Remote Sensing for Seagrass Mapping

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Outline

- Theory of detecting seagrass by remote sensing
- Basics of image classifications
- Accuracy Assessment

Background of coastal habitat mapping

Coastal habitats such as seagrass beds, coral reefs, mangroves and tidal flats are important for many marine organisms.

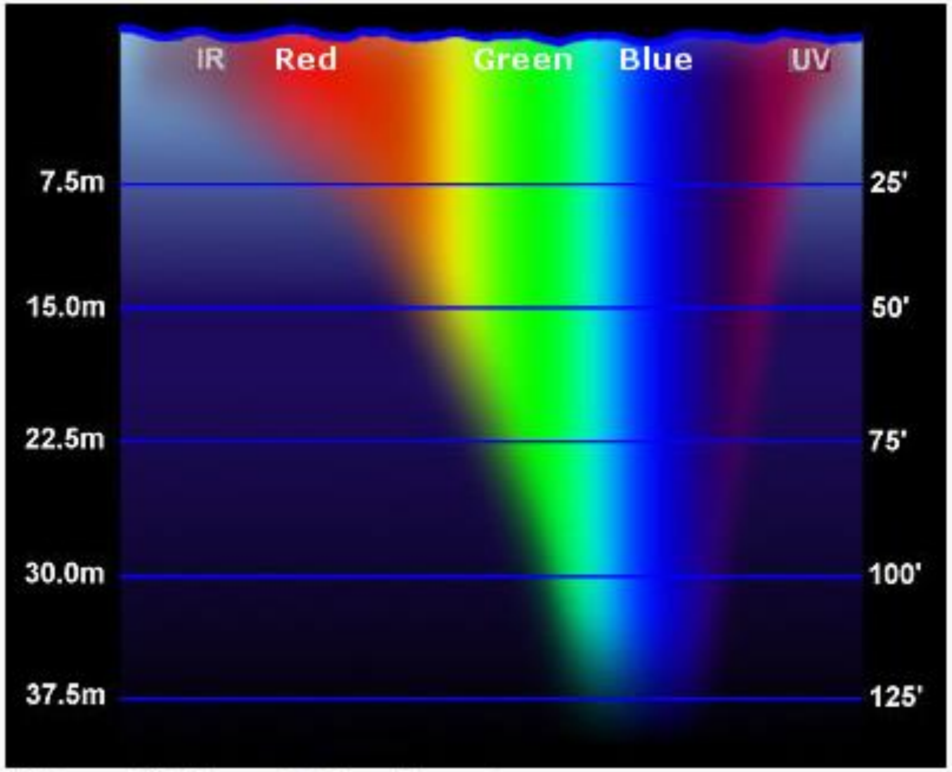
However, these habitats are damaged all over the world due to mainly human impacts.

Thus, it is important to monitor and conserve habitats for sustainable development for coastal area.

Remote sensing is one of the efficient methods for coastal monitoring. RESTEC have conducted mapping these habitats by remote sensing in variable projects.

Satellite data

What type of sensor is appropriate for coastal water?
Optical sensor is useful in coastal water. Light with visible wavelength penetrates into water, although light with other wavelength only reaches water surface.



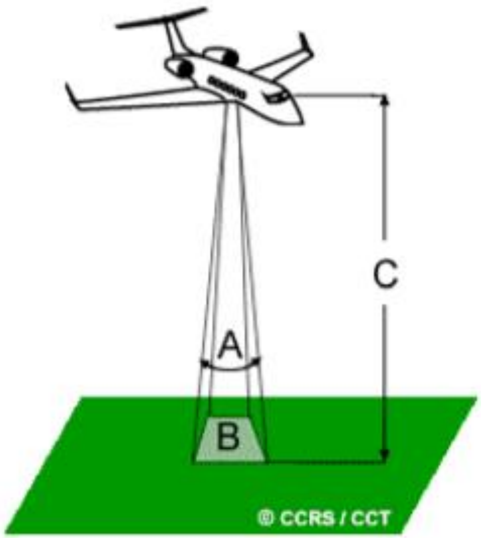
Patterns of light penetration into water.
Source: Tom Morris, Fullerton College.

Satellite data

Spatial resolution and pixel size

Spatial resolution is the size of the smallest possible feature that can be detected. It depends primarily on their Instantaneous Field of View (IFOV). The IFOV is the angular cone of visibility of the sensor (A) and determines the area on the Earth's surface which is "seen" from a given altitude at one particular moment in time (B). This area on the ground is called the resolution cell and determines a sensor's maximum spatial resolution. Spatial resolution is expressed as a length of a side of the cell.

Pixel size in the satellite image (the length on the earth surface correspond with a side of the pixel) is almost equal to or larger than the spatial resolution.



IFOV and Spatial resolution

Pixel size

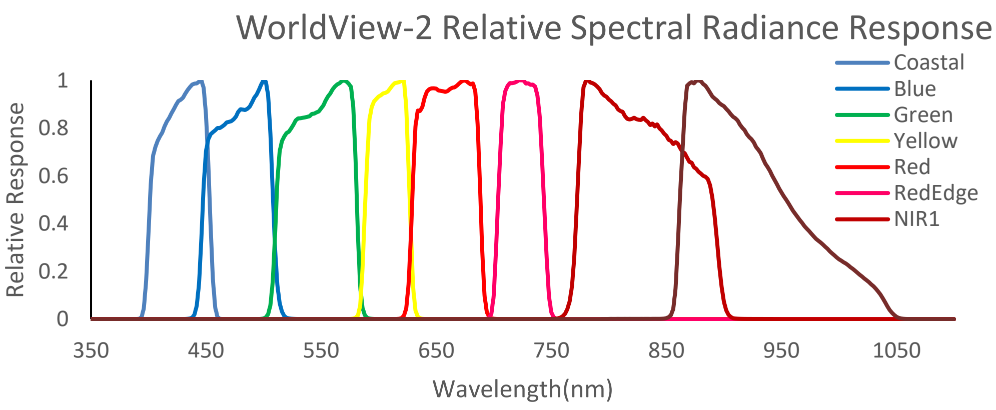
Satellite data

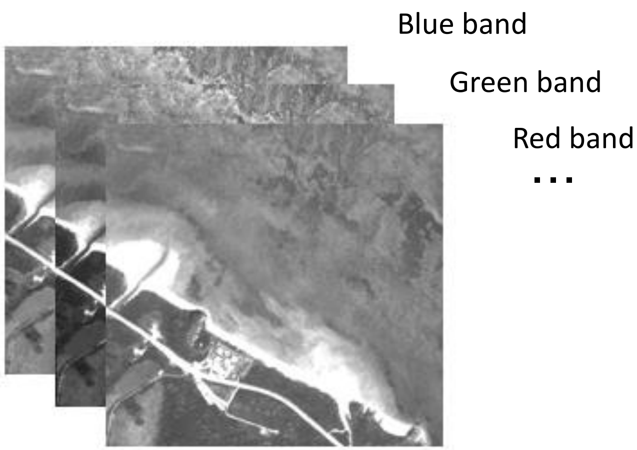
Spectral resolution and spectral bands

The satellite image is composed of several images for each spectral band.

Spectral resolution describes the ability of a sensor to define fine wavelength intervals.

The finer the spectral resolution, the narrower the wavelength range for a particular channel or band.

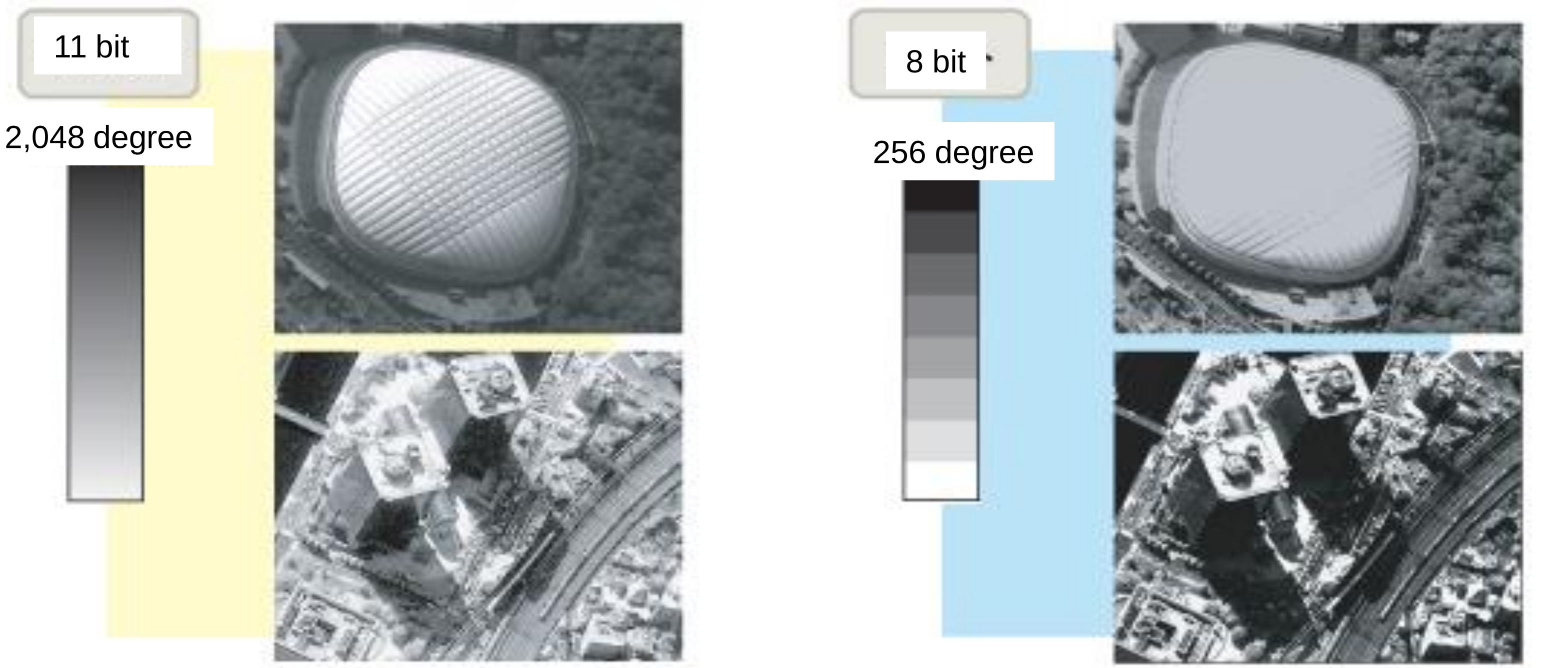




Satellite data

Radiometric resolution and dynamic range

A sensor's sensitivity to the magnitude of the electromagnetic energy determines the radiometric resolution. The finer the radiometric resolution of a sensor, the more sensitive it is to detecting small differences in reflected or emitted energy.
The maximum number of brightness levels available depends on the number of bits used in representing the energy recorded (dynamic range).



11 bit image has more information than 8 bit image. Brighter or darker part is distinguishable

Satellite data

High spatial resolution is required for habitat mapping
Observation width is also important for large scale mapping

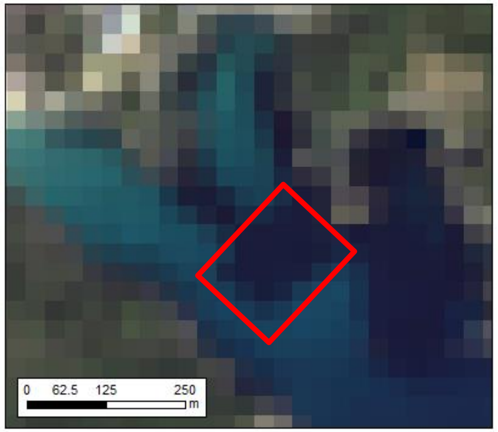
Satellite Sensor	LANDSAT-8 (OLI/Multi)	SPOT6/7 (Multi)	RapidEye (Multi)	IKONOS (Multi)	WorldView-2/3 (Multi)
Bands	8(Visible 4、Near-inrared 1, SWIR 3)	4(Visible 3、Near-infrared 1)	5(Visible 4、Near- infrared 1)	4(Visible 3、Near- infrared 1)	8(Visible6、Near- infrared 2)
Spatial Resolution (Pixel Size)	30 m	8 m	6.5 m	4 m	1.84 m / 1.24 m (2 m)
Dynamic Range	12 bit	12 bit	12 bit	11 bit	11 bit
Observation width	1,400 km	60 km	77 km	11 km	16 km
Launched year	2013/02	2012/09 (SPOT-6) 2014/06 (SPOT-7)	2008/8	1999/9	2009/10
Price	Free				

Broad-Scale Mapping

Macro-Scale Mapping

Satellite data

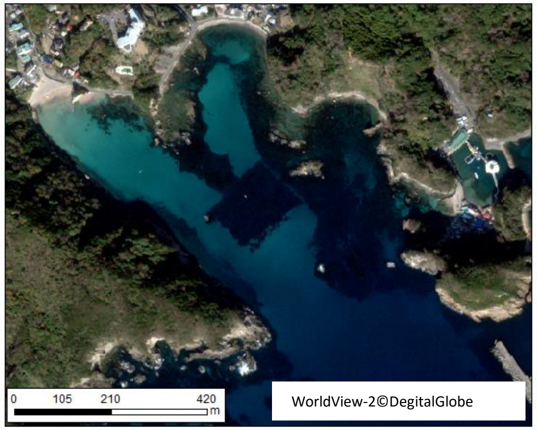
Following Images are obtained over the Oura bay in Japan.
Seaweed beds distribute on artificial reefs at the center of the images (red square area).

WorldView-2	Rapid Eye	Landsat-8
Spatial Resolution: 1.84 m Pixel Resolution: 2 m Acquisition Date: Jan/2011	Spatial Resolution: 6.5 m Pixel Resolution: 5 m Acquisition Date: Dec/2011	Spatial Resolution: 30 m Pixel Resolution: 30 m Acquisition Date:2016
		

Seagrass and Seaweed Mapping

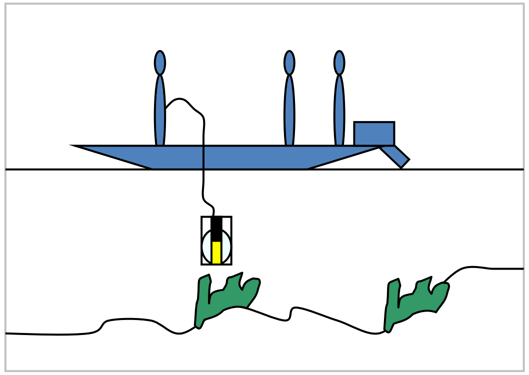
■ Sensor : optical sensor (WorldView-2/3/4, RapidEye, SPOT-6/7, Landsat-8, Sentinel-2)

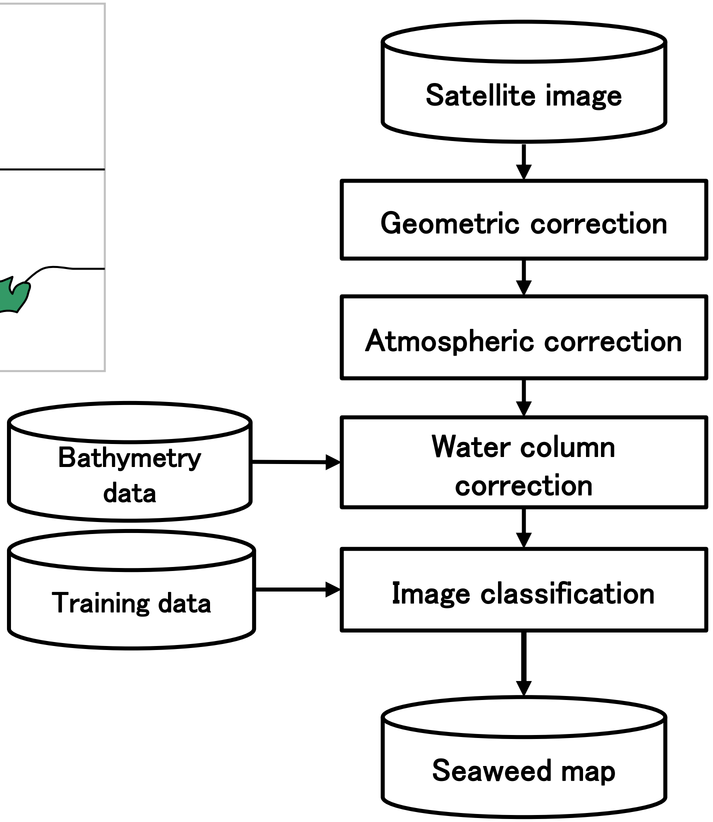
■ Atmospheric correction and water column correction are key processes.



Satellite image

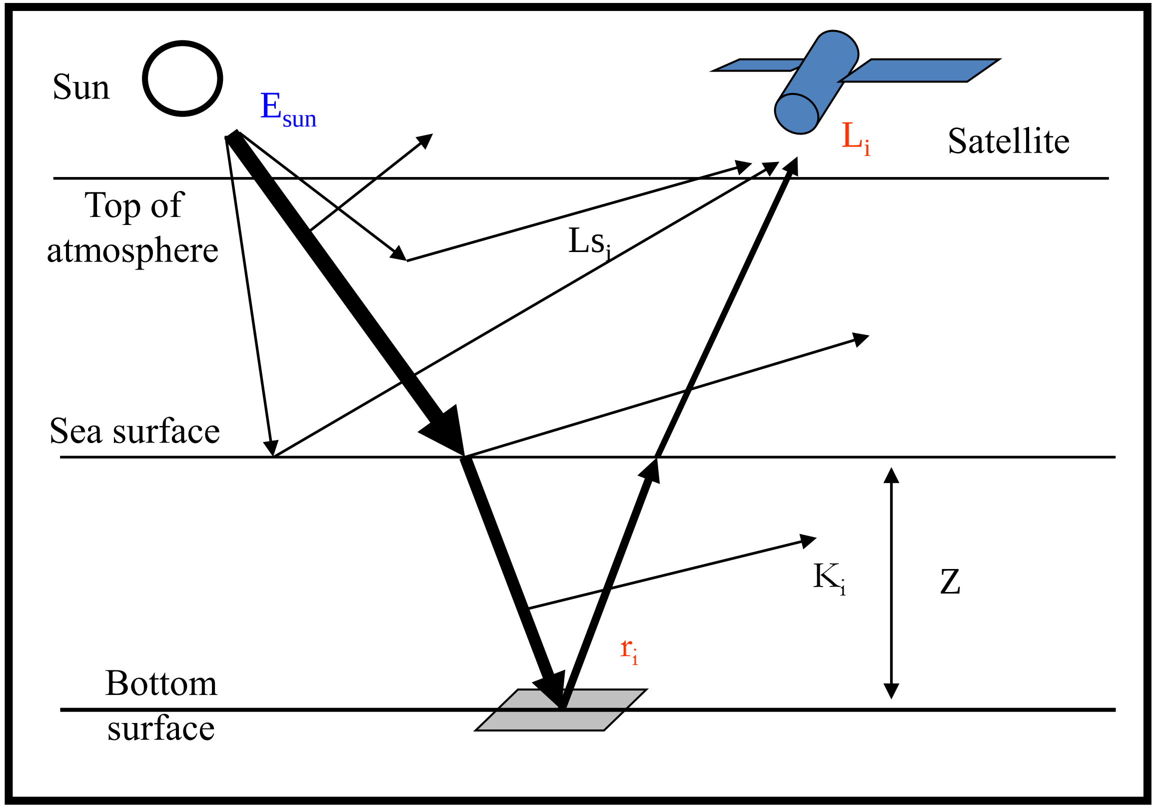

Seaweed map


Field survey



Radiometric Correction

Radiometric correction is a 'calibration of recorded variance values reflected from (or emitted by) the ground scene' (Canada Center for Remote Sensing).
In case of a sea bottom habitat type mapping, we remove the effect of atmosphere and water column to obtain the information about sea bottom surface reflectance.
Correction is conducted based on the optical model.



L: the radiance recorded by satellite sensor

Ls: the external reflection from the water surface and scattering in the atmosphere

a: a coefficients about down welling irradiance at sea surface level

r: sea bottom surface reflectance

K: effective attenuation coefficient of the water

g: a geometric factor to account for the path length through the water

Z: the water depth

$$Li = Ls_i + a_i \cdot r_i \cdot \exp(-K_i \cdot g \cdot Z)\ (W/m^2/sr)$$

(Lyzenga 1978)

Radiometric Correction

■ Conversion to TOA (Top of atmosphere) radiance

$$L_{\lambda Pixel,Band} = \mathrm{Gain}_{Band} \cdot DN_{Pixel,Band} + \mathrm{Offset}_{\ Band}$$

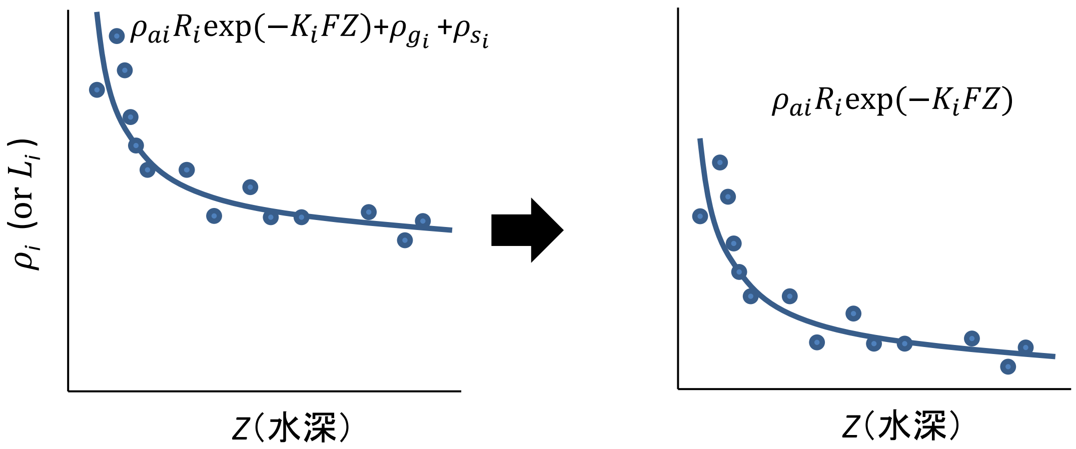
■ Conversion to TOA reflectance

$$\rho_{\lambda_{Pixel,Band}} = \frac{L_{\lambda_{Pixel,Band}} \cdot d_{ES}^{2} \cdot \pi}{Esun_{\lambda_{Band}} \cdot cos(\theta_s)}$$

d_{ES} : Sun-Earth distance
E_{sun} : Sun’s downwelling irradiance
Θ_s : Sun’s zenith angle

■ Atmospheric Correction

Removal of ρ_{s_i} （Ls_i in TOA radiance）



Radiometric Correction

■Water Column Correction

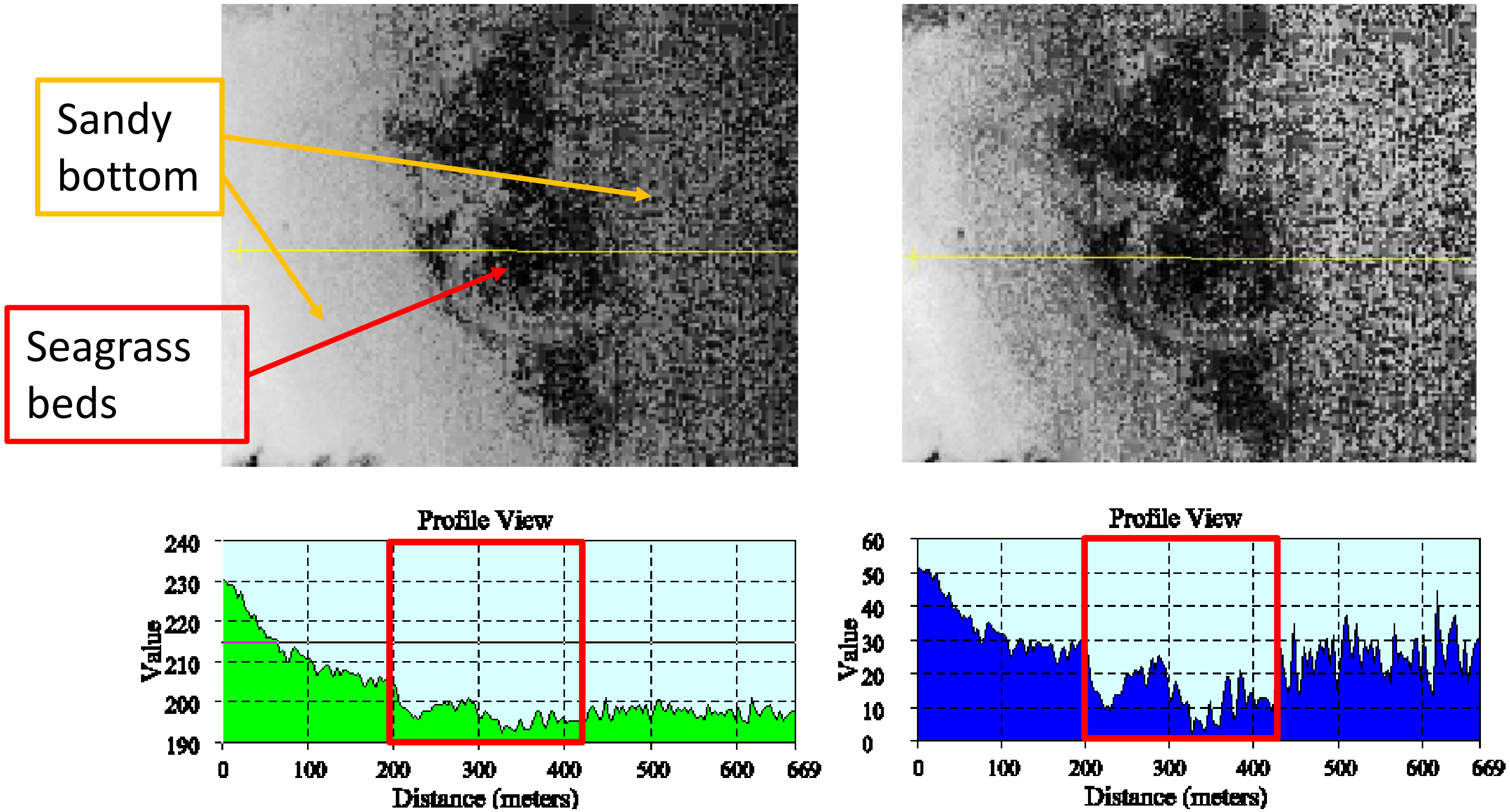
・DII (depth in-variant index: Lyzenga, 1981)

- –Use ratio of 2 bands
- –Equation: $DII_{ij} = \ln((\rho_i{}') - [(Ki / Kj)\ln(\rho_j{}')]$
- –Coefficients (*Ki / Kj*) are required (obtained from regression equation)

・BRI (bottom surface reflectance index: Sagawa *et al*, 2010)

- –Index linearly related with bottom surface reflectance for each band
- –Equation : $BRI_i = (\rho_i{}')\exp(Ki \cdot g \cdot Z)$
- –Coefficients (*Ki*) and bathymetry data (*Z*) are required
- –(*Ki* are obtained from regression equation)
- –BRI has more information about reflectance spectra than DII

Water Column Correction



Before

After

Reflectance spectra for habitat types and substrates

Example for spectral reflectance for seaweeds and substrates
Around 450 to 650 nm band is important for coastal mapping
Seaweeds, sand and rock have different curves.

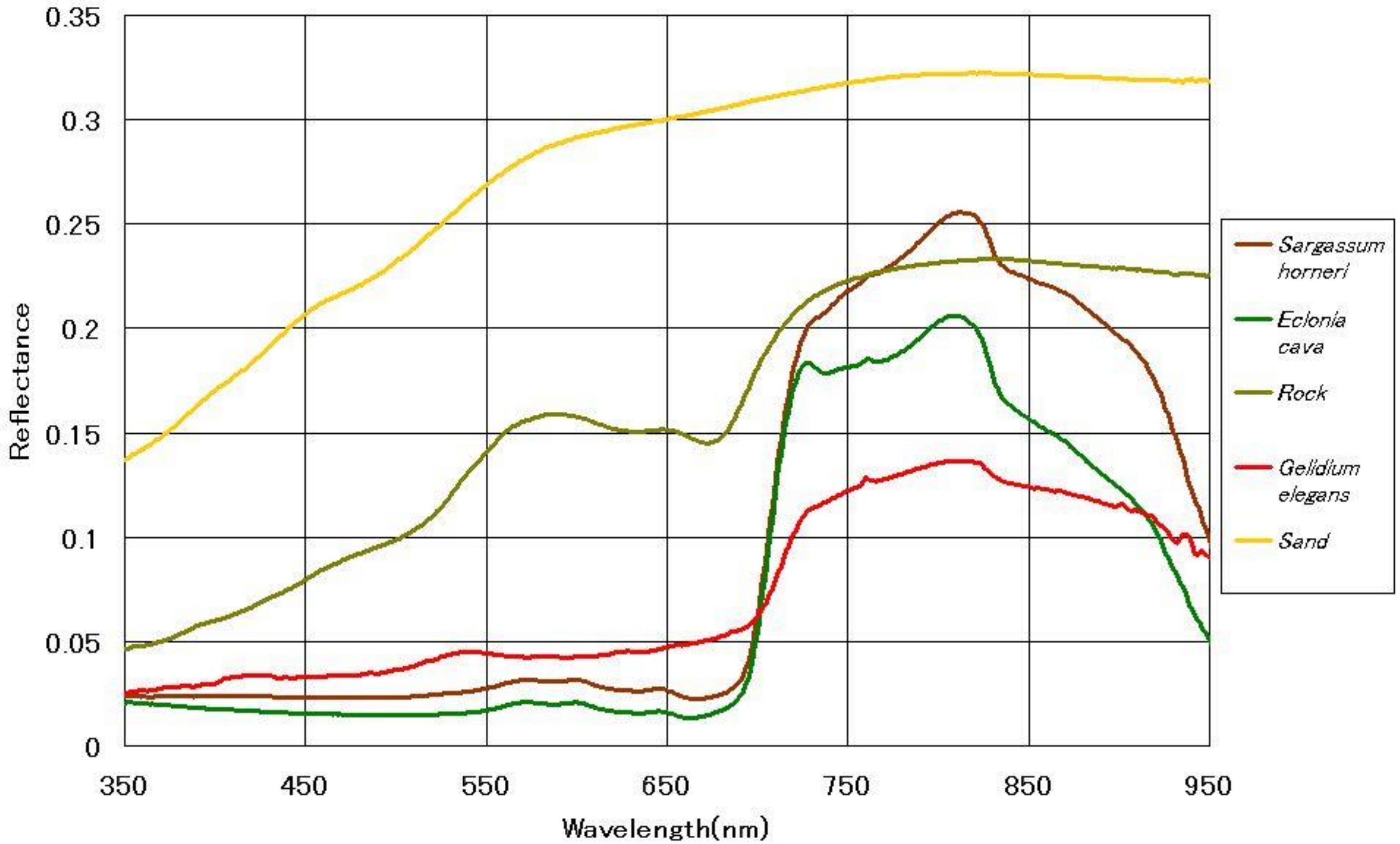
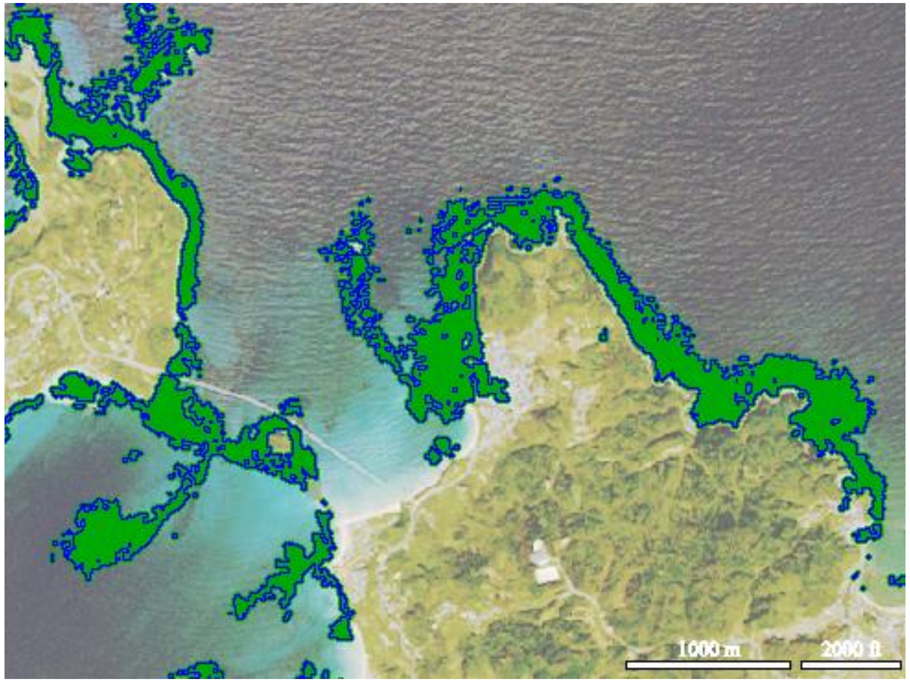


Image Classification

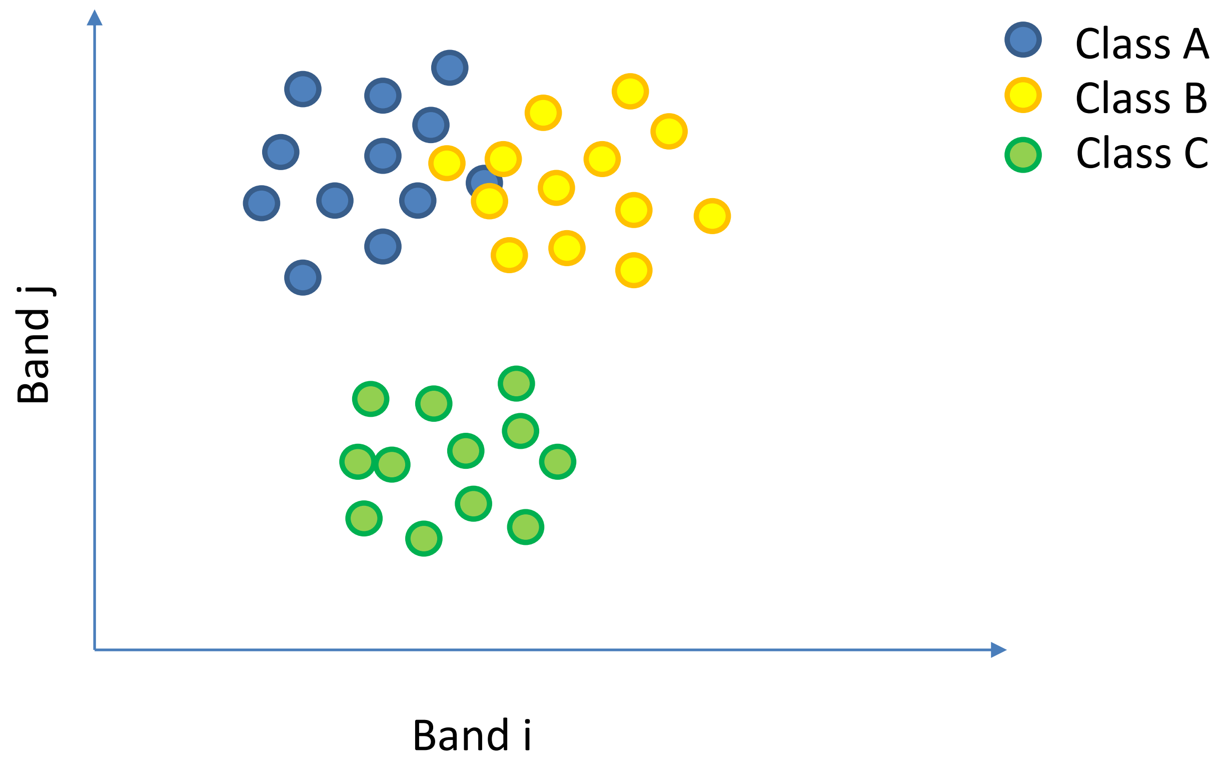
■ Supervised Classification
・Euclidian Distance Method
・Maximum Likelihood Method
・Support Vector Machine
・Random Forest

■ Unsupervised Classification
・K-means



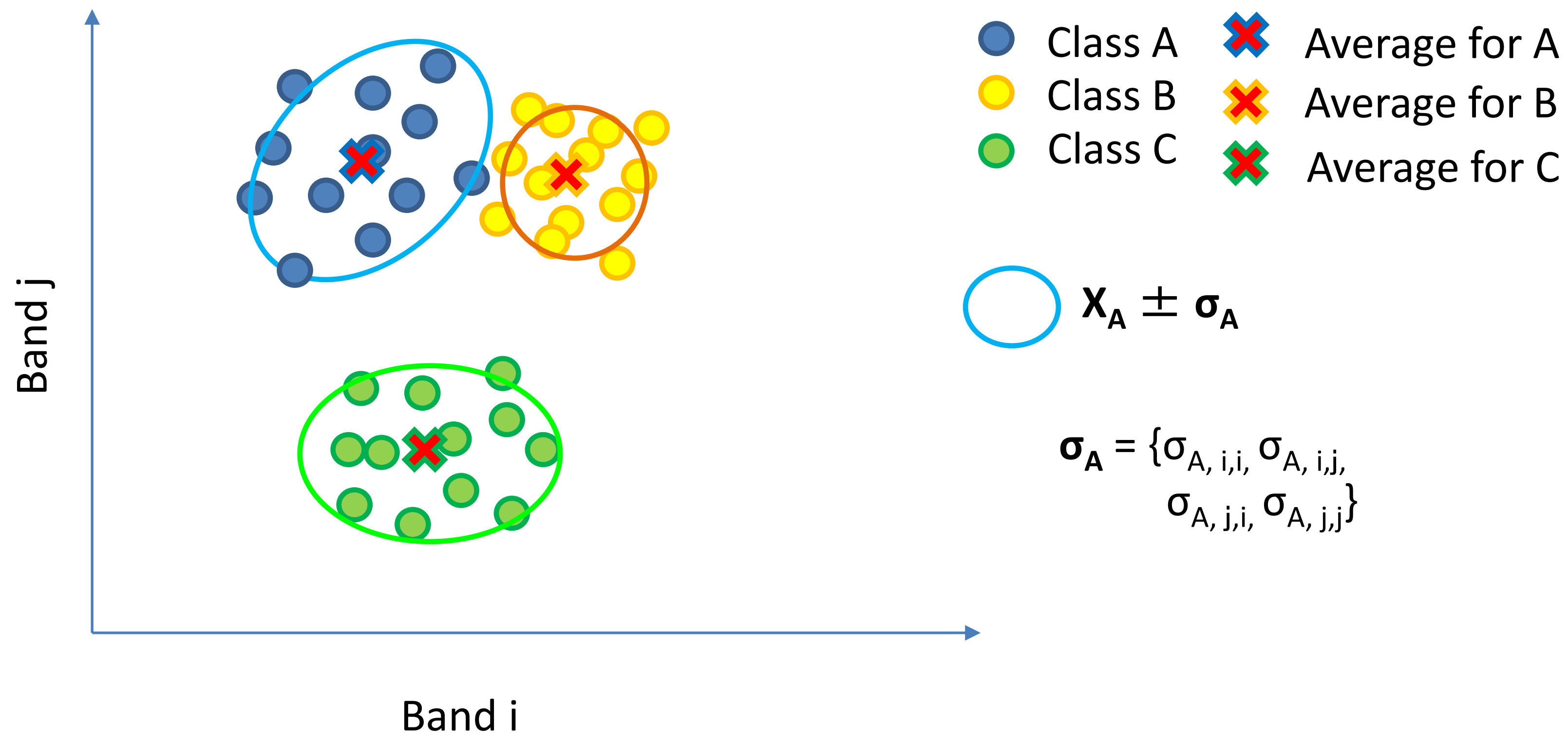
■ Example data distribution

A pixel data value of a satellite image has *n* dimension composed of *n* wavelength bands.
Below image shows an example of data distribution for band *i* and *j.*
Color of data correspond to class categories such as habitat types and substrate types.



■ Supervised classification and statistics

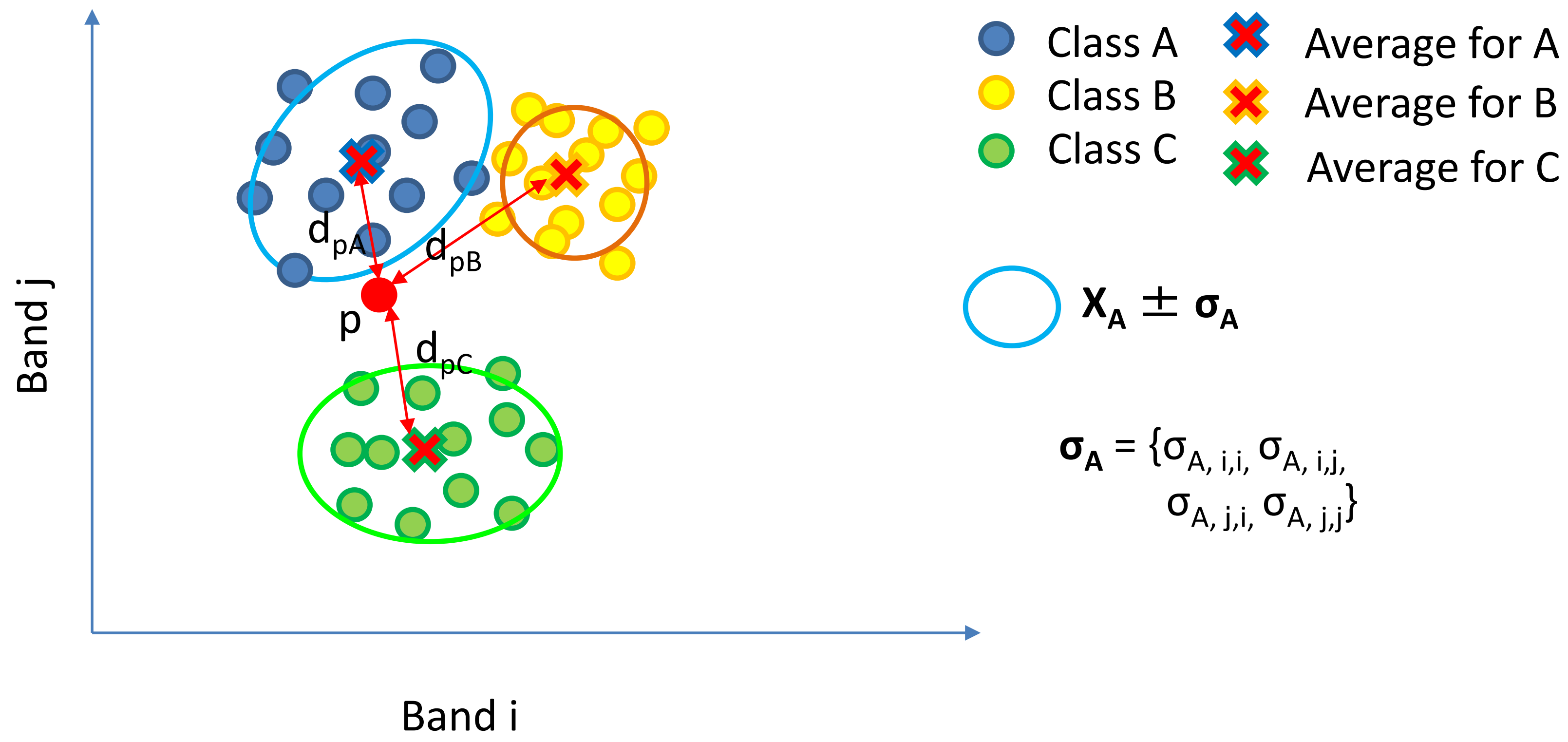
In case of supervised classification, we have sample data for each class as supervised data.
Average $\mathbf{X}_c$ and standard deviation $\boldsymbol{\sigma}_c$ are calculated for class *c* value using supervised data.



■ Supervised classification: Statistical approach

To classify a pixel *p*, distance between *p* and each class *c* is calculated as $d_{p,c}$

p is classified to the class with minimum distance.



■ Euclidian distance method: Statistical approach

Euclidian distance method uses euclidian distance as $d_{p,c}$

Boundary for classification is shown in red break line in below image.

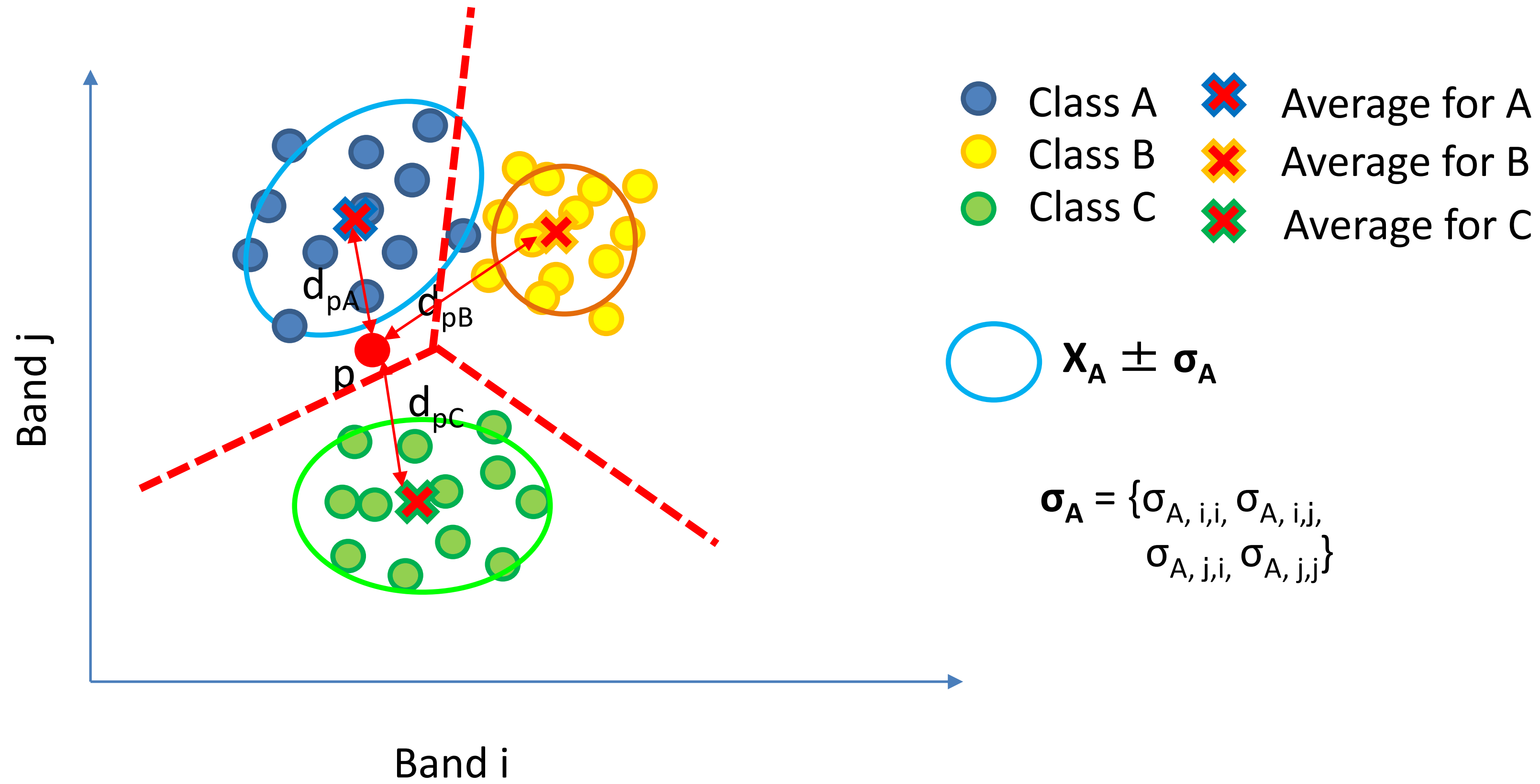


Image Classification

■ Maximum likelihood method: Statistical approach

Maximum likelihood method uses mahalanobis distance as $d_{p,c}$

Boundary for classification is shown in red break line in below image.

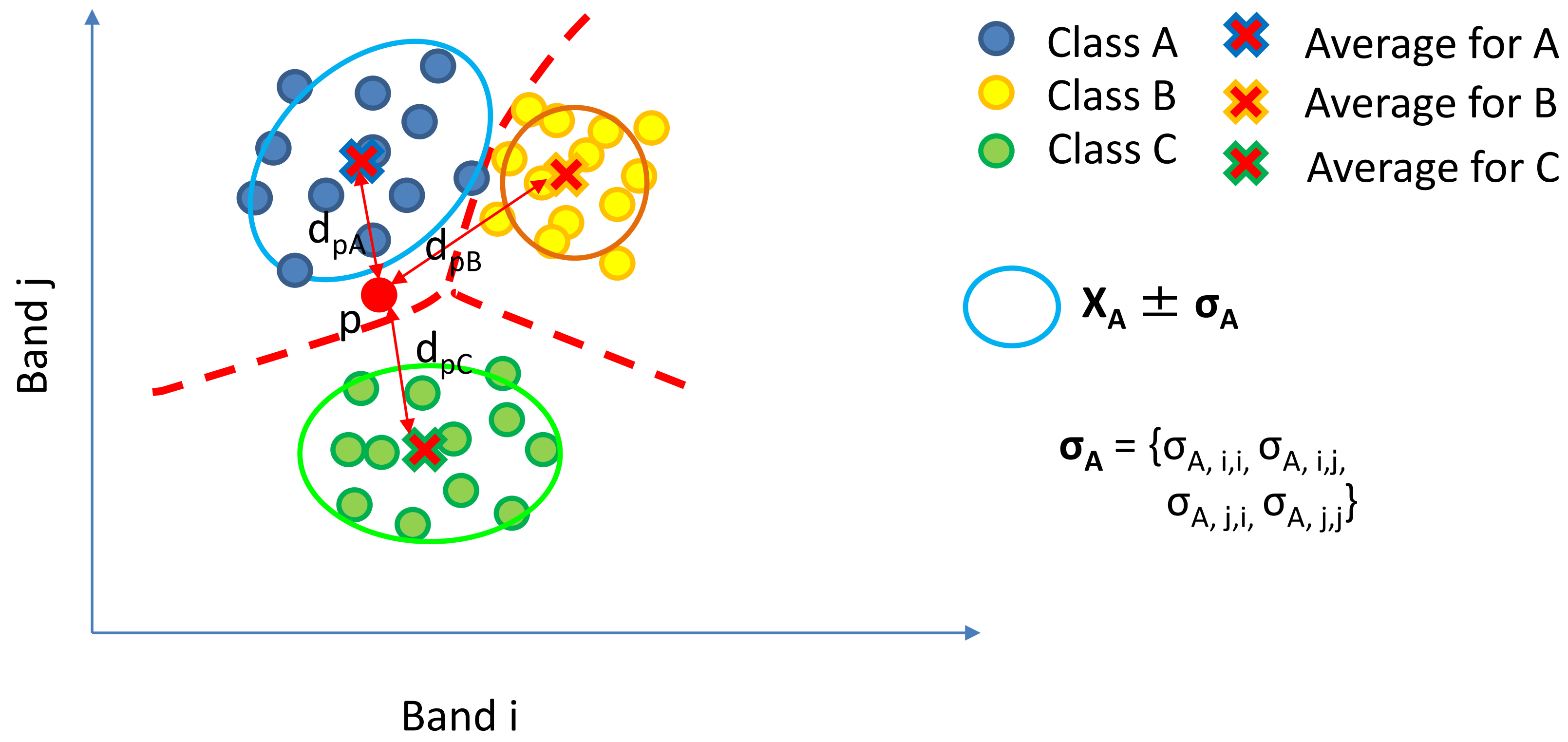


Image Classification

■ Support Vector Machine (SVM): Machine learning approach
SVM determines a decision boundary to maximize margin from support vectors.

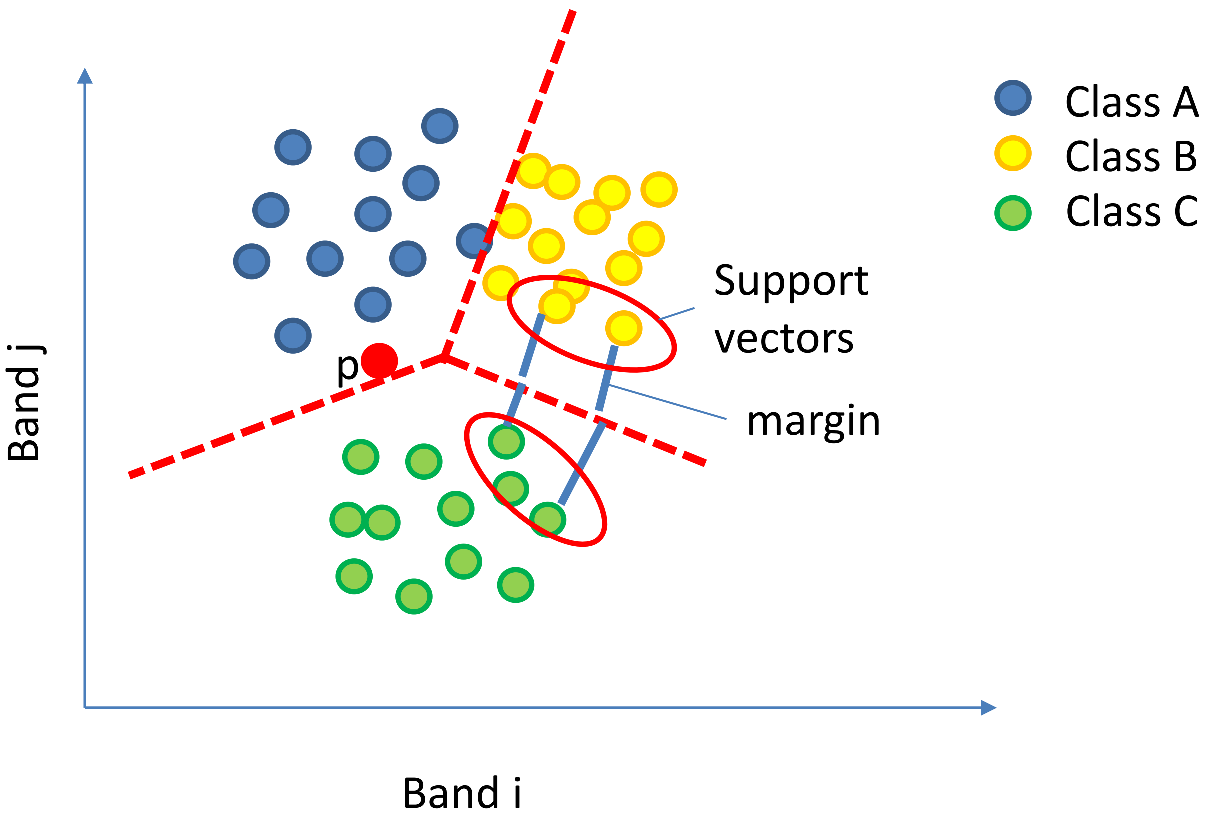


Image Classification

■ Random Forest: Machine learning approach
Random Forest conducts classification based on plural decision trees.

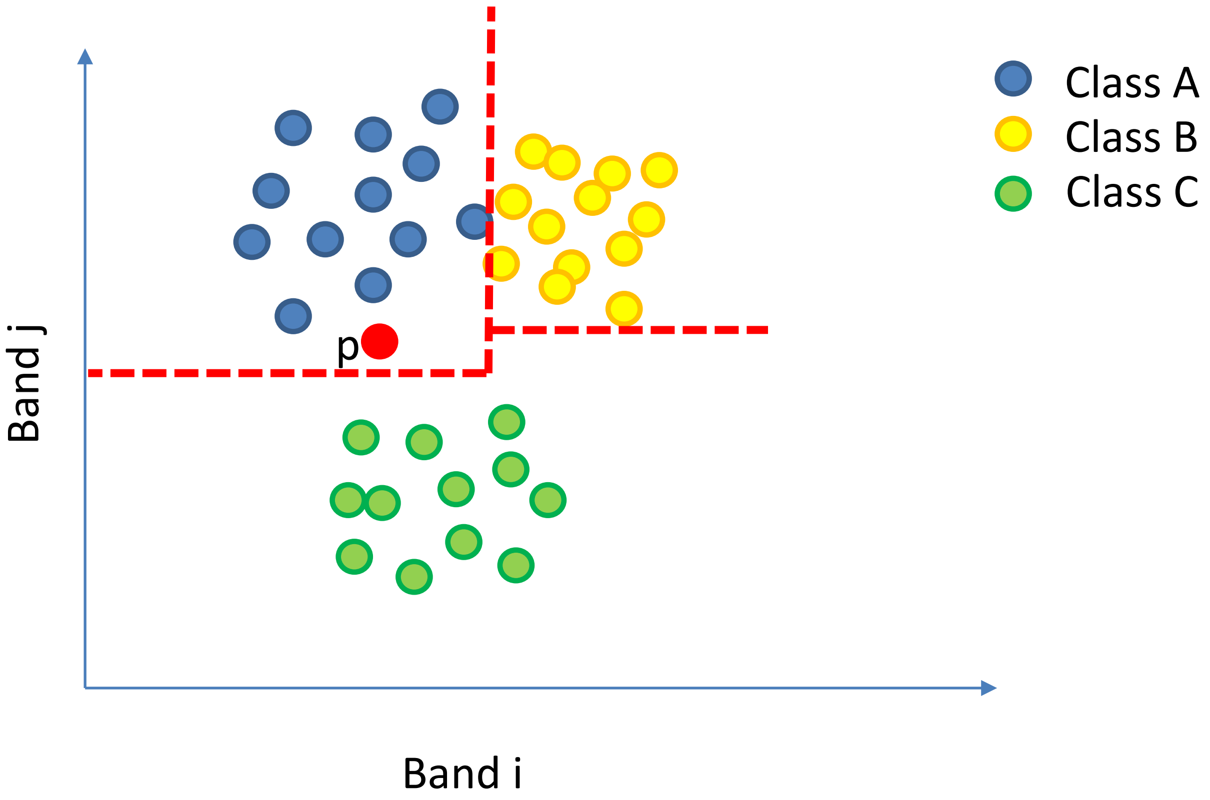


Image Classification

■ Unsupervised classification

A weight of each cluster is set systematically or randomly.
A pixel is classified to a cluster with minimum distance.

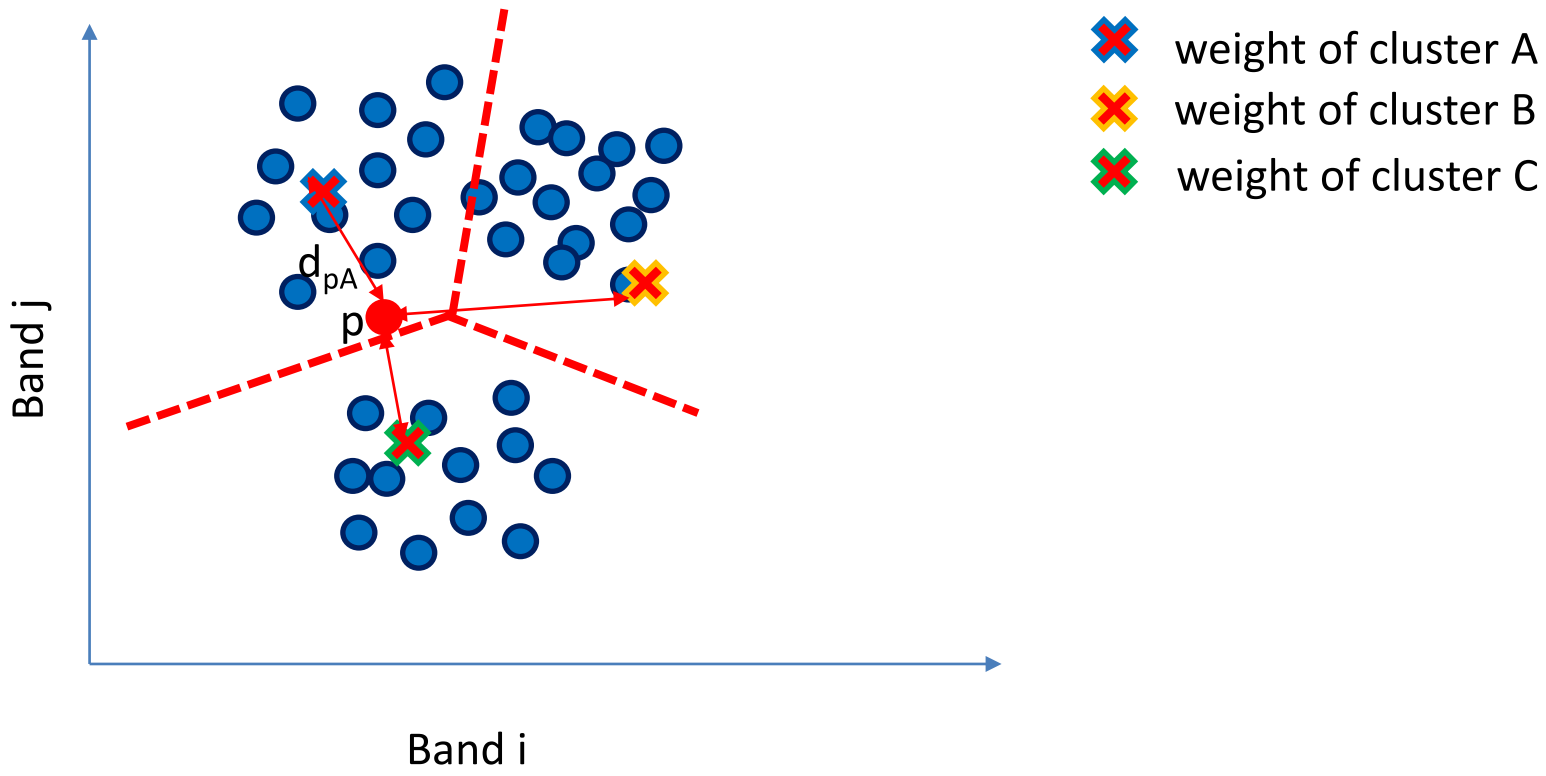
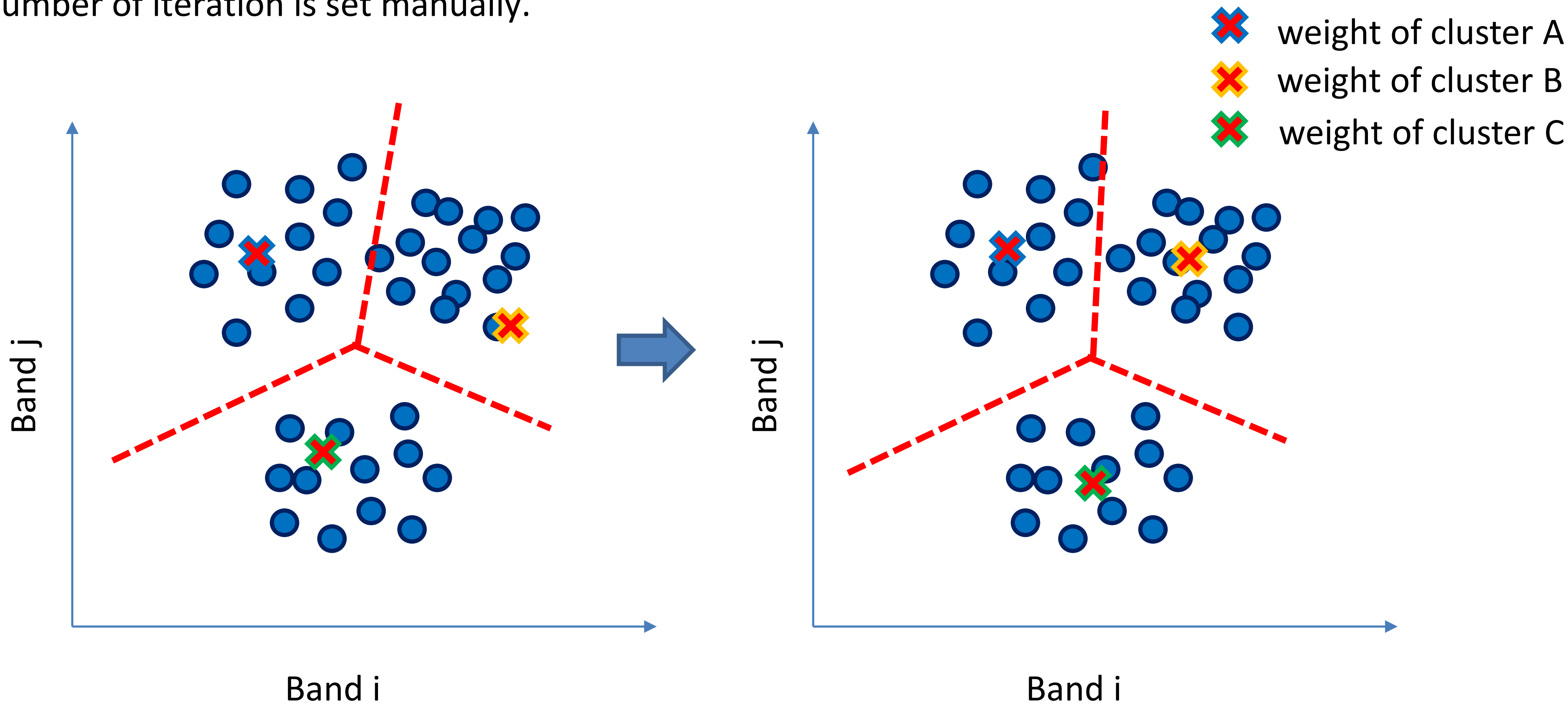


Image Classification

■ k-means

A weight of each cluster will be calculated again with clustered data.
Number of iteration is set manually.



Field Survey to link satellite data with reality

Importance of field survey

- To improve accuracy of satellite image analysis
- To evaluate the accuracy of satellite image analysis

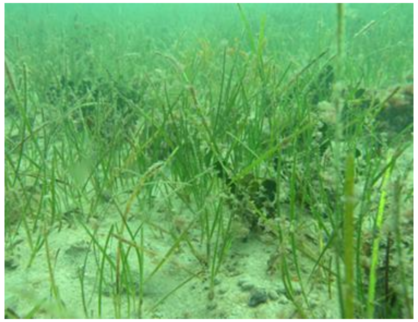
What information we have to collect in the field?

- Surface types for classification in target area with accurate position data. It is recommended 80 sites data for each class (30 for analysis and 50 for accuracy assessment) .
- Depth data with accurate position data for bathymetry analysis. 3 lines of data using echo sounder witch cover the target depth zone are recommended.

Field Survey to link satellite data with reality

Visual Observation

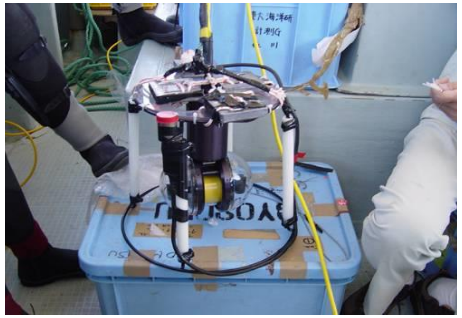
- We can know detail information about seagrass.
- Only few points we can survey in a day.
- It is difficult to measure accurate position during diving.
- It is hard to access for high current area or deep water.

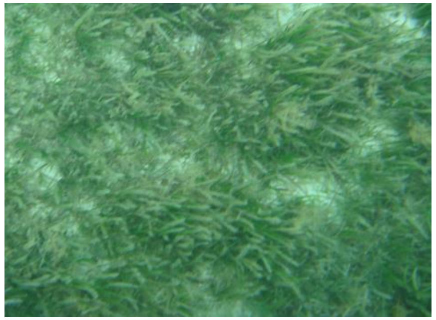


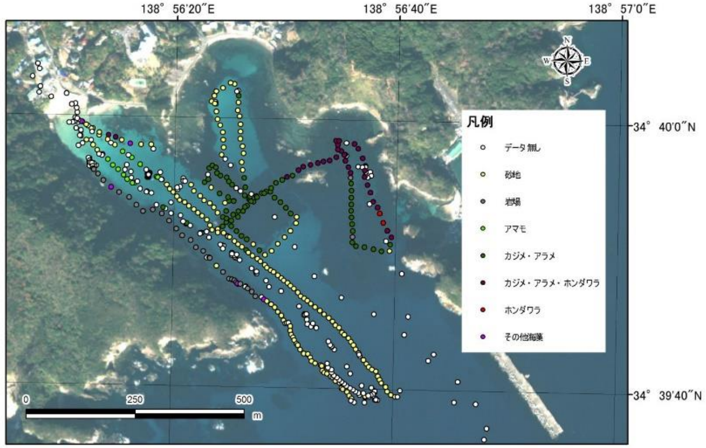
Field Survey to link satellite data with reality

Aquatic Video Camera or Glass Box observation from the boat

- We can know seagrass or not but difficult to know the species.
- Much more points we can survey comparing with field survey.
- It is difficult to measure accurate position for deep water (> 5m).







WorldView-2(c) DigitalGlobe, Inc.

Classification Accuracy

Classification Accuracy is calculated using error matrix (or confusion matrix).
The proportion of pixels correctly classified is called ‘overall accuracy’.
It is desirable to calculate Kappa coefficient or Tau coefficient in addition to overall accuracy.

	Reference			
Classification	**Seagrass**	**Sand**	**Row Total**	**User Accuracy (%)**
Seagrass	280	256	536	52.2
Sand	171	995	1166	85.3
Column Total	451	1251	1702	
Producer Accuracy (%)	62.1	79.5		
Overall Accuracy (%)	74.9			
Tau coefficient	0.542			

Overall accuracy = Number of correctly classified pixel / Total number of reference pixel = (280+995)/1702 = 74.9
Producer accuracy = Correctly classified reference pixel for each class / Total number of reference pixel for each class
User accuracy = Correctly classified reference pixel for each class / Total number of classified pixel for each class

Classification Accuracy

Kappa analysis is a discrete multivariate technique used to assess classification accuracy from an error matrix. Kappa analysis generates a Khat statistic or Kappa coefficient (K) that has a possible range from 0 to 1.

$$K = \frac{N \sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_{i+} . x_{+i})}{N^2 - \sum_{i=1}^{r} (x_{i+} . x_{+i})}$$

where r = number of rows in a matrix, xii is the number of observations in row i and column i, xi+ and x+i are the marginal totals of row i and column i respectively, and N is the total number of observations (accuracy sites).

Classification Accuracy

Ma and Redmond (1995) recommended use of the Tau coefficient (*T*) in preference to the Kappa coefficient. The main advantage of Tau is that the coefficient is readily interpretable. For example, a Tau coefficient of 0.80 indicates that 80% more pixels were classified correctly than would be expected by chance alone.

$$T = \frac{P_o - P_r}{1 - P_r} \text{ where } P_r = \frac{1}{N^2} \sum_{i=1}^{M} n_i . x_i$$

Po is the overall accuracy; M is the number of habitats; i is the ith habitat; N is the total number of sites; ni is the row total for habitat i and xi is the diagonal value for habitat i (i.e. number of correct assignments for habitat i).

RESTEC

Sense your Earth