. While striping may be present in most channels to some extent, it affects mostly the SWIR and lower signal-to-noise ratio (SNR) channels.

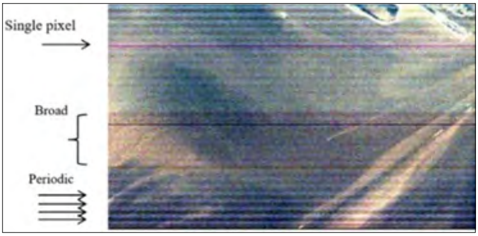


Figure 7.6: Striping in a Hyperion image FCC RGB = (468, 447, 427) nm. Scan direction is from left to right. Source: https://doi.org/10.1117/12.2014317.

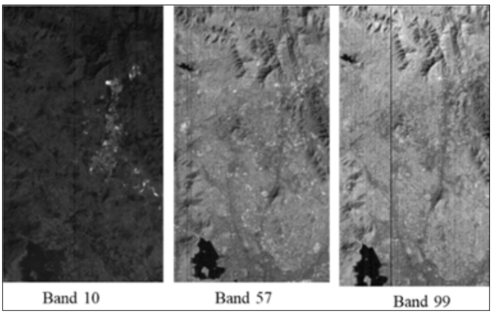


Figure 7.7: Examples of Vertical Striping in a Hyperion bands of Udaipur Scene.

Due to the high resolution of the images, the particular pixels do not hold much information compared to the whole image. During de-striping, the values of abnormal pixels or bad columns are approximated to an average or average mean and standard deviation of the neighboring set of pixels.

In order to perform segmentation and classification on hyperspectral data sets, it is essential to pre-process the images to ensure accurate spectral profiles and expected pixel values. This typically involves applying various techniques such as spectral calibration, atmospheric correction, noise reduction, and radiometric calibration to prepare the image data for analysis. The complete processing of the hyperspectral data is summarized in Figure 7.8.

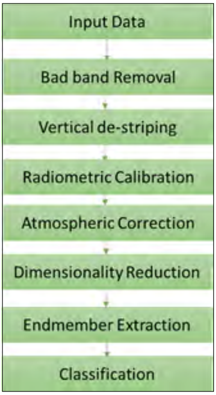


Figure 7.8: Processing chain of the hyperspectral data.

7.9 Dimensionality Reduction

Hyperspectral images typically comprise hundreds of bands that offer high spatial and spectral information. However, the large size of these images can present significant constraints regarding data handling and processing. For a more concise and meaningful interpretation, it may be necessary to reduce the dimensionality of the image without sacrificing any information. The dimensionality reduction can be achieved either by feature selection and second one by feature extraction. Feature extraction methods involve creating a new subset of features by selecting or combining existing information within the feature space. On the other hand, feature selection involves analyzing a subset of features chosen from the original set of features. It is achieved by using dimensionality reduction algorithms such as Principal Component Analysis (PCA) and Minimum Noise Fraction (MNF) (Green et al., 1988; Lee et al., 1990).

PCA is one of the best methods for feature extraction for dimensionality reduction. PCA transforms multidimensional image data into a new uncorrelated set of axis or vector spaces known as the principal axis (Rodarmel et al., 2002; Wold et al., 1987). The maximum variance is observed along its first axis in the transformed dataset. The second axis, which is mutually orthogonal to the first, will exhibit the next highest variance, followed by subsequent axes in descending order of variance, and the PCA images are ordered based on the eigenvalues in decreasing order of variance. This means that the image with the highest variance is assigned the first principal component, followed by the second highest variance for the second component, and so on until all components are determined. Useful PCA images are then selected based on the eigenvalues or visual interpretation. However, sometimes even lower-order PCs may contain valuable information. Figure 7.9 shows the PCA images derived from Hyperion data showing the majority of the variability is accounted for in the first few PCA bands and that the remaining bands contain noise. Comparing PC1 to PC9 in Figure 7.9 shows that each PC is different from all the others (because all are de-correlated). The use of PCA band combinations proves to be highly effective in distinguishing between different surface materials highlighted with various colors, as in Figure 7.9 (extreme right).

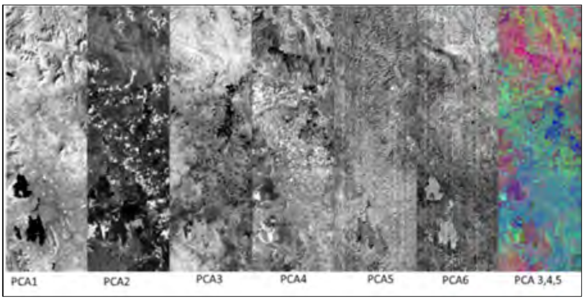


Figure 7.9: PCA components of Hyperion image over Udaipur showing the increase the noise component from the PCA 1 to PCA 6 and discrimination of different surface materials in PCA RGB combination.

Minimum Noise Fraction (MNF) is a two-step component transformation used to identify the number of critical informative bands in high-dimensionality data, segregate the noise, and reduce computational bands for further processing (Green et al., 1988). Minimum noise fraction (MNF) transform is a linear transform performed in two steps. First, noise whitening is applied in which the noise covariance matrix is generated to decorrelate and rescale the noise in the data. Then Principal Component Analysis (PCA) transform is performed on the noise-whitened data to obtain the MNF components. MNF (Minimum Noise Fraction) relies on the eigenvectors derived from the covariance structure of the noise present in the image dataset. Unlike PCA (Principal Component Analysis), MNF is particularly advantageous in generating images ordered based on image quality. Figure 7.10 shows the first six MNF bands of the Hyperion data cube showing how the information is decreasing and the noise component is increasing towards the higher components. The first ten bands are free from the noise effect (Figure 7.10). As shown in Figure 10, eigenvalues approach value of 2 beyond the first 20 MNF bands are considered suitable and noise free for classification. After MNF band 20, eigenvalues are constant and parallel to the horizontal axis.

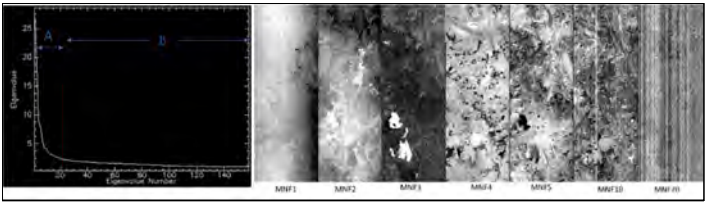


Figure 7.10 (left): Graphical representation of the eigen values versus eigen numbers for the Hyperion Udaipur image. 'A' region represents image data with high eigen values and B region having low eigen values (high values of noise). (Right) MNF transform output channels for the Hyperion data cube showing steadily increase in the noise level.

7.10 Endmembers Extraction

End members are considered the purest pixels in an imaged scene (Keshava & Mustard, 2002). Spectral unmixing is often performed to unmix the mixed pixels components in the hyperspectral image into their respective end members and abundances. The abundance fractions represent the proportion of each end member that contributes to the mixed pixel spectrum. The Pixel Purity Index (PPI) algorithm is used to extract the purest spectral signature from the data cube (Boardman et al., 1995). The end members spectra are further used to find the different classes present in the whole image. The accuracy of this spectral profile totally depends on the pre-processing corrections applied to the image. Figure 7.11 (left) shows the PPI output with pure pixels in 10000 iterations which are used as the candidate points. Figure 7.11 (middle) shows the n-D visualizer utilized to visualize data in n-dimensional space. It allows users to locate, identify, and cluster the purest pixels and the most extreme spectral responses, also known as endmembers, within a dataset (ENVI User's Guide, 2001). Different pixel classes are marked in different colors, and the reflectance spectra of endmembers represent vegetation, water, and soil class. These end members are utilized further for the classification of image (Figure 7.11, right).

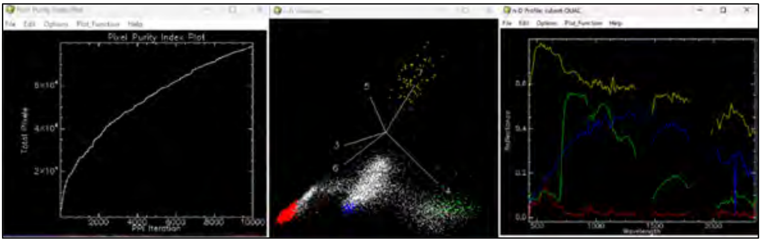


Figure 7.11: PPI output showing number of pure pixels extracted (left), n-D visualizer used to locate pure pixels (middle), and pure pixels endmember extracted (right).

7.11 Classification

Classification is an information extraction technique that uses spectral analysis algorithms to characterize the study scene based on the spectral reflectance of different objects or features. This process allows for identifying and categorizing different classes or land cover types present in the imagery based on their unique spectral signatures. (Pignatti et al., 2009). The classification algorithm assigns a unique label or class to each pixel vector in an image based on a given set of observations. These observations typically consist of spectral signatures or other relevant features extracted from the pixels, and the classification process aims to categorize each pixel into predefined classes or categories based on its similarity to the observed patterns.

Two main approaches are used in hyperspectral classification: Supervised and Unsupervised, based on the usage of the training datasets. Most common approaches for identification or classification of hyperspectral data are Spectral Angle Mapper, Spectral feature Fitting, Maximum likelihood (ML) methods, Neural Networks architectures (Zhong & Zhang, 2012), Support Vector Machine (SVM) (Melgani & Bruzzone, 2004), Bayesian approach (Mohamed & Farag, 2005) as well as Kernel methods (Camps-Valls et al., 2006).

7.11.1 Supervised Classification

This method relies on training samples for different classes of interest the user provides. The image is classified into the desired categories based on the training samples. The resultant accuracy is high since the user's domain knowledge is utilized in this classification. However, this collection of training samples is a tedious and time-consuming task. The user first selects the classes of interest which correspond to information classes. The algorithm compares the similarity between the known and unknown pixels. The unknown pixels are assigned to a particular class based on the highest likelihood of matching with a member of that class.

Spectral Angle Mapper - SAM is a supervised classification algorithm that employs spectral angular information to classify hyperspectral data (Kruse et al., 1993). In this method, each pixel in a hyperspectral image is represented as an n-dimensional vector, with n being the number of spectral bands. The algorithm calculates the spectral angle between the target spectrum and a reference. The variation in the angle between the image-derived spectrum and the end member spectrum is the measure of discrimination in SAM classification. A smaller angle represents a closer match to the reference spectrum and vice-versa. The pixels farther beyond a specified maximum angle threshold (in radians) will remain unclassified (Figure 7.12).

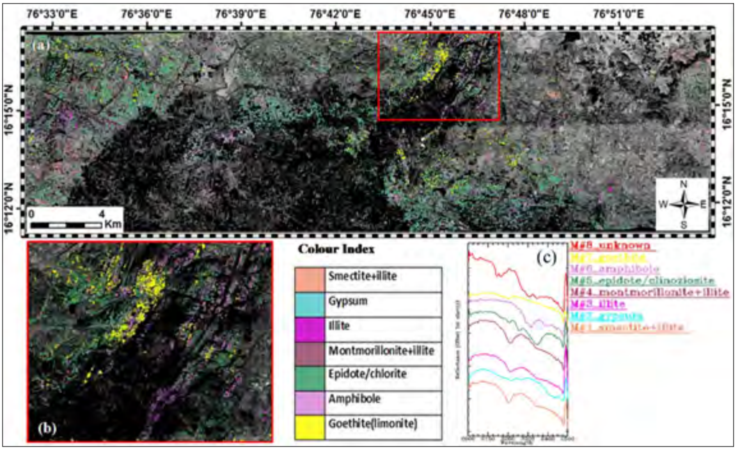


Figure 7.12: (a) SAM classification image of the part of Hutti-Maski area, Karnataka India using AVIRIS-NG data (b) Close view of the mineralised zone (c). Reflectance spectra of endmembers selected using n-D visualizer.

Spectral Feature Fitting (SFF) – This algorithm operates on the continuum-removed image and a reference spectrum. It compares the continuum-removed image spectra with the reference spectral library spectra and performs the least square fitting. The correlation coefficient of the fits determines the best matching between spectral features of the reference and image spectra (Boardman & Kruse, 1994). Continuum-removed image spectra can be derived by dividing the original spectrum of each pixel in the original image by the continuum curve

$$Scr = \frac{S}{C}$$

Where, Scr = Continuum removed spectra, S = Original Spectra, C = Continuum curve

Minimum distance classifier (MDC) – This utilizes the distance between pixels in the feature space for image classification. MDC uses a similarity measure, which categorizes two modes as similar if their feature differences fall below a specified threshold. In the feature space, points with similarities (belonging to the same class) are clustered together (Wacker et al., 1972). The mean vector of these feature points is then computed and serves as the center of the respective category. The dispersion of surrounding points is described by the covariance matrix. Each category's points are measured similarly, and distance serves as the primary basis for evaluating the similarity of samples. For Distance calculation, approaches available like Ming's distance, Mahalanobis distance, absolute value distance, Euclidean distance, Che's distance, and Barth's distance are widely utilized.

Maximum Likelihood Classifier (MLC) - The Maximum Likelihood Classifier (MLC) is a nonlinear classification method based on the Bayesian criterion. It calculates the statistical feature values for every training sample during classification and establishes a classification discriminant function (Bruzzone et al., 2001). This function determines the probabilities of each pixel in the hyperspectral image containing various classes. These probabilities are then utilized to classify the test sample into the category with the highest probability, subject to a provided probability threshold. The pixel remains unclassified with probabilities smaller than the threshold. Other Supervised algorithms commonly used are Neural Network Classification and Support Vector Machine algorithms.

7.11.2 Unsupervised classification algorithms

Hyperspectral datasets come with the curse of high dimensionality. Dimensionality reduction is applied to hyperspectral data for feature extraction by selecting only the most prominent bands. In unsupervised methods, similar pixels are automatically grouped into clusters using standard statistical criteria. Unsupervised classification methods are independent of any prior knowledge of the training dataset. The familiar unsupervised methods are principal component analysis (PCA), independent component analysis (ICA) (Villa et al., 2011), K-Means, ISODATA, and Hierarchical Clustering.

K-means: K-Means Clustering is a centroid-based algorithm that groups the unlabelled dataset into diverse clusters by iteratively updating cluster centroids and assigning pixels to the closest one (MacQueen, 1967). The clusters are associated with a centroid, and the algorithm works on minimizing the sum of distances between the data point and their corresponding cluster. In terminology, K defines the number of predetermined clusters to be created. K-means clustering enables the data to be grouped into distinct categories, serving as a convenient means to identify the groups within an unlabelled dataset independently without requiring a training dataset.

ISODATA- Iterative Self-Organizing Data Analysis technique is an extension of the K-Means algorithm and is the most commonly used algorithm. The method is an iterative clustering technique that offers the flexibility of cluster merging and splitting, guided by user-defined parameters. This aspect makes it more adaptable and versatile compared to the K-means algorithm. In ISODATA, the number of clusters selects automatically and assumes that each class obeys a multivariate normal distribution (Ball & Hall, 1965). The algorithm assigns arbitrary cluster centers and calculates cluster means and covariance. The pixels are subsequently classified into the nearest cluster. New cluster means and covariances are calculated based on all the pixels within that cluster. This process is repeated for several iterations until the change between iterations is considered 'sufficiently low.' The modification is quantified in two ways- by measuring the distance the cluster mean has changed from one iteration to the next or by calculating the percentage of pixels that have changed between iterations.

7.12 Spectral unmixing

The spectral unmixing technique involves extracting and identifying pure pixels/endmembers from the hyperspectral dataset. For each image pixel, fractional abundances are determined, representing the proportion of each end member present (Bioucas-Dias et al., 2012). This approach enables the representation and recognition of various materials or components within the hyperspectral image, making it valuable for applications such as remote sensing, mineral exploration, agriculture, and environmental monitoring.

Unmixing algorithms operate based on the anticipated type of mixing, which can be linear or nonlinear mixing. The observed reflectance spectrum is a weighted combination of individual material spectra in linear mixing. Each material spectrum is multiplied by a corresponding weight, representing the relative amount or abundance of that material in the pixel. As shown in Figure 7.13, the reflecting surface is similar to a checkerboard mixture, and there is no multiple scattering between components. The spectra observed in the reflected radiation of a hyperspectral image have a linear relationship with the fractional abundance of the substances present in the imaged area (Keshava & Mustard, 2002). Linear unmixing model is either geometrical- or statistical-based.

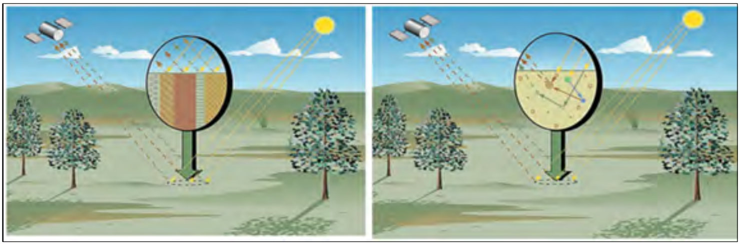


Figure 7.13: Illustration showing linear (left) and nonlinear (right) mixing. Solar radiation reflects from the surface through a single bounce in linear mixing. In a nonlinear mixing scenario, solar radiation interacts with an intimate mixture that induces multiple bounce interactions (right). (Source - Keshava & Mustard, 2002).

Conversely, nonlinear mixing is usually due to physical interactions (classical or multi-layered, level or at a microscopic or intimate level) between multiple materials in the scene (Bioucas-Dias et al., 2012) (Figure 7.14). Classical spectral mixing occurs when light scatters from one or more objects, reflected from additional surfaces, before being measured by the hyperspectral imager. Nonlinear mixing is generally explained by an intimate or multilayer model, as given by Borel & Gerstl (1994). Figure 7.14 illustrates two nonlinear mixing scenarios: an intimate mixture, in which the materials are close, and a multi-layered scene, where there are multiple interactions among the scatterers at the different layers.

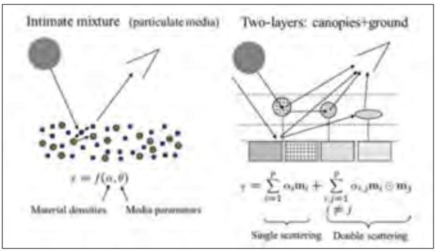


Figure 7.14: Non-linear mixing models: intimate mixture (left); multi-layered scene (right) (Source: http://dx.doi.org/10.1109/JSTARS.2012.2194696).

Unmixing processing steps typically involve atmospheric correction, dimensionality reduction, and unmixing. It can be achieved through endmember determination plus inversion or by utilizing sparse regression or sparse coding approaches. The key to linear unmixing is to determine spectral endmembers that capture the spectral variability present in a given scene. Various algorithms can derive these end members, utilizing criteria such as field knowledge, ratios, or PCA. The results of spectral unmixing, including endmember spectra and abundance estimates, form the foundation of hyperspectral image classification routines used to identify the material composition of mixtures. Unmixing is another significant research topic in hyperspectral processing, particularly in addressing the subpixel target detection problem.

Summary

In conclusion, hyperspectral image analysis is a powerful tool for understanding and interpreting complex data sets. Given the numerous applications in agriculture, environmental monitoring, and mineral exploration, it is crucial to ensure accurate and reliable hyperspectral data analysis. The interpretation of hyperspectral data can provide valuable insights and inform decision-making processes in a range of industries. However, the resulting information may be incomplete, inaccurate, and even misleading without proper data processing and analysis. Therefore, it is essential to employ rigorous analytical techniques and expertise in interpreting hyperspectral data to ensure its effective use in various applications. By using sophisticated algorithms and mathematical models, hyperspectral image analysis can extract valuable information from the spectral data collected by remote sensing devices.

However, hyperspectral data analysis is challenging due to its high dimensionality. Having a comprehensive understanding of the underlying principles is crucial for accurately identifying and characterizing the materials or components present in the hyperspectral imagery. This knowledge helps in distinguishing real signal variations from noise, artifacts, or atmospheric interference, thereby ensuring reliable and meaningful results from hyperspectral data interpretation.

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Satellite Data Plates - Images at a Glance

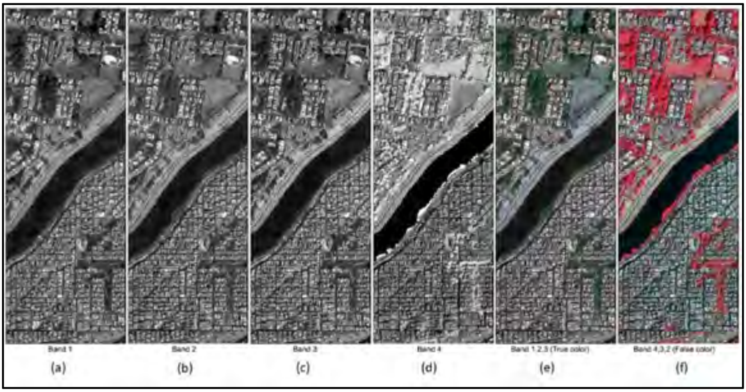


Figure 1: Cartosat-3 Satellite data of a part of Delhi. (a) Band 1, (b) Band 2, (c) Band 3, (d) Band 4, (e) True color composite and (f) False color composite

Figure 2: Min-Max Linear Stretch using Carto-3 (Part of Delhi)

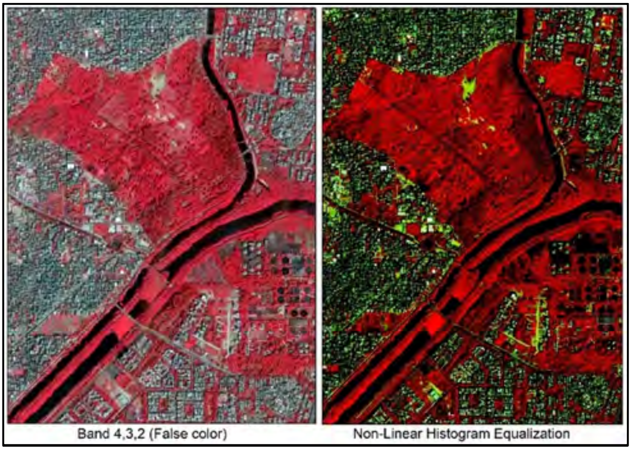
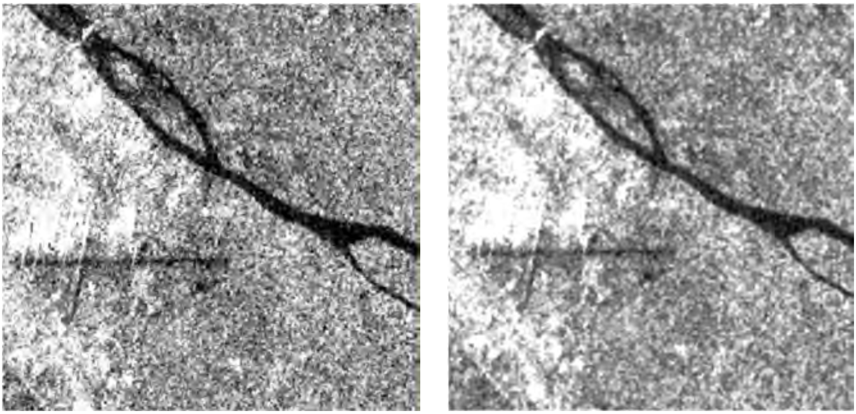


Figure 3.: Non-Linear Histogram equalization using Carto-3 data of a Part of Delhi

Figure 4: Low pass filtered image of Cartosat-3 data

Figure 5: High pass filtered image of Cartosat-3 data



(Sigma 0) After applying Lee Filter

Figure 6: EOS 4 image of 28March 2023 over Kanpur UP

Glossary

A

ALOS - Advanced Land Observing Satellite. 55P,

AppEEARS - Application for Extracting and Exploring Analysis Ready Samples. 13P

B

BIL format - Band interleaved by line. P5, BIP format - Band interleaved by pixel. P5, BSQ format - Band Sequential. P5

C

CRT - Cathode Ray Tubes.

P9, CI - Chlorophyll Index. P38, CNN - Convolutional neural network, P96

D

DN - Digital numbers P3,

DEM - Digital elevation model. P19

E

EPSG - European Petroleum Survey Group.

P6, European Space Agency. P113, Earth Observing System. P55,

Enhanced Vegetation Index, P36

G

GIS - Geographic information systems

P 22, GCP - Ground control points P 22, GEDI - Global Ecosystem Dynamics Investigation. P 55

I

ISODATA - Iterative Self-Organizing Data Analysis Technique, P 138

L

LAI - Leaf Area Index P 37,

LiDAR P 55

K

K-means P 80, KNN - K-nearest neighbor P 66

M

MOSDAC –

Meteorological & Oceanographic Satellite Data Archival Centre – P18

N

O

P

R

S

T

U

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