Remote Sensing

Ch. 4 Image Interpretation & Analysis
(Part 2 of 2)

4.5 Image Enhancement

- **Image Enhancements** are used to **make it easier for visual interpretation** and **understanding** of imagery.

- Although **radiometric corrections** for illumination, atmospheric influences, and sensor characteristics may be done prior to distribution of data to the user, the image may still **not be optimized for visual interpretation**.

- With **large variations in spectral response** from a **diverse range of targets** (e.g. forest, deserts, snowfields, water, etc.) ➔ **No generic radiometric correction** could **optimally account** for and display the **optimum brightness range** and **contrast** for all targets.

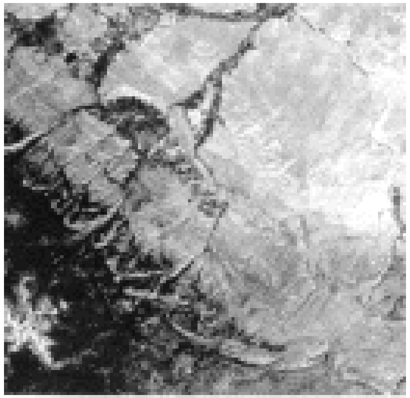
- Thus, for each application and each image, **a custom adjustment of the range** and **distribution of brightness values** is usually necessary.

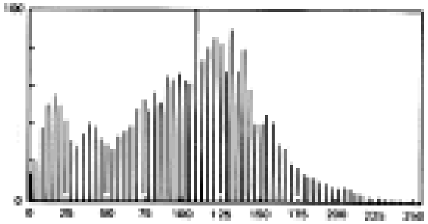
4.5 Image Enhancement

- In **raw imagery**, the useful data often populates **only a small portion of the available range** of digital values (commonly 8 bits or 256 levels).

- **Contrast enhancement** involves changing the original values so that more of the available range is used, thereby **increasing the contrast between targets and their backgrounds**.

- A **histogram** is a **graphical representation** of the brightness values that comprise an image. The **brightness values (i.e. 0-255)** are displayed along the **x-axis** of the graph. The **frequency of occurrence** of each of these values in the image is shown on the **y-axis**.





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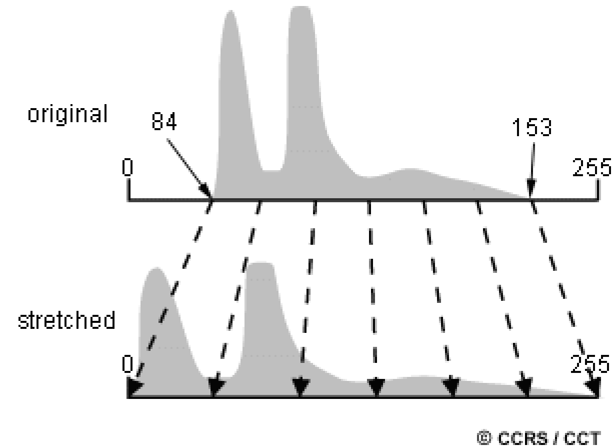
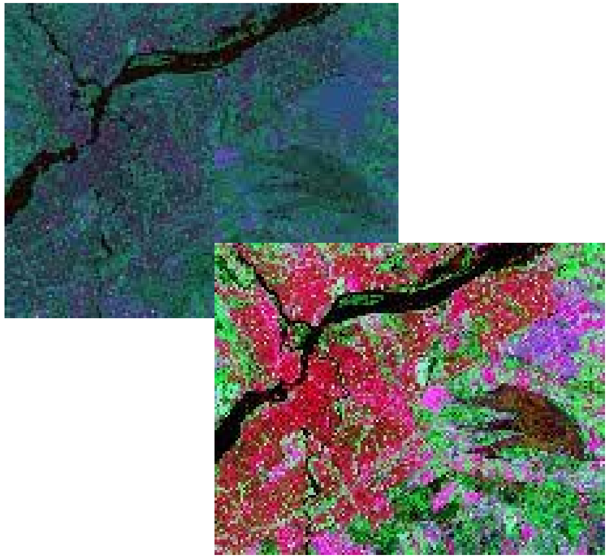
4.5 Image Enhancement

- By **manipulating the range of digital values** in an image, we can apply various **enhancements** to the data. There are many different methods of enhancing contrast.

(1) The simplest type of enhancement is a **linear contrast stretch**. This involves identifying **lower and upper bounds** from the histogram (usually the **min & max brightness** values in the image or **±σ (standard deviation) from mean** value) and applying a transformation to **stretch this range to fill the full range**.

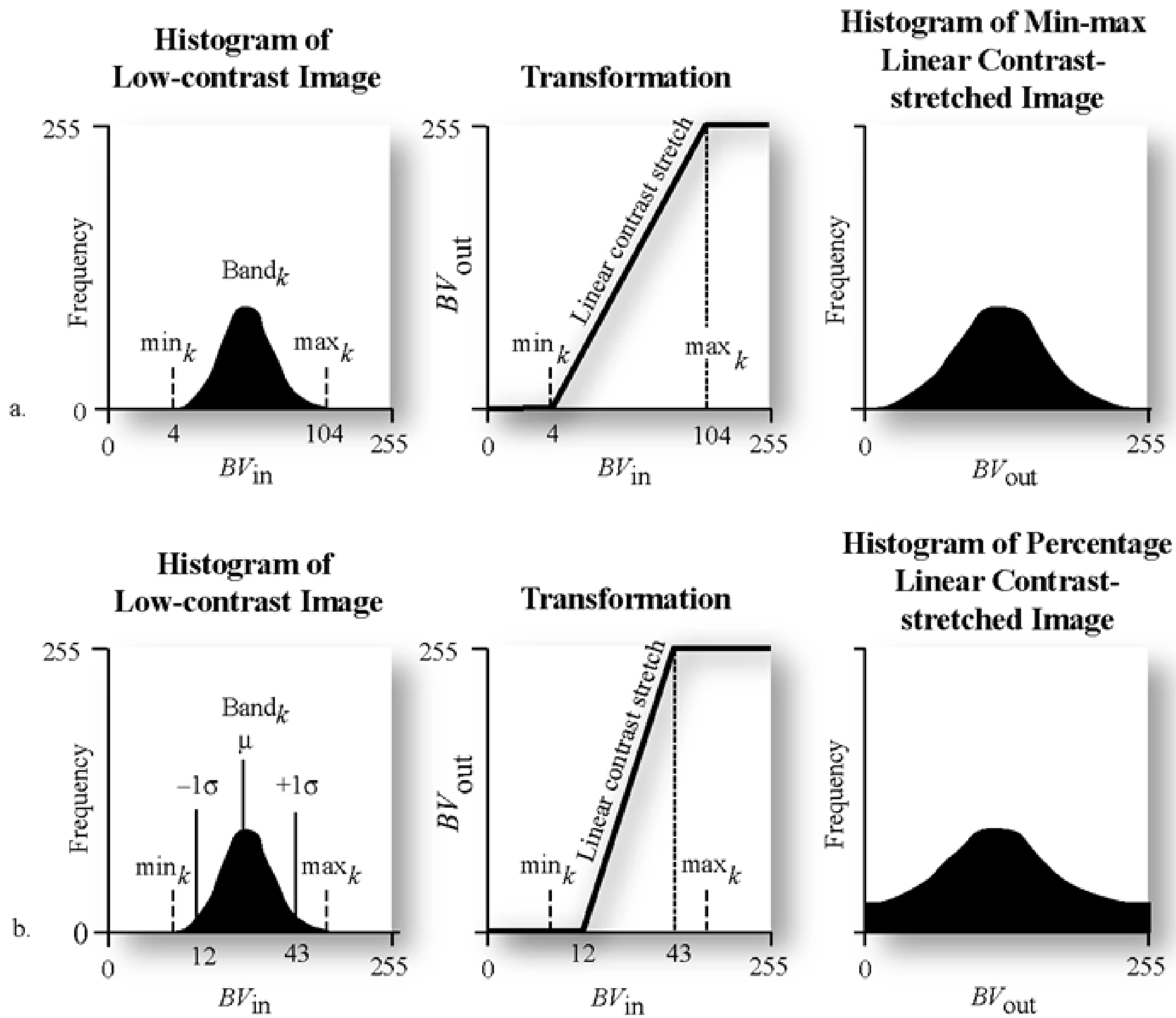
- In our example, the min value (occupied by actual data) in the histogram is **84** and the max value is **153**. These **70 levels** occupy less than one-third of the **full 256 levels** available. A linear stretch uniformly expands this small range to cover the full range of values from 0 to 255. This **enhances the contrast** in the image with light toned areas appearing lighter and dark areas appearing darker, making visual interpretation much easier.





The increase in contrast in an image before (left) and after (right).

4.5 Image Enhancement



(a) Min-max Linear contrast stretch (b) Percentage (e.g. standard deviation) Linear contrast stretch

Linear contrast stretch

$$BV_{out} = \frac{(BV_{in} - \min)}{(\max - \min)} quant$$

where

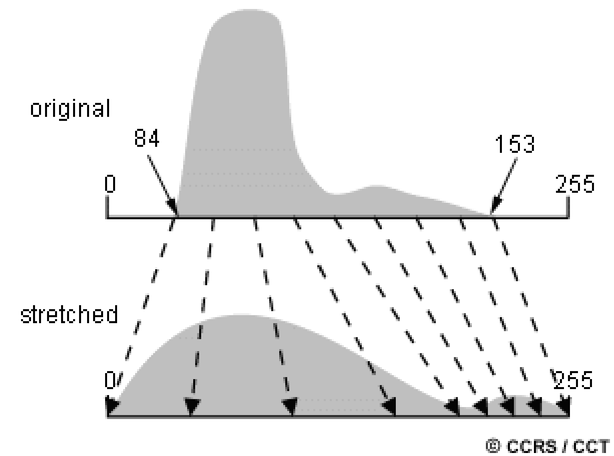
- ***BV$_{in}$*** is the original input brightness value
- **quant$_k$** is the range of the brightness values that can be displayed (e.g., 255)
- **min$_k$** is the min value in the image
- **max$_k$** is the max value in the image
- ***BV$_{out}$*** is the output brightness value

$$0_{out} = \frac{(4_{in} - 4)}{(104 - 4)} 255$$

$$255_{out} = \frac{(104_{in} - 4)}{(104 - 4)} 255$$

4.5 Image Enhancement

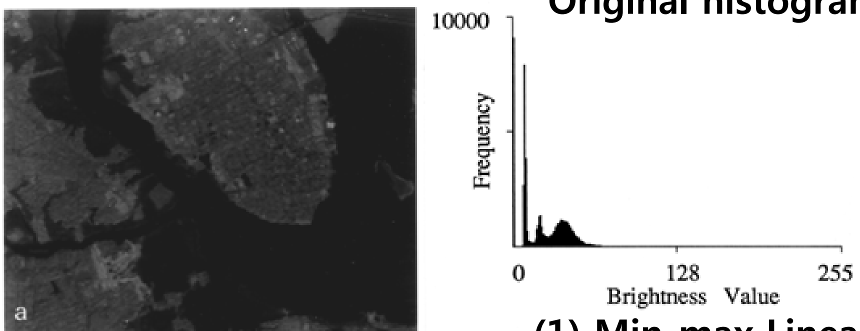
(2) A uniform distribution of the input range of values across the full range may not always be an appropriate enhancement, particularly if the input range is not uniformly distributed. In this case, a **histogram-equalized stretch** may be better. This stretch assigns **more display values (range) to the frequently occurring portions** of the histogram. In this way, **the detail in these areas will be better enhanced** relative to those areas of the original histogram where values occur less frequently.



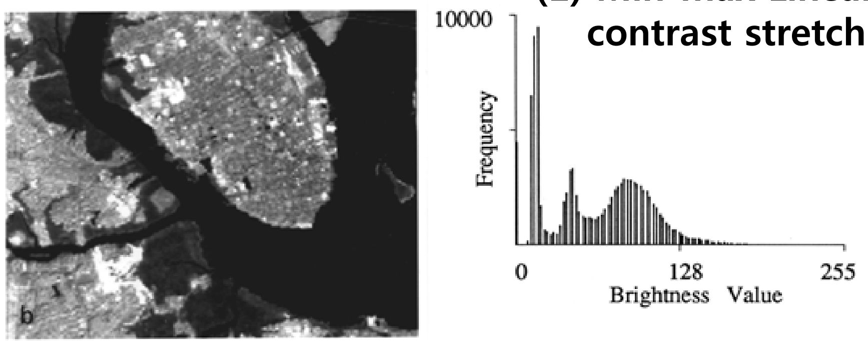
(3) In other cases, it may be desirable to **enhance the contrast in only a specific portion of the histogram**. For example, suppose we have an image of the **mouth of a river,** and the water portions of the image occupy the digital values from 40 to 76 out of the entire image histogram. If we wished **to enhance the detail in the water,** perhaps to see variations in sediment load, we could **stretch only that small portion of the histogram represented by the water (40 to 76) to the full grey level range (0 to 255)**. All pixels below or above these values would be assigned to 0 and 255, respectively, and the detail in these areas would be lost. However, the detail in the water would be greatly enhanced.

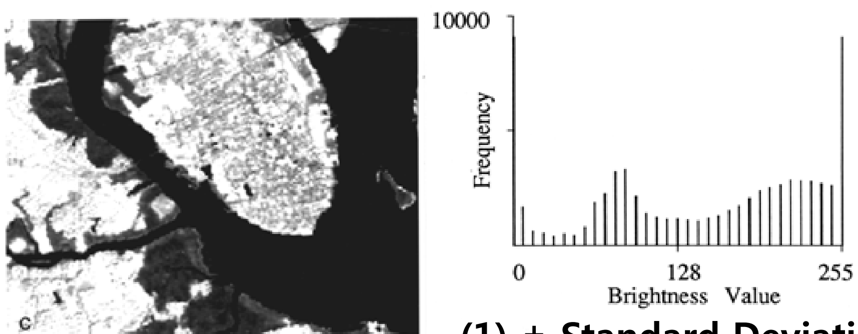
4.5 Image Enhancement

Original histogram



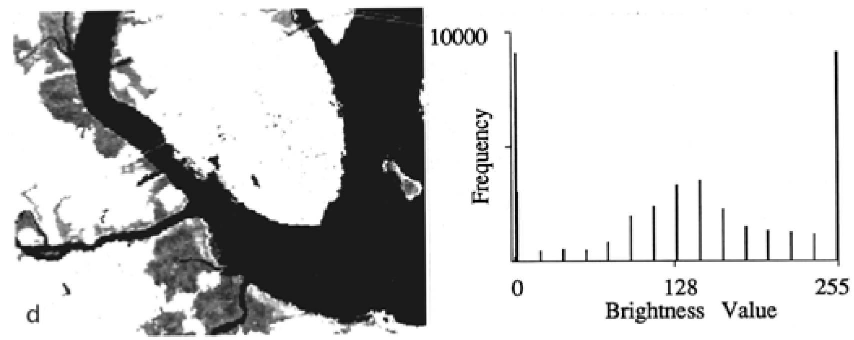
(1) Min-max Linear contrast stretch

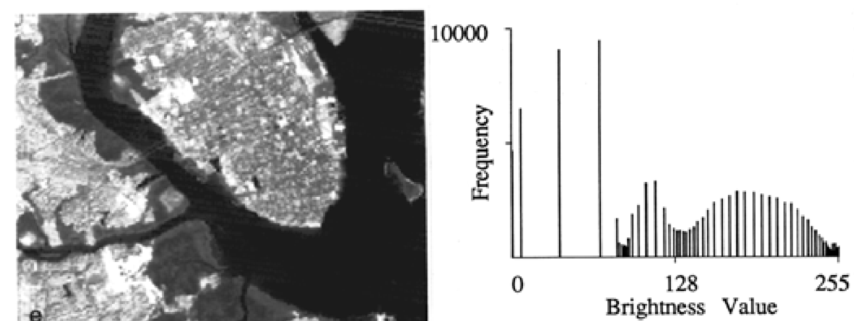




(1) ± Standard Deviation Linear contrast stretch

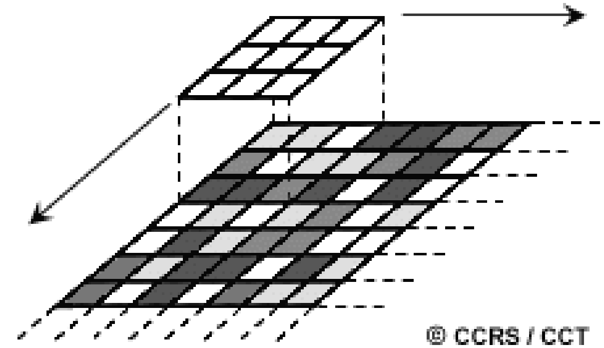
(3) Specific percentage linear contrast stretch designed to highlight wetland





(2) Histogram-equalized stretch

4.5 Image Enhancement



- **Spatial filtering** encompasses another set of digital processing functions which are used to **enhance the appearance** of an image.

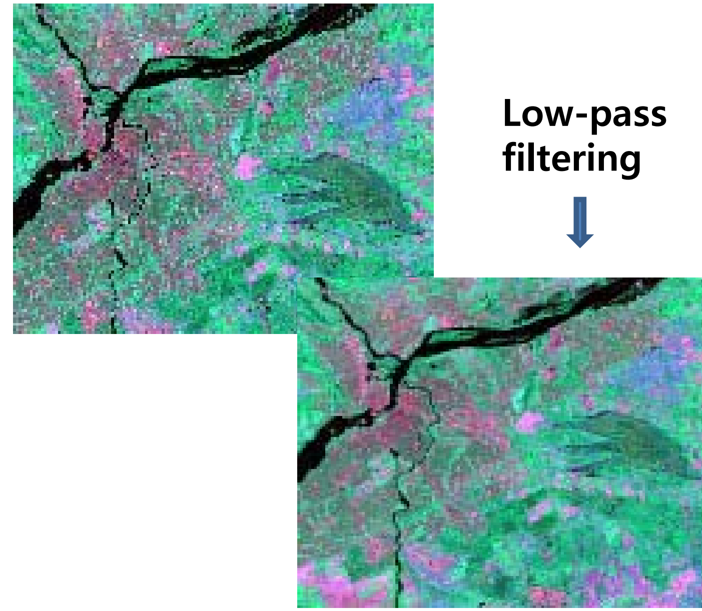
- **Spatial filters** are designed to **highlight** or **suppress** specific features in an image based on their **spatial frequency**. Spatial frequency refers to **the frequency of the variations in tone** that appear in an image.

  - ✓ **high spatial frequencies : "Rough" textured areas** of an image, where the changes in tone are abrupt over a small area.
  - ✓ **low spatial frequencies : "Smooth" textured areas** with little variation in tone over several pixels.

- A common **filtering procedure** involves **moving a 'window' of a few pixels** in dimension (e.g. 3x3, 5x5, etc.) over each pixel in the image, applying a mathematical calculation using the pixel values under that window, and replacing the central pixel with the new value. The window is moved and the calculation is repeated until the entire image has been filtered and a "new" image has been generated. By varying the calculation performed and the weightings of the individual pixels in the filter window, filters can be designed to enhance or suppress different types of features.

4.5 Image Enhancement

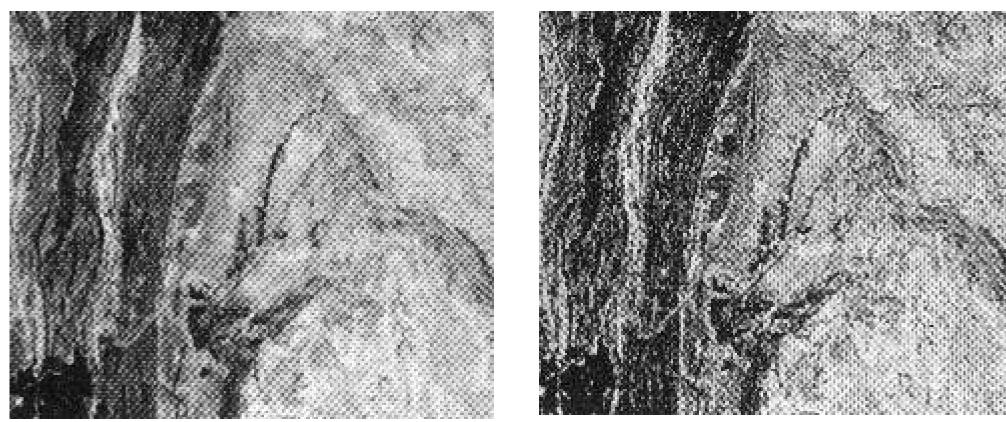
(1) Low-pass filters are designed to **emphasize larger, homogeneous areas of similar tone** and **reduce the smaller detail** in an image. Thus, low-pass filters generally serve to **smooth the appearance** of an image. **Average** and **median filters**, often used for radar imagery, are examples of low-pass filters.



Low-pass filtering

(2) High-pass filters do the opposite and serve to **sharpen the appearance of fine detail** in an image. :

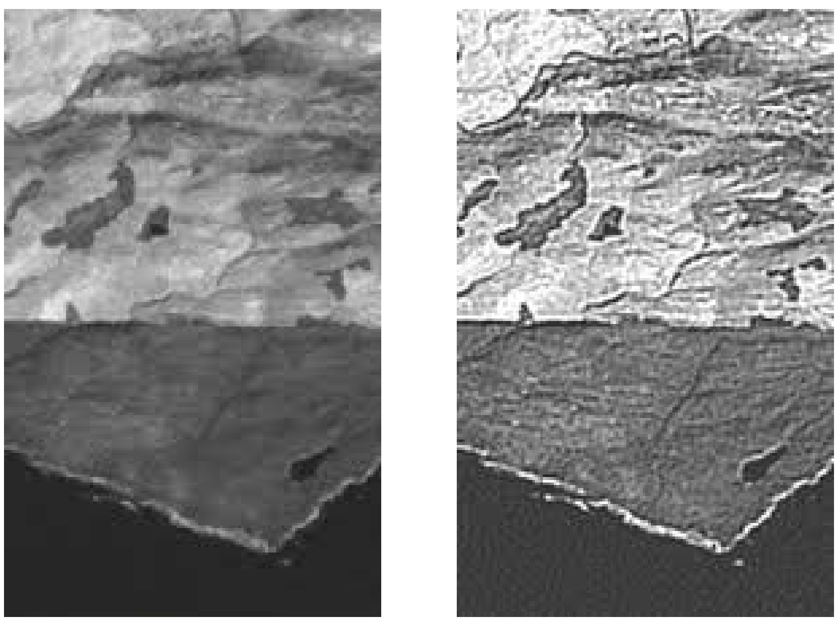
One implementation of a high-pass filter first applies a low-pass filter to an image and then subtracts the result from the original, leaving behind only the high spatial frequency information.



High-pass filtering

4.5 Image Enhancement

(3) Directional or **edge detection filters** are designed to **highlight linear features**, such as roads or field boundaries. These filters can also be designed to enhance features which are **oriented in specific directions**, making these useful for radar imagery and for geological applications such as the detection of linear geologic structures.



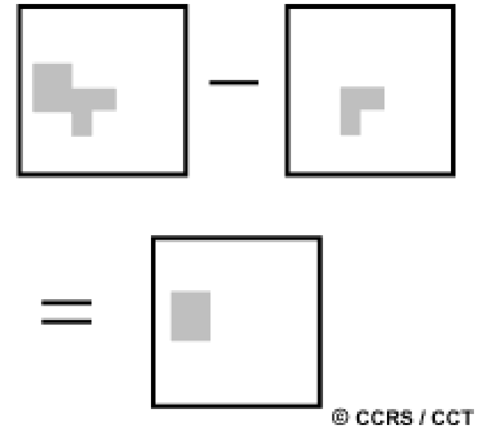
Edge Detection : Lakes & Streams

Edge Detection : Fractures & Shoreline

4.6 Image Transformations

- Image **transformations** typically involve the **manipulation of multiple bands** of data, whether from a single multi-spectral image or from two or more images of the same area acquired at different times (i.e. multi-temporal image data). Either way, image transformations **generate "new" images** from two or more sources which **highlight particular features** or **properties** of interest, better than the original input images.

4.6 Image Transformations



- **Image subtraction** is often used **to identify changes** that have occurred between images collected on different dates.

- Typically, **two images** which have been **geometrically registered**, are used with the pixel (brightness) values in one image (1) being subtracted from the pixel values in the other (2). Scaling the resultant image (3) by adding a constant (127 in this case) to the output values will result in a suitable 'difference' image. In such an image,

  ✓ areas where there has been **little** or **no change** (A) between the original images, will have resultant brightness values **around 127 (mid-grey tones),**
  ✓ while those areas where **significant change** has occurred (B) will have values **higher or lower than 127** - **brighter** or **darker** depending on the 'direction' of change in reflectance between the two images .

- This type of image transform can be useful for mapping changes in **urban development** around cities and for identifying areas where **deforestation** is occurring, as in this example.

4.6 Image Transformations

- **Image division** or **spectral ratioing** is one of the most common transforms applied to image data. Image ratioing serves to **highlight subtle variations** in the spectral responses of various surface covers. By ratioing the data from two different spectral bands, the resultant image **enhances variations in the slopes of the spectral reflectance curves** between the two different spectral ranges that may otherwise be masked by the pixel brightness variations in each of the bands.

- The following example illustrates the concept of spectral ratioing. **Healthy vegetation reflects strongly in the near-infrared portion** of the spectrum while **absorbing strongly in the visible red**. **Other surface types**, such as soil and water, show **near equal reflectances** in both the near-infrared and red portions. Thus, a ratio image of Landsat **MSS Band 7** (Near-Infrared - 0.8 to 1.1 mm) **divided by Band 5** (Red - 0.6 to 0.7 mm) would result in ratios much **greater than 1.0 for vegetation**, and ratios **around 1.0 for soil and water**.

  - ✓ Thus the **discrimination of vegetation from other surface cover types** is significantly enhanced.
  - ✓ Also, we may be better able to **identify areas of unhealthy or stressed vegetation**, which show low near-infrared reflectance, as the ratios would be lower than for healthy green vegetation.

4.6 Image Transformations

- Another **benefit of spectral ratioing** is that, because we are **looking at relative values (i.e. ratios)** instead of absolute brightness values, variations in scene illumination as **a result of topographic effects are reduced**.

➔ Thus, although **the absolute reflectances** for forest covered slopes may vary depending on their orientation relative to the sun's illumination, **the ratio of their reflectances** between the two bands should always be very similar.

Sensor	Image Ratio	EM Spectrum	Application
Landsat TM	Bands 3/2	red/green	Soils
Landsat TM	Bands 4/3	PhotoIR/red	Biomass
Landsat TM	Bands 7/5	SWIR/NIR	Clay Minerals/Rock Alteration

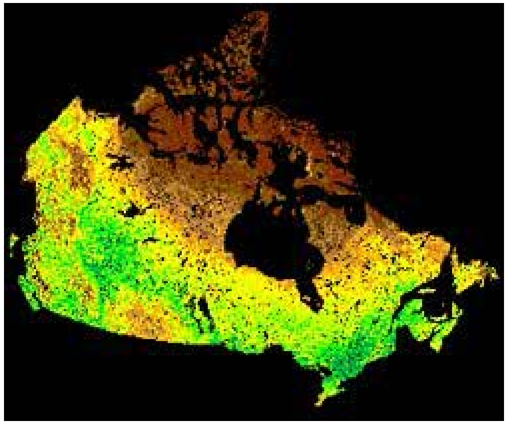
4.6 Image Transformations

- More **complex ratios** involving the sums of and differences between spectral bands for various sensors, have been developed for **monitoring vegetation conditions**. One widely used image transform is the **Normalized Difference Vegetation Index (NDVI)** which has been used to monitor vegetation conditions on continental and global scales using the **AVHRR** sensor onboard the NOAA series of satellites. NDVI is calculated as follows:

NDVI = (Band 2 – Band 1) / (Band 2 + Band 1)

with **the visible** (**Band 1**; 0.58-0.68 μm) and **near infrared** (**Band 2**; 0.725-1.10 μm) regions of the electromagnetic spectrum.

- The principle behind NDVI is that **Band 1** is in the red-light region of the EM spectrum where chlorophyll causes considerable **absorption** of incoming sunlight, whereas **Band 2** is in the near-infrared region of the spectrum where a plant's spongy mesophyll leaf structure creates considerable **reflectance**. As a result, vigorously growing **healthy vegetation** has low red-light reflectance and high near-infrared reflectance, and hence, **high NDVI** values.



Green/Yellow/Brown represent decreasing magnitude of the vegetation index. NDVI image of Canada.

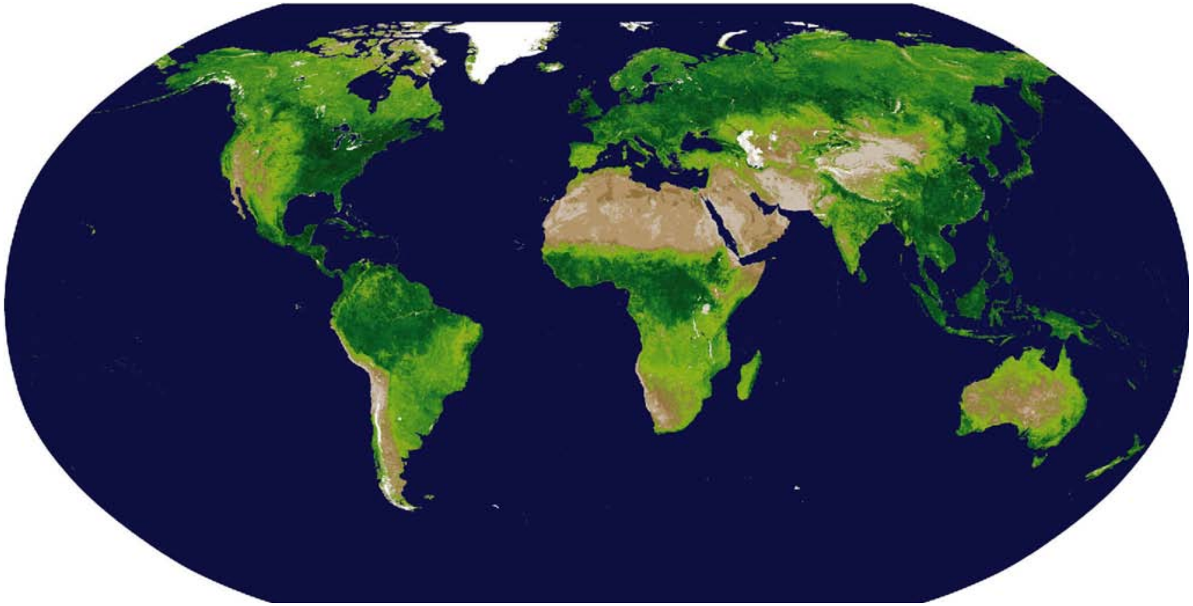
4.6 Image Transformations

- This relatively simple algorithm can be applied to other sensors, such as MSS &TM, and produces output values in the range of **-1.0 to 1.0**. **Increasing positive NDVI values**, shown in increasing shades of green on the images, indicate **increasing amounts of green vegetation**. NDVI values near zero and **decreasing negative values** indicate **non-vegetated features** such as barren surfaces (rock and soil) and water, snow, ice, and clouds.

$$NDVI6 = \frac{MSS6 - MSS5}{MSS6 + MSS5}$$

$$NDVI7 = \frac{MSS7 - MSS5}{MSS7 + MSS5}$$

$$NDVI_{TM} = \frac{TM4 - TM3}{TM4 + TM3}$$



Enhanced vegetation index map of the world

4.6 Image Transformations

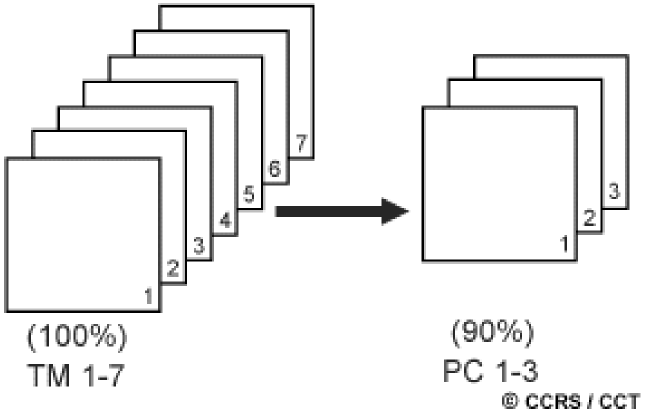
- **Different bands** of multispectral data are often **highly correlated** and thus **contain similar information**. For example, Landsat MSS Bands 4 and 5 (green and red, respectively) typically have similar visual appearances since reflectances for the same surface cover types are almost equal. **Image transformation** techniques based on complex processing of the statistical characteristics of multi-band data sets can be used to **reduce this data redundancy** and correlation between bands.

- One such transform is called **principal components analysis**. The objective of this transformation is **to reduce the dimensionality (i.e. the number of bands)** in the data, and **compress as much of the information** in the original bands **into fewer bands.** The "new" bands that result from this statistical procedure are called components. This process attempts to **maximize (statistically) the amount of information (or variance)** from the original data **into the least number of new components**.

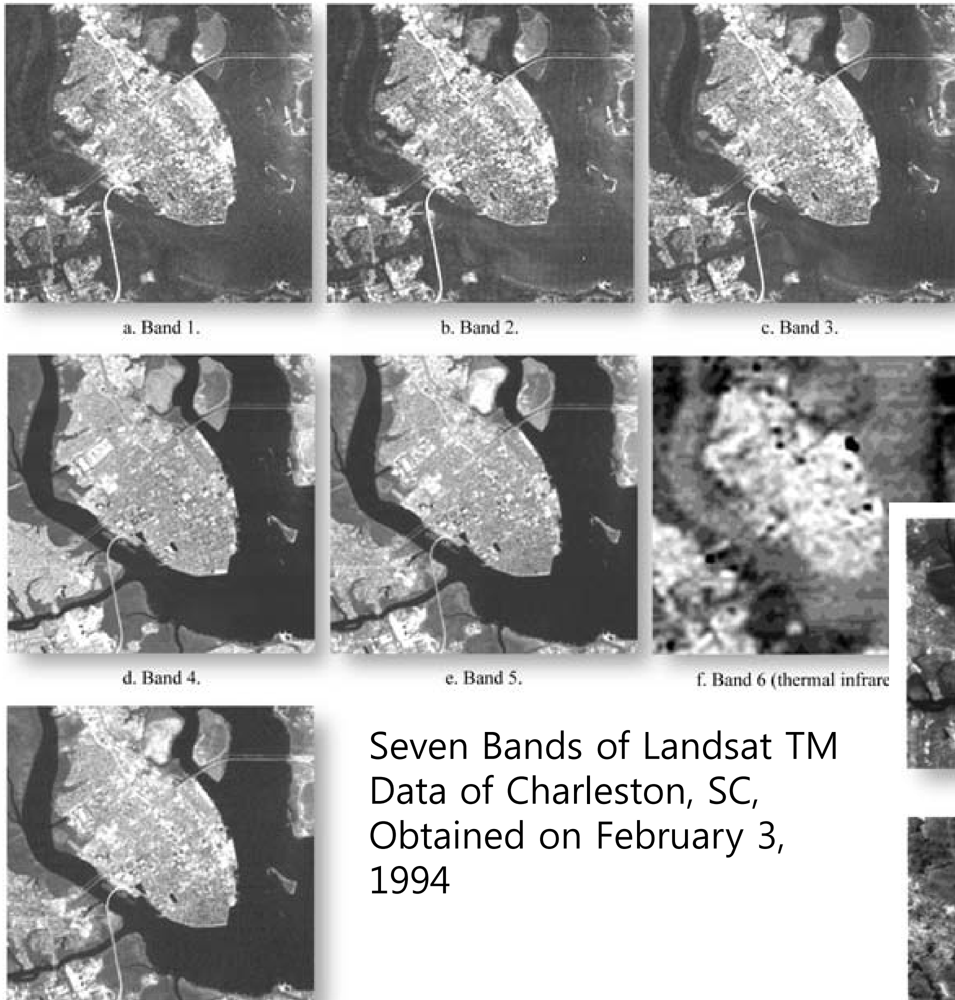
4.6 Image Transformations

- As an example of the use of **principal components analysis**, **a seven band Thematic Mapper (TM) data** set may be transformed such that **the first three principal components contain over 90 percent of the information** in the original seven bands.

- Interpretation and analysis of these three bands of data, combining them either visually or digitally, is **simpler** and **more efficient** than trying to use all of the original seven bands. Principal components analysis, and other complex transforms, can be used either as an enhancement technique to improve visual interpretation or to reduce the number of bands to be used as input to digital classification procedures, discussed in the next section.



Landsat 5 Thematic Mapper Data of Charleston, SC

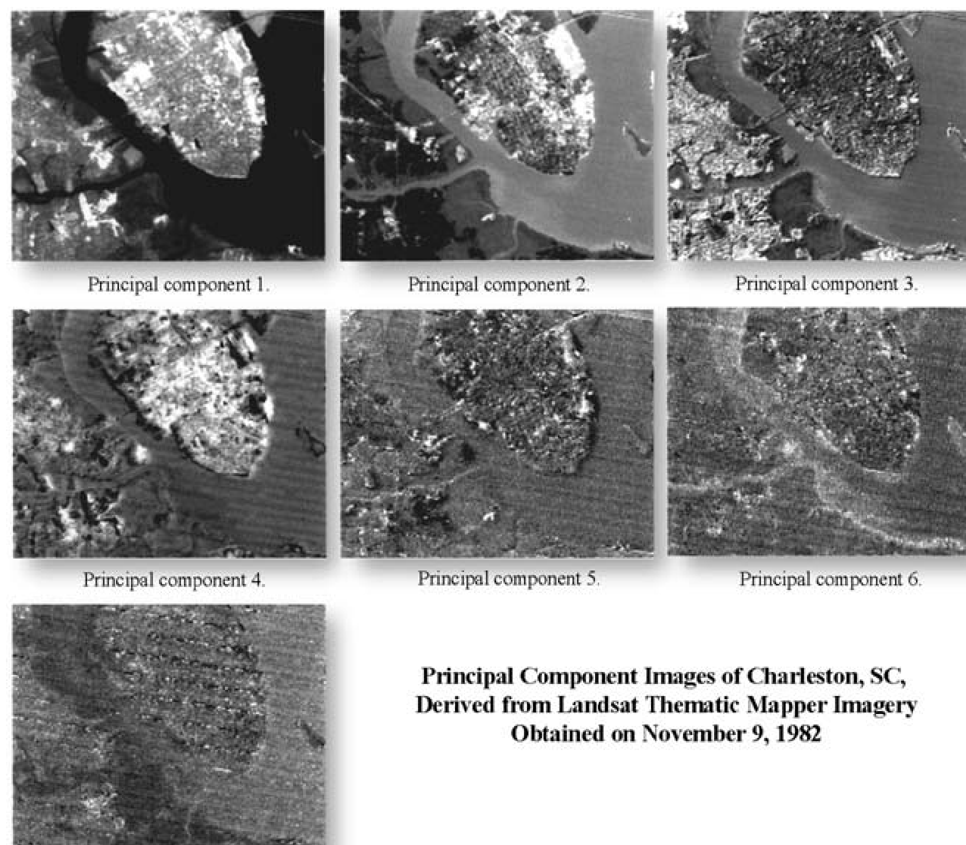


a. Band 1. b. Band 2. c. Band 3.

d. Band 4. e. Band 5. f. Band 6 (thermal infrare

g. Band 7.

Seven Bands of Landsat TM Data of Charleston, SC, Obtained on February 3, 1994



Principal component 1. Principal component 2. Principal component 3.

Principal component 4. Principal component 5. Principal component 6.

Principal component 7.

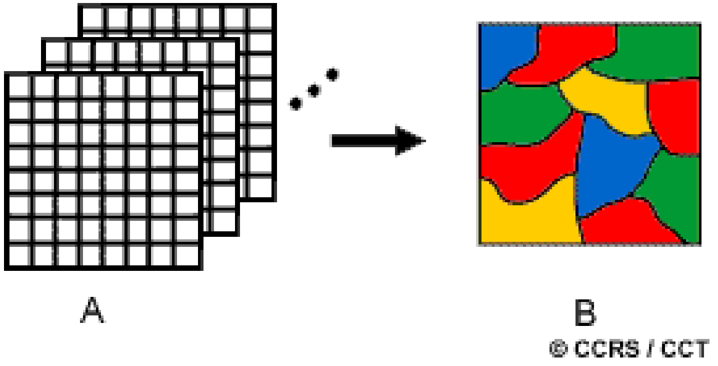
Principal Component Images of Charleston, SC, Derived from Landsat Thematic Mapper Imagery Obtained on November 9, 1982

4.7 Image Classification and Analysis

- A **human analyst** attempting to **classify features** in an image uses the elements of visual interpretation to **identify homogeneous groups of pixels** which represent various features or land cover classes of interest.

- **Digital image classification** uses the spectral information represented by the digital numbers in one or more spectral bands, and attempts to **classify each individual pixel based on this spectral information**. This type of classification is termed **spectral pattern recognition**.

- In either case, the objective is to **assign all pixels** in the image **to particular classes** or themes (e.g. water, coniferous forest, deciduous forest, corn, wheat, etc.). The resulting classified image is comprised of a mosaic of pixels, each of which belong to a particular theme, and is essentially **a thematic "map"** of the original image.



4.7 Image Classification and Analysis

- When talking about classes, we need to distinguish between **information classes** and **spectral classes**.
    - ✓ **Information classes ➔** are those **categories of interest** that the analyst is actually trying to identify in the imagery, such as *different kinds of crops*, *different forest types* or *tree species*, *different geologic units* or *rock types*, etc.
    - ✓ **Spectral classes ➔** are groups of **pixels that are uniform (or near-similar)** with respect to their brightness values in the different spectral channels of the data.

- The objective is to **match the spectral classes** in the data **to the information classes** of interest. Rarely is there a simple one-to-one match between these two types of classes.
    - ✓ Rather, **unique spectral classes** may appear which do **not necessarily correspond to any information class** of particular use or interest to the analyst.
    - ✓ Alternatively, **a broad information class** (e.g. forest) may **contain a number of spectral sub-classes** with unique spectral variations. Using the forest example, spectral sub-classes may be due to variations in age, species, and density, or perhaps as a result of shadowing or variations in scene illumination.

- It is the analyst's job to decide on the utility of the different spectral classes and their correspondence to useful information classes.

4.7 Image Classification and Analysis

• Common classification procedures can be broken down into two broad subdivisions based on the method used:

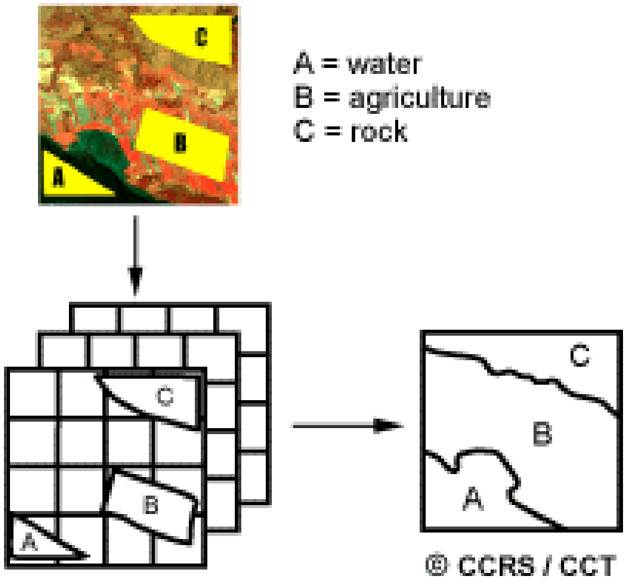
(1) **supervised classification** and

(2) **unsupervised classification**.

• In a **supervised classification**, **the analyst identifies** in the imagery homogeneous representative samples of the different surface cover types (**information classes**) of interest. These samples are referred to as **training areas**.

• The selection of appropriate training areas is based on the analyst's familiarity with the geographical area and their knowledge of the actual surface cover types present in the image. Thus, the **analyst** is "**supervising**" the **categorization** of a set of specific classes.

• The numerical information in all spectral bands for the pixels comprising these areas are used to "train" the computer to recognize spectrally similar areas for each class.



4.7 Image Classification and Analysis

- The computer uses a special program or algorithm (of which there are several variations), to determine the numerical "**signatures**" for each training class. Once the computer has determined the signatures for each class, each pixel in the image is compared to these signatures and labeled as the class it most closely "resembles" digitally.

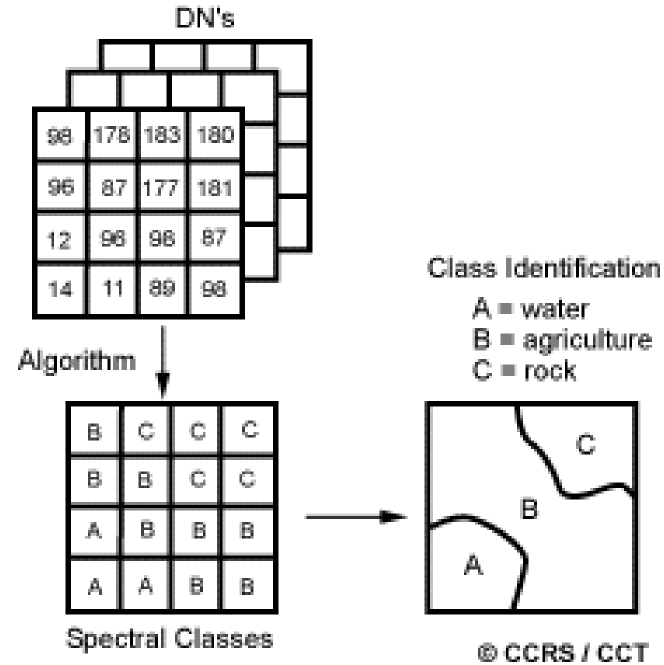
- Thus, in a supervised classification we are **first identifying the information classes** which are then used to **determine the spectral classes** which represent them.

Information classes ➔ Spectral classes

4.7 Image Classification and Analysis

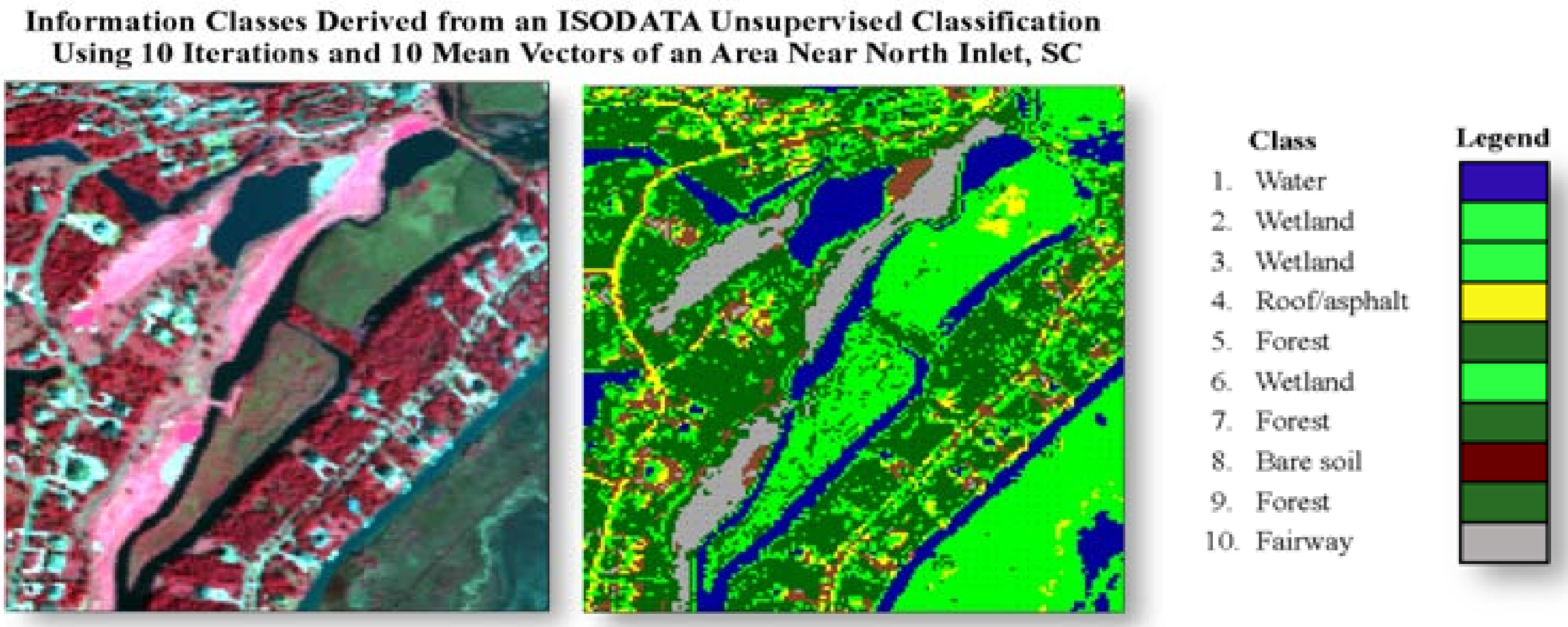
- **Unsupervised classification** in essence reverses the supervised classification process. **Spectral classes are grouped first**, based solely on the numerical information in the data, and are **then matched by the analyst to information classes** (if possible).

- Programs, called **clustering algorithms**, are used to determine the **natural (statistical) groupings** or structures in the data. Usually, the analyst specifies how many groups or clusters are to be looked for in the data. In addition to specifying the desired number of classes, the analyst may also specify parameters related to the separation distance among the clusters and the variation within each cluster.



- The final result of this iterative clustering process may result in some clusters that the analyst will want to subsequently combine, or clusters that should be broken down further - each of these requiring a further application of the clustering algorithm. Thus, unsupervised classification is **not completely without human intervention.** However, it does not start with a pre-determined set of classes as in a supervised classification.

4.7 Image Classification and Analysis



A color composite of multi-spectral data.

Classification map derived from 10 ISODATA clusters.

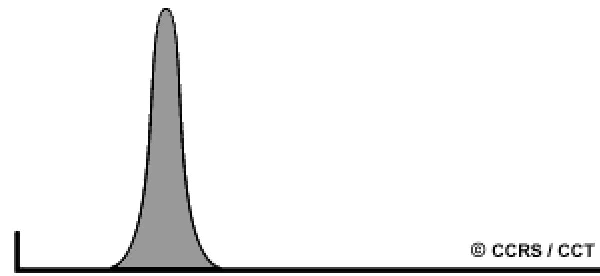
4.7 Image Classification and Analysis

Did You Know?
"...this image has such lovely texture, don't you think?...“

...**texture** was identified as one of the key elements of visual interpretation, particularly for **radar image interpretation**. **Digital texture classifiers** are also available and can be an alternative (or assistance) to spectral classifiers. They typically perform a "moving window" type of calculation, similar to those for spatial filtering, to estimate the "texture" based on the variability of the pixel values under the window. **Various textural measures** can be calculated to attempt to discriminate between and characterize the textural properties of different features.

4.7 Image Classification and Analysis

QUIZ You want to perform a classification on a satellite image, but when examining its histogram, you notice that the range of useful data is very narrow. Prior to attempting classification, would you enhance the image with a linear contrast stretch?



ANS

4.7 Image Classification and Analysis

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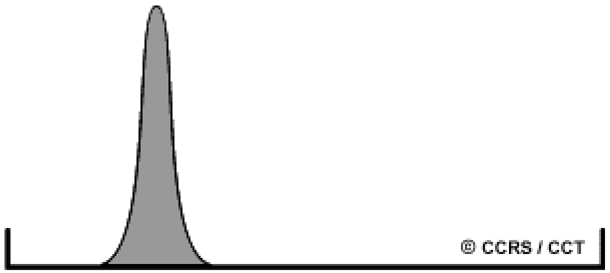
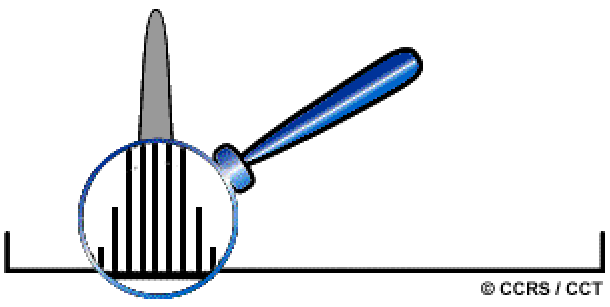


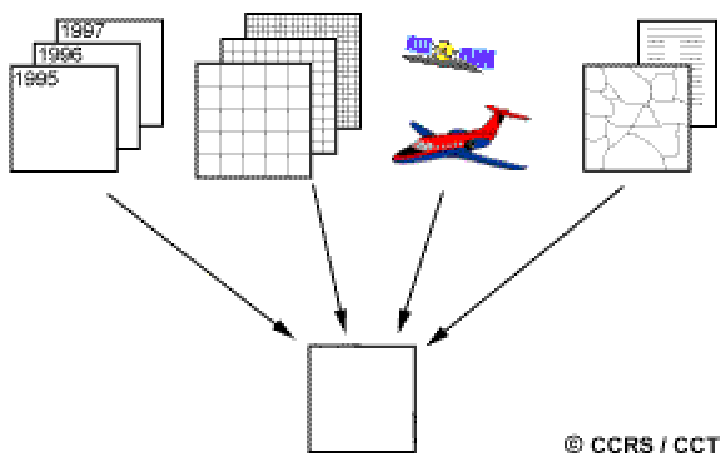
ANS An '**enhancement**' of an image is done **exclusively for visually** appreciating and analyzing its contents. An enhancement would not add anything useful, as far as the classification algorithm is concerned. Another way of looking at this is: if two pixels have brightness values just one digital unit different, then it would be very difficult to notice this subtle difference by eye. But for the computer, the difference is just as 'obvious' as if it was 100 times greater.



An enhanced version of the image may help in selecting 'training' sites (by eye), but you would still perform the classification on the unenhanced version.

4.8 Data Integration and Analysis

- In the early days of analog remote sensing when the only remote sensing data source was aerial photography, the capability for integration of data from different sources was limited. Today, with most data available in digital format from a wide array of sensors, data integration is a common method used for interpretation and analysis. **Data integration** fundamentally involves the **combining or merging of data from multiple sources** in an effort to extract better and/or more information. This may include data that are **multi-temporal, multi-resolution, multi-sensor**, or **multi-data type** in nature.



4.8 Data Integration and Analysis

- Imagery collected at different times is integrated to identify areas of change. **Multi-temporal change detection** can be achieved through simple methods such as **image subtraction**, or by other more complex approaches such as **multiple classification comparisons** or classifications using integrated multi-temporal data sets.

- **Multi-resolution data merging** is useful for a variety of applications. The merging of data of a **higher spatial resolution** with data of **lower resolution** can significantly **sharpen the spatial detail** in an image and **enhance the discrimination** of features.

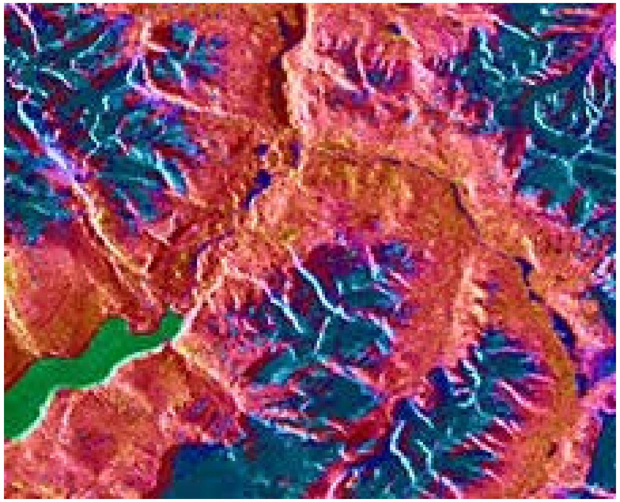
- **SPOT data** are well suited to this approach as the **10 m panchromatic** data can be easily merged with the **20 m multispectral** data. Additionally, the multispectral data serve to retain good spectral resolution while the panchromatic data provide the improved spatial resolution.

4.8 Data Integration and Analysis

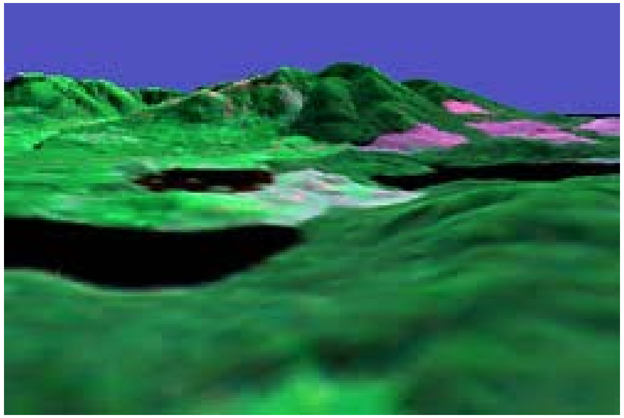
- Data from different sensors may also be merged, bringing in the concept of **multi-sensor data fusion**.

- An excellent example of this technique is the combination of **multi-spectral optical data with radar imagery**. These two diverse spectral representations of the surface can provide complementary information.

  ✓ The **optical data** provide detailed **spectral information** useful for discriminating between surface cover types,
  ✓ while the **radar imagery** highlights the **structural detail** in the image.



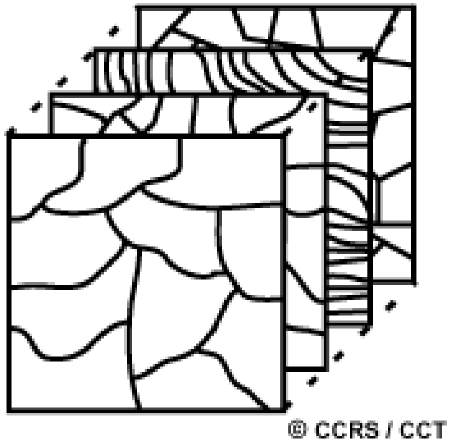
4.8 Data Integration and Analysis



- **Applications of multi-sensor data integration** generally **require** that the data be **geometrically registered**, either to each other or to a common geographic coordinate system or map base. This also allows other **ancillary** (supplementary) data sources to be integrated with the remote sensing data.

- For example, elevation data in digital form, called **Digital Elevation** or **Digital Terrain Models (DEMs/DTMs)**, may be combined with remote sensing data for a variety of purposes. DEMs/DTMs may be useful in image classification, as effects due to terrain and slope variability can be corrected, potentially increasing the accuracy of the resultant classification. DEMs/DTMs are also useful for generating **three-dimensional perspective views** by draping remote sensing imagery over the elevation data, **enhancing visualization** of the area imaged.

4.8 Data Integration and Analysis



- Combining data of different types and from different sources, such as we have described above, is the pinnacle of data integration and analysis. In a digital environment where all the data sources are geometrically registered to a common geographic base, the potential for information extraction is extremely wide. This is the concept for analysis within a digital **Geographical Information System (GIS)** database.

- Any data source which can be referenced spatially can be used in this type of environment. A DEM/DTM is just one example of this kind of data. Other examples could include digital maps of **soil type**, **land cover** classes, **forest species**, **road networks**, and many others, depending on the application.

- The results from a classification of a remote sensing data set in map format, could also be used in a GIS as another data source to update existing map data. In essence, by **analyzing diverse data sets together**, it is possible to **extract better and more accurate information** in a synergistic manner than by using a single data source alone.