


Remote Sensing and GIS
Prof. Rishikesh Bharti
Department of Civil Engineering
Indian Institute of Technology – Guwahati


Lecture – 19
Hyperspectral Remote Sensing - IV

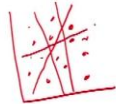
In this lecture we will continue our hyper spectral remote sensing topic. So let us start with the SVM support vector machine.

(Refer Slide Time: 00:39)

Support Vector Machine (SVM)


भारतीय प्रौद्योगिकी संस्थान गुवाहाटी
INDIAN INSTITUTE OF TECHNOLOGY GUWAHATI

- ❖ SVM optimizes linear separation/classification of datasets in feature space.
- ❖ The basis of classification lies in the notion that only the datasets lying on the class boundary are necessary for discrimination.
- ❖ This task is done by a best suited hyperplane that segregates the datasets.
- ❖  A best suited hyperplane is the one with maximum margin.
- ❖ Maximization of margin can minimize the problem of misclassification.



REMOTE SENSING AND GIS

Dr. R. Bharti

So, what exactly support vector machine is and how we can use this for our data classification right? So SVM optimizes linear separation or classification of data set in feature space. The basis of classification lies in the notion that only the Data Sets lying on the class boundaries are necessary for discrimination right.

So, here we are taking the example of two feature classes and then in between we can put a hyper plane or in simple word, we can say we are putting a line to segregate these two classes. So, this task is done by the best suited hyper plane that segregates the data set. So, basically hyper plane is nothing but the boundary we are drawing between two different types of data set present in the input data right.

The best suited hyper plane is one with maximum margin. Just imagine a case where you have two classes and in between you can or you will be able to draw a line which can

separate these two classes right. And the best line will be the one with both classes have equal distance or some separate Right. So, that is what I am trying to tell you here.

So, the best suited hyper plane is one with maximum margin maximization of margin can minimize the problem of Mis-classification. So, just assume you have this input data set right. Now, how can you draw a line or how can you segregate this into two classes. So, either by drawing a line here or by line here or by line here. So, in any of these cases, you will end up with two different classes.

Whether these classes whatever you have identified whether they are correct or not that we need to say that is why we have to use some logic. Accordingly we will decide where our hyper planes should be right.

(Refer Slide Time: 02:58)

Support Vector Machine (SVM)

Let us take example of two feature sets randomly distributed in 'n' dimensional space.

Training datasets are plotted as

$\{x_i, y_i\}$ where $i = 1, \dots, k$ and $y_i \in \{-1, 1\}$ in n-D space.

Mathematically selecting the optimized hyperplane follows two conditions:

1. Datasets belonging to a class should lie to the same side of the hyperplane
2. Distance between the closest dataset of either class and the hyperplane should be as large as possible.

Since hyperplane is a line on a 2-D represented space, the general equation can be written as,

$$m.x + c = 0$$

REMOTE SENSING AND GIS

Dr. R. Bharti

So, let us take Example of two feature set randomly distributed in n-dimensional space. So, training datasets are plotted as this right and where i is one to k right in n-D space. Mathematically selecting the optimized hyper plane follows the two conditions. First one is data sets belong to a class of light to the same side of the hyper plane right. So, here this is what written the second case is distance between the closest data set of either class or the hyper plane should be as large as possible, right. Since hyper plane is a line on a 2D represented space the general equation can be written as this and this is nothing but the “mX + c” right.

(Refer Slide Time: 03:59)

Support Vector Machine (SVM)



$$m \cdot x + c = 0$$

where x is a point lying on the hyperplane, m is normal to the hyperplane, $\frac{|c|}{\|m\|}$ is the perpendicular distance from the hyperplane to the origin. $\|m\|$ is the Euclidean norm of m .

For linear segregation, the hyperplanes separately defined as:

$$m \cdot x_i + c \geq +1 \text{ (for } y_i = +1) \quad \checkmark \quad \text{----- for Class A} \quad \checkmark$$

$$m \cdot x_i + c \leq -1 \text{ (for } y_i = -1) \quad \checkmark \quad \text{----- for Class B} \quad \checkmark$$

Combining the conditions for the two classes:

$$y_i(m \cdot x_i + c) - 1 \geq 0 \quad \text{----- eq. (1)}$$

So, where x is a point lying on the hyper plane M is normal to the hyper plane and $|c|/\|m\|$ is the perpendicular distance from the hyper plane to the origin and norm M is the Euclidean norm of M right. So, I hope this is clear. Now, for linear segregation, the hyper planes separately defined as this $mX + c$ this is the form now, here for y_i , we have a range from -1 to +1 right.

So, this is the Class A in the next class we have this -1 that is the class for B So, combining these two equation from this and this, we have arrived at this particular equation, right.

(Refer Slide Time: 04:58)

Support Vector Machine (SVM)



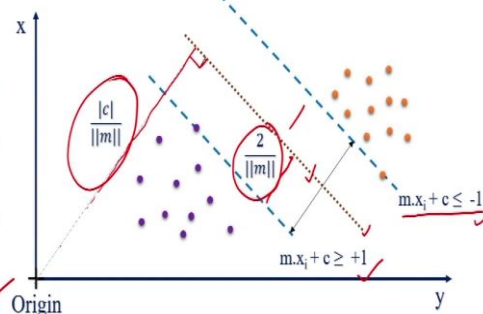
The training data points on these two hyperplanes are called as support vectors and are central to the optimized hyperplane.

The margin between these planes is $\frac{2}{\|m\|}$

The maximization of this margin leads to the following constrained optimization:

$$\min \left\{ \frac{1}{2} \|m\|^2 \right\} \quad \checkmark$$

under the inequality constraints of eq. (1) \checkmark



The training data point on these two hyper planes are called as support vectors and the central line which we were calling hyper plane, right. So, let us see this example. Here assuming we

have very two distinct type of classes in the input data. And it is very easy to draw a line here because both are separated with some distance both means, both classes. Now, here the margin between these planes is $2/\|m\|$.


So, this is what we are trying to draw and the hyper plane will be in the centre right. So, if you see from origin I have drawn this line right. So, this line is meeting here and once we have this perpendicular then the distance will be $|c|/\|m\|$, and here, this is the distance between hyper plane and these two support vectors. So, this is $2/\|m\|$. So, here also you will have the same.

And this is the condition for right hand side of this hyper plane where y_i is minus one and here y_1 is $+1$. So, the maximization of this margine leads to the following constraint optimization that is using this one and this is under the equality constraint of equation when the previous one which we have derived or which we have arrived by using this $y_i = +1$ and $y_i = -1$.

Till now I discussed the ideal condition where both the classes are very far from each other and it is very easy to draw a line right. But what about in natural condition or what about your remotely sensed image where you want to derive may be n number of classes, so and may be 2, 3, 4, 5 or 6 classes or maybe 10 classes, then how do we distinct or how do we draw this hyperplane?

(Refer Slide Time: 07:16)

Support Vector Machine (SVM)

 भारतीय प्रौद्योगिकी संस्थान गुवाहाटी
INDIAN INSTITUTE OF TECHNOLOGY GUWAHATI

Generally, classes are linearly non-separable and thus constraints of eq. (1) cannot be satisfied.

To overcome this problem, new set of variables called as Slack variables are introduced.

$$\{\xi_i\}_{i=1}^Z$$

Thus, eq. (1) changes to


$$y_i(m \cdot x_i + c) > 1 - \xi_i \quad \text{----- eq. (2)}$$

Above equation is justified in case of outlier when ξ_i are very large and a penalty term $C \sum_{i=1}^Z \xi_i$ is added to penalize solutions for which ξ_i are very large.

REMOTE SENSING AND GIS
Dr. R. Bharti

So, generally classes are linearly non separable and this constraint of equation-1 cannot be satisfied right remember that equation-1 when to overcome this problem new set of variables are introduced which is known as slack variables which is this one right. This equation-1 when get changed to this one where this ξ is introduced? Ever the equation is justified in case of outlier when ξ_i are very large and a penalty term this one is added to penalize solution for this ξ_i are very large. So, there is very simple method only thing is you need to understand and you need to change this slightly or you can mould this method according to your application.

(Refer Slide Time: 08:17)

 भारतीय प्रौद्योगिकी संस्थान गुवाहाटी
INDIAN INSTITUTE OF TECHNOLOGY GUWAHATI

Support Vector Machine (SVM)

$$C \sum_{i=1}^n \xi_i$$

Constant C governs the magnitude of the penalty associated with training samples that does not lie on the appropriate side of the decision boundary.

With large value of C , there is a possibility of SVM over-fitting and with small value of C , an inappropriately large a fraction of support vectors may be derived.

With the addition of the penalty term, the optimization problem becomes

$$\min \left\{ \frac{\|m\|^2}{2} + C \sum_{i=1}^n \xi_i \right\}$$

Here, $\frac{\|m\|^2}{2}$ tries to maximize margin whereas $C \sum_{i=1}^n \xi_i$ tries to penalize the cases not located on the appropriate side of the decision boundary.


If the classes are overlapping in feature space, then $C \sum_{i=1}^n \xi_i$ can be too large and the hyperplane may not generalize well.

REMOTE SENSING AND GIS
Dr. R. Bharti

So, here the constant C , again we are going to introduce this constant C that governs the magnitude of the penalty associated with training samples. That does not lie on the appropriate side of the decision boundary with large value of C , there is a possibility of SVM overfitting and with a small value of C and in appropriately large a function of Support Vector may be derived with the addition of the penalty term the optimization problem become this right. Here the $\|m\|^2/2$ tries to maximize margine where this tries to penalize the cases not located on the appropriate side of the decision boundary. So, that is how we are going to improve our method in each of the iteration. If the classes are overlapping in feature space, then this can be too large and the hyper plane may not be generalized well.

(Refer Slide Time: 09:34)

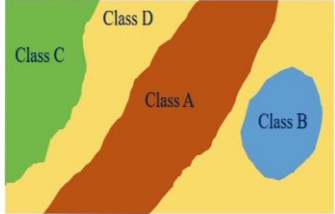
Support Vector Machine (SVM)



भारतीय प्रौद्योगिकी संस्थान गुवाहाटी
 INDIAN INSTITUTE OF TECHNOLOGY GUWAHATI

- ❖ SVM perform very well for two different feature classes,
- ❖ In the classification of remote sensing images, SVM can be used for more than two classes,
- ❖ A very common techniques is 1AA technique (Melgani and Bruzzone, 2004),
- ❖ 1AA approach is simply division of an N-class dataset into N two-class cases,
- ❖ If there are 4 distinct classes (A, B, C & D), classification would be affected by classifying Class A against non-Class A areas or Class B against non-Class B and so on.

✓



REMOTE SENSING AND GIS
Dr. R. Bharti

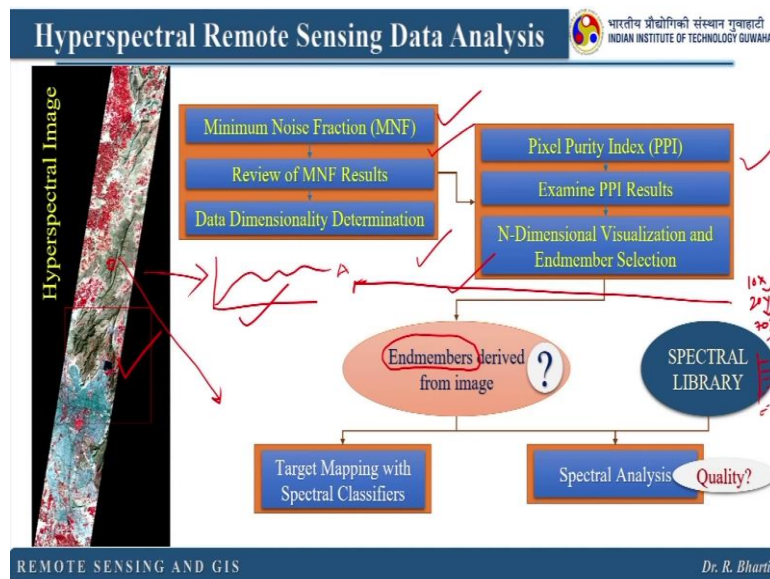
So, let us see what are the advantages we have when we are using this support vector machine? Right so, as we know that support vector machine performs very well, for two different features classes, in the classification of remote sensing images SVM can be used for more than two classes, right. Because that is the regular practice we generally want to derive more classes from a remotely sensed images.

A very common technique is 1AA technique right the 1AA approaches simply division of an N-class dataset into N two-class cases. This example I have put to explain what exactly and how exactly we are performing this support vector machine. So, if there are four distinct classes, namely A B C and D classification would be affected by classifying Class A against non-Class A areas or Class B against non-Class B and so on. So, here basically we start with one class and the rest all are in one class.

So, ultimately you will get two classes then further we introduce the next class and the rest other classes will be considered in one group right. And so on we derive this SVM support vector machine hyper plane and then once the iteration is over, then you will finally get the four classes and that is expected to be good so till now, I have introduced a different methods, different procedures how to analyse this hyper spectral remote sensing data.

Now, let us see how exactly we are performing this right. So, I am not going to show you any software related thing this is only related to the methodology right. So, the concept you need to understand. So, let us start with this.

(Refer Slide Time: 11:44)



This is a hyper spectral data captured by Hyperion sensor, which is available in this space. Nowadays, it is not in working condition, but this is from the archive data. So, you can see this is only three band your See because for colour composite we need at least three band then only you can represent any data, but rest all other bands all 242 bands are in the background. So, whenever you click on any of the pixel of this image you will get 242 spectral values right. So, then you can easily identify what the material is, but exactly how.

So, for this data analysis, as we have already discussed, this MNF has to be performed and the inherent data dimensionality need to be identified. Once we are done with that, then we go to PPI pixel purity index, and then we derive the end members. And once we have the endmember, then we use that endmembers to classify this particular image. Right and once we classified, then you can analyse the result and you can estimate the accuracy of your data.

But, here we have identified end member from the image itself. So, how do we know what chemical composition or what the material is right. Because that is very important to understand, then only you can say, each pixel of this image which belongs to first endmember has this chemical composition unless until you do not perform a spectral analysis of the end member extracted from the image you cannot say what is the chemical composition? Or, what material or object is right. So, for that we need to use a spectral library that is very important you cannot avoid this step. So, now here what we are going to do we are going to use this spectral library is spectra which is expected to be pure or which is captured of pure materials. And then you will use the image derived endmembers together.

And you will try to match these two and you will find the best match with the different mixing of the library spectrum. So, once you find a particular mix, which is matching well with your image derived endmember that means, that spectra whatever you have mixed in different proportion that will give you the chemical composition of the end member extracted from the image.

I hope this is clear. I will try to explain one more time. So that you should not have any confusion in this. So basically by performing this and this ultimately we have got the end member right and let us assume this is the end member from this particular image by following this procedure. Once we know this is end member A let us call it A then we perform spectral classification.

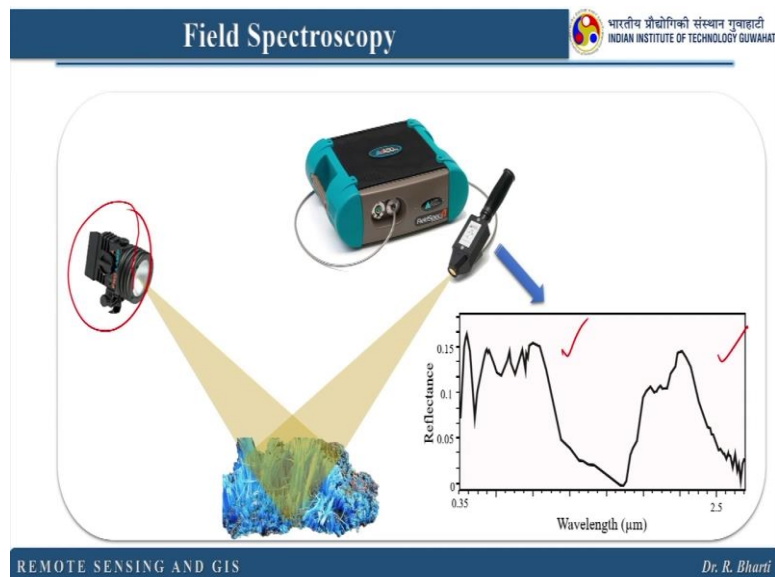
Like SVM or any other method you can use here or SFF by doing so, you will get an output that will do your classified image. So, each pixel will either belong to A B or C whatever end member you have provided, and which was extracted from the image itself right and which was expected to be pure. But pure means what we don't know what is the chemical composition or what material you are or what pixel you have selected and what is the chemical composition of that pixel. So to know that we need to use a spectral library. And how do we generate a spectrum library, we collect a pure mineral or vegetation or maybe object and we collect the spectral signature, we save it in a library. And then when time comes to analyse your end members, which was extracted from the image, we use such libraries.

And we try to match the spectral library spectra and end member derived from the image in different proportion. So here, you will mix the spectral library spectra in different proportion. And then you try to match with this. Then if you find that 10% of X, 20% of Y and 70% of the head is matching well with your A that means this particular pixel which is here contains 10% of X, 20% of Y and 70% of Z right.

So that is why we are going to perform the spectral analysis. So, this is very, very important. Unless until you do not do this you cannot show the result whatever you have derived from this image in addition to that, the quality of this spectral library that also matters, because the

way you have collected the spectrum to generate your spectral library that also plays a very critical role here.

(Refer Slide Time: 17:48)



So, now let us understand, how do we generate this spectral library and what are the parameters which we need to take care. Because once you have a perfect spectrum library or a standard spectrum library. You can use those spectrum to analyse your image. Now, here this is the example of filter spectroscopy, you are familiar with this image right here, either we will do this measurement in sunlight or maybe with a lamp.

So controlled environment and then we measure the spectra, which is here through this spectroradiometer. So, this is just for the example, the instrument photograph is just to show you how this is done in the field and in the lab. This is not to support any company right. So, ultimately we have got this spectral feature with which is captured from your spectroradiometer.

(Refer Slide Time: 18:56)

Field Spectroscopy	
❖ Since Newton's discovery of composite nature of white light in 1664, spectroscopy has been used to study properties of terrestrial and extraterrestrial objects.	
❖ All organic and inorganic substances exhibit diagnostic spectral features throughout the electromagnetic spectrum that enable identification of chemical composition and relative abundance of constituents.	
❖ Diagnostic spectral absorption features of natural and manmade materials are mainly governed by electronic and vibrational processes.	
❖ With the advent of Imaging Spectroscopy or Hyperspectral Remote Sensing (HRS) by combining spectroscopy and imaging technologies, lithological discrimination and mineral potential mapping were possible from the space and airborne platforms.	
❖ Hyperspectral Remote Sensing is extensively used for lithological discrimination and mineral potential mapping.	
REMOTE SENSING AND GIS	Dr. R. Bharti

Now, let us see why we exactly involve in spectroscopy. To since Newton's discovery of composite nature of white light in 1664 spectroscopy has been used to study properties of terrestrial and extra-terrestrial objects right. All the organic and inorganic substances exhibit diagnostic spectral feature throughout the electromagnetic spectrum that enables identification of chemical composition and relative abundance of constituents.


Diagnostic spectral absorption feature of natural and man-made materials are mainly governed by electronic and vibrational processes right. With the advent of imaging spectroscopy or hyper spectral remote sensing by combining the power of spectroscopy and imaging technology.

Lithological discrimination Mineral potential mapping and there are many other application where possible from space and airborne platforms. So, this is just to give you a flavour or the background of this particular method. Why it is so powerful and how we are using this right. So, hyper spectral remote sensing is extensively used for Lithological discrimination and Mineral potential mapping.

Let us see some critical information which you need to know before you start using this hyper spectral technology. The accuracy of identification and abundance estimation from a hyperspectral remote sensing depends on the quality of spectral library. This is what I highlighted in previous slides right. Therefore, a well characterized spectral repository of material or object with their physical, chemical and mineralogical details is need to be generated.

(Refer Slide Time: 21:13)

Field Spectroscopy



भारतीय प्रौद्योगिकी संस्थान गुवाहाटी
INDIAN INSTITUTE OF TECHNOLOGY GUWAHATI

- ❖ The accuracy of identification and abundance estimation from HRS depends on the quality of the spectral library.
- ❖ Therefore, a well-characterized spectral repository of materials/objects with their physical, chemical and mineralogical details is need to be generated,
- ❖ The reflectance spectra are significantly influenced by several parameters such as,
 - ✓ Instrument calibration,
 - ✓ Source-sensor geometry,
 - ✓ Roughness of the surface,
 - ✓ Anisotropy of investigating surface,
 - ✓ Field of View (FOV),
 - ✓ Spectral analysis techniques.

- ✓ A standard protocol of spectral acquisition needs to be followed to match the field spectra with the spectra measured from space.
- ✓ This will provide reliability to collected spectra.

REMOTE SENSING AND GIS

Dr. R. Bharti

The reflectance spectra are significantly influenced by several parameters such as instrument calibration, Source sensor geometry, roughness of the surface, Anisotropy of investigating surface, field of view and spectral analysis technique. So, all these listed parameters plays a very critical role in this spectroscopy. Now let us see one by one why they are so important when we talk about instrument calibration. This has to be performed before your spectral measurement.

I hope you remembered the lecture where I have explained the working Principle of spectroradiometers. So there do you remember that I explained dark current right. Where we used to measure the signal emitted by the instrument itself right. So that is why I am mentioning here instrument calibration is very important. Next point is source sensor geometry. So, if you remember my previous lectures, suppose this is how your surface is illuminated.

So here you have sun or maybe a source lamp, which is illuminating this particular surface. And this particular direction is used to measure the reflected energy. So, what if we change our position from here to here that reflected amount will be different, because surface is not isotopic. So, that is why we need to take care of this source sensor geometry in addition to the field of view.

Because here we are talking about the field spectroscopy. So, here you have a certain field of view, which can be used and then accordingly you fix this h so it will cover your target. In

case if you increase the height, then it will cover more than your object and you will end up analysing the wrong object right or maybe the mixed spectra. So, that is why it is very important to take care of this source sensor geometry.

There is one more interesting fact that satellites are seeing our Earth's surface or maybe any other planet with certain angle right. So that angle and the field measured spectra angle has to be same or the lab spectral measurement has to be same, then only you can match this field acquired or the lab acquired spectra with the satellite spectra right. So, otherwise what will happen?


You will have different response from the same material because your look angle source sensor geometry was different. Now, the next point is roughness of the surface. So, here the surface roughness plays very critical role, why? Because that will introduce the BRDF concept. Now, next is anisotropy of investigating surface, the composition of the material also controls this particular measurement right.

So, if the material is bright, it will emit or it will reflect more and the next one is field of view so I have already explained here then spectral analysis technique, what technique what method you are using to analyse this is spectra with respect to library spectra right. So, these two things are very, very important. A standard protocol of spectral acquisition need to be followed to match the field spectra with the spectra measured from space.

Why because you need to have this similar mechanism or similar protocol or similar method of the spectral measurement in your lab and as well as in your field then only you can upscale this information to satellite scale. This will provide reliability of collected spectra. So, once you have followed the standard protocol, then you can match your method is spectra with any other spectra measured elsewhere right.

If both of them are measured using some standard protocol right so what advantages we have when we are involved in Field spectroscopy? So, that is why I have put this question.

(Refer Slide Time: 26:15)

Field Spectroscopy

भारतीय प्रौद्योगिकी संस्थान गुवाहाटी
INDIAN INSTITUTE OF TECHNOLOGY GUWAHATI

✓ WHY FIELD SPECTROSCOPY?

- ❖ Provides full control,
- ❖ Known instrument and its sensitivity,
- ❖ Source-sensor geometry,
- ❖ Spectral measurement strategy,
- ❖ Dynamic field conditions can be addressed,
- ❖ Direct measurement of radiance, downwelling radiance, irradiance and surface reflectance.
- ❖ Spectral library: Information to upscale the lab/field information to satellite scale.

REMOTE SENSING AND GIS
Dr. R. Bharti

Why field is spectroscopy? So, it provides you full control of this acquisition process. So, you have full control on the instrument, you know, whether it is working well or not, what is the weather condition what is the time when you want to measure what is the object which you are trying to look?

Because you can adjust the height and the field of view right. The second point is known instrument and its sensitivity whether your instrument is sensitive enough to capture may be hundreds of spectra in one second right. So, those information is are available to you when you are involved with field Spectroscopy or lab spectroscopy. Source-sensor geometry you have full control spectral measurement strategy.

How frequently you want to measure at what time you want to measure, what target you want to measure everything you can decide dynamic field condition can be addressed, because if you see morning 9 o'clock 12 o'clock and evening 5 o'clock the illumination conditions are different weather condition is different. So accordingly you can decide whether you want to collect this spectra or whether you want to have the spectra in this particular condition.

Yes or no? That is your decision right direct measurement of radiance, downwelling radiance, irradiance and surface reflectance can be done here. In remotely sensed image if you want to calculate surface reflectance you need to model this complete atmosphere. But here since your distance between the target and the sensor is very, very less. So, it is expected that influence is or the influence of atmosphere is negligible right.

So, it also depends what is the weather condition what is the instrument which is used. So, all these parameters play a very critical role and that advantage we have when we are involved in field spectroscopy and ultimately we can generate the spectral library. So, that is the information required to upscale the lab or field information to satellite scale. There are different spectral libraries available for Earth and planetary exploration.

That is from different universities different organization which are listed here. I will show you one by one. If you want to access them, you just visit their website and follow these set of instructions, either you have to enroll or in other words, you have to do the registration and then you can download the data, or else they might have instructed how to get or how to access their data set. So, I am just trying to tell you.

(Refer Slide Time: 29:17)

The slide is titled "Spectral Library" and features a list of spectral libraries with checkmarks. At the top right is the logo of the Indian Institute of Technology Guwahati. At the bottom, it says "REMOTE SENSING AND GIS" and "Dr. R. Bharti".

- ✓ The United States Geological Survey (USGS) spectral library,
- ✓ The John Hopkins University (JHU) spectral library,
- ✓ The Jet Propulsion Laboratory (JPL) spectral library,
- ✓ ASTER spectral library: a compendium of data from JPL, JHU and USGS libraries in a standard data format,
- ✓ Arizona State University (ASU) library for planetary exploration,
- ✓ Emission and Reflectance Spectral Library (EARS�) by the Council of Industrial Research Organisation (CSIRO), Australia,
- ✓ Reflectance Experiment Laboratory (RELab) spectral library.

Spectral libraries may have been generated with different source sensor geometry, sampling rate and spectral spread...


What are the different options available to you? When you are involved in Earth and planetary exploration. The first library is from USGS, the United States Geological Survey spectral library. The next is JHU that is John Hopkins University spectral library. The third one is the Jet Propulsion Laboratory that is known as JPL spectral library.

The next spectral library is ASTER spectral library. That is a compendium of data from JPL JHU and USGS library in a standard data format, right. So these you can access by contacting them. Then next is ASU, Arizona State University Library for planetary exploration. Then you have EARS� emission and reflectance spectral library by the Council of Industrial Research Organization.

CSIRO Australia and the last one in this list is RELab reflectance experimental laboratory. So, all these libraries are developed by using different sets of protocol different instrument different field of view different samples. So, whenever you are involved in using this one, then you need to take care of this source sensor geometry, sampling rate and a spectral spread which have been used while generating this spectral library. Otherwise, again you will introduce more error in your analysis. So that is why I have written here.

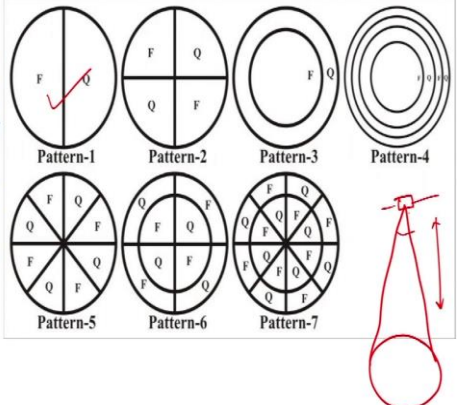
(Refer Slide Time: 31:01)

Spectral Measurement


 भारतीय प्रौद्योगिकी संस्थान गुवाहाटी
 INDIAN INSTITUTE OF TECHNOLOGY GUWAHATI

Grain-size, fabric, and composition significantly influence reflectance and emission spectra.

Rishikesh Bharti, D. Ramakrishnan, K.D. Singh and M. Nithya, Relevance of Mineral Texture on Bidirectional Reflectance and Emission Spectroscopy: Implications for Geological Remote Sensing. Geoscience and Remote Sensing Symposium (IGARSS), IEEE International, 22-27 July 2012, 3046-3049.



REMOTE SENSING AND GIS
Dr. R. Bharti

Let us see some of the constraint when we are involved in spectral measurement. So, I will explain you some of the research and then you will get to know what are the different constraints are available or what are the different constraints in hyperspectral remote sensing.

So, here I want to highlight this grain size fabric and composition significantly influenced reflectance and emissions spectra right. So, here you can see there are seven different patterns which I have used to generate the spectrum library right. So, here just to explain this, you just consider when you are having this particular pattern at particular height I have fixed my sensor right.

So this is your h and this field of view is known so just to make sure you need to calculate $2\tan(\theta/2)$ and you can focus on your target right. And by this way, I have generated different spectral library of these seven patterns. So, here the total amount of quartz and feldspar was same, only thing is their arrangement was changed right. So, for this purpose, we have used a goniometer.

(Refer Slide Time: 32:32)

Goniometer
भारतीय प्रौद्योगिकी संस्थान गुवाहाटी
INDIAN INSTITUTE OF TECHNOLOGY GUWAHATI

Developed and patented by D. Ramakrishnan (2012). Wide-field goniometer for spectroscopic measurement of albedo and emissivity in laboratory and field.

Prof. Desikan Ramakrishnan
Professor, Department of Earth Sciences
Indian Institute of Technology Bombay

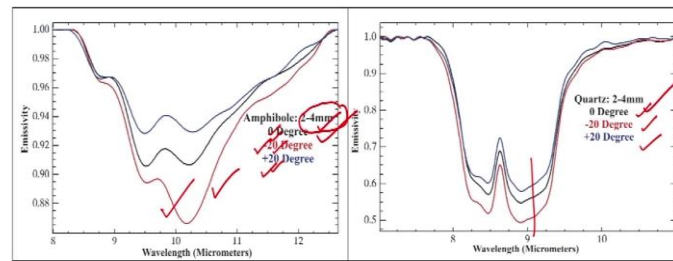


REMOTE SENSING AND GIS
Dr. R. Bharti

And here this goniometer is basically developed and patented by Prof. D. Ramakrishnan. He is a professor in Department of Earth Sciences IIT Bombay. So, you can see this attachment here you can use to focus your fibre optic cable to your sample, so sample was somewhere here, right in the centre. And here you have flexibility to change or to rotate the position of this particular sensor in this direction as well as in this direction.

So, you have full control on azimuth and zenith. For more detail about this work you can refer this paper by using this goniometer and the previously shown seven different arrangement of the same quantity of quartz and feldspar the spectra were measured. Once your sensor is at zero degree that means it is nadir looking that we considered as 0 and when you are moving in this direction and this direction, so you can exactly know where is your 20 degree right.

(Refer Slide Time: 33:52)



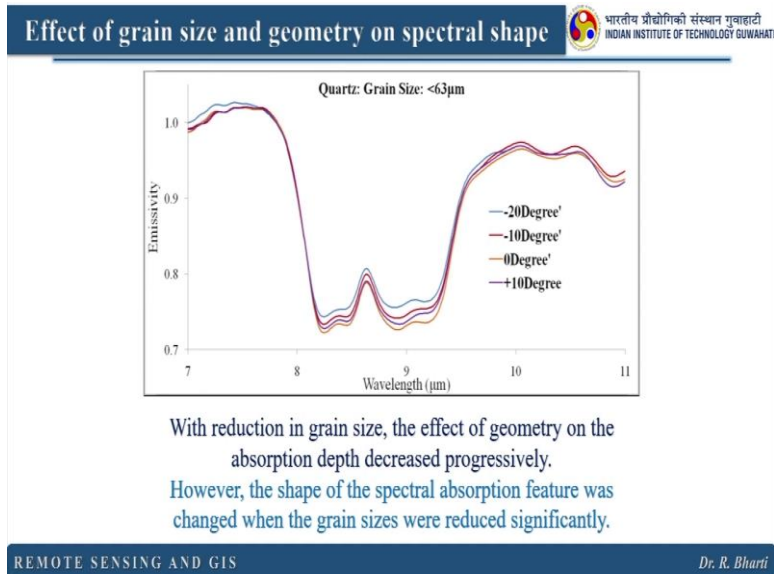
Independent of grain size, the geometry also affects the depth of absorption features

So by doing or by using this instrument, we have measured the Amphibole spectra of 2-4 mm grain size from 0 degree that is nadir looking and then -20 degree and +20 degree in both sides right. And here you can see for the same sample, when you are changing the position of measurement, the spectral response is different but remember here only the depth of the absorption is getting changed.

So, that means if you have measured the spectra in different angles, you can easily find out what material it is, but when you want to estimate the composition, then it may give you some wrong result right in another experiment, where we have used quartz 2-4 mm and again 0 degree, -20 degree and +20 degree and then, we have got this spectra again there is a change or there is a shift in the intensity.

So, only the intensity is changing right. So independent of grain size the geometry also affect the depth of absorption feature.

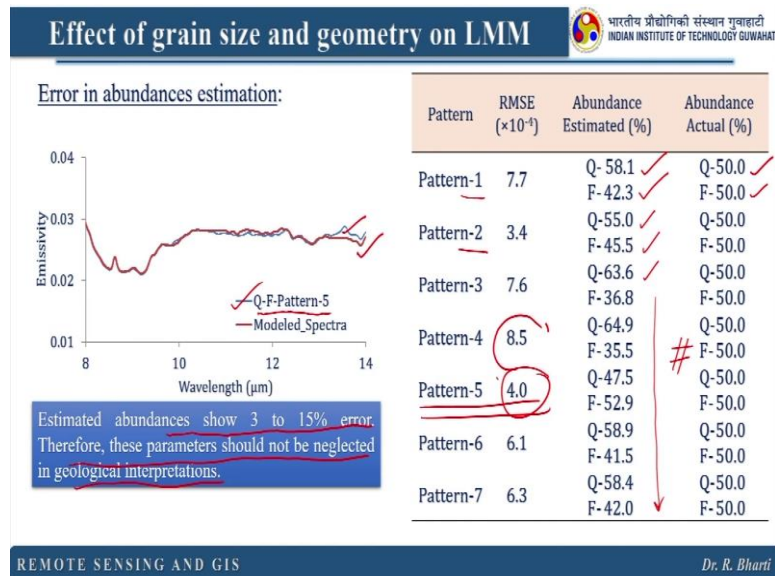
(Refer Slide Time: 35:08)



That is the result of this experiment. Now, if you want to see the effects of grain size and geometry on spectral shape just see this spectral response, where we have used quartz and the grain size was 2mm to 4mm and here we have 0, 10 degree, 20 degree in both the direction right. And here you can see in all the cases you have different spectral response, but remember position is not changing only the intensity is changing right. With reduction in grain size, the effect of geometry on the absorption depth decreases progressively.

However, the shape of spectral absorption feature was changed when the grain sizes were reduced significantly. The next graph shows the quartz grain, but the size is changed 0.7 to 2 mm. And here also we have 0, 10 and 20 right. So, you can see the result here in the third case, where the size was less than 63 micro meter. Now here you see so does not matter what exactly your grains are, but this explains, with reduction in grain size, the effect of geometry on absorption depth decreases progressively however, the shape of spectral absorption feature was changed when the grain sizes were reduced significantly right.

(Refer Slide Time: 36:54)



Now, what exactly we have done by measuring this information, we have tried to estimate the error introduced by this grains and arrangement right. So grains and geometry. So, here the first pattern, where we have used 50% of feldspar and 50% of quartz and then we try to simulate this and we tried to match this with the measured spectra and then we found that from the estimated one quartz is coming 58.1% feldspar is 42.3%.

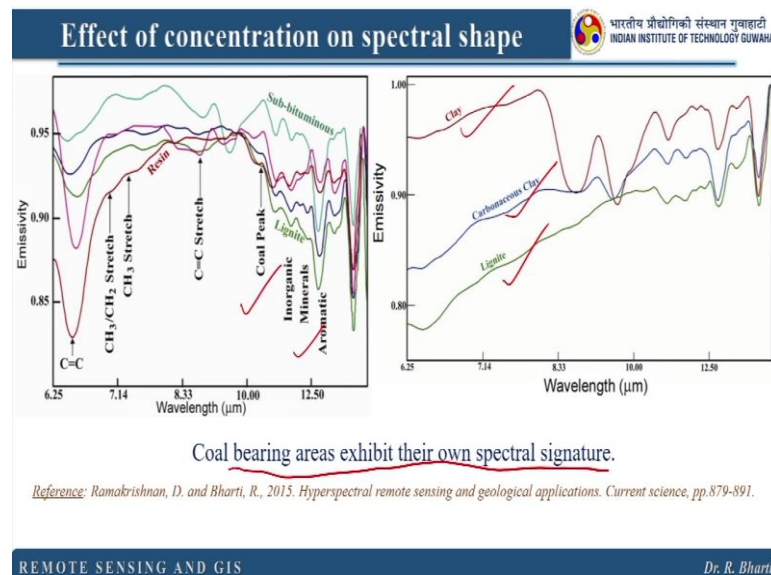
That means, there is a error in abundance estimation why so because when we are changing the grain sizes and when we are changing the geometry, it has their own effects now in the second pattern also, you see it is 55 45.5 here it is 63. So, you can see here all these values are not close to this that means you are having significant error in the abundance estimation. You can see here when we are talking about Pattern-4.

So, Pattern-4 is having maximum error right RMSE error, if you want to visualize how exactly these errors are coming. So, you can see here this is quartz feldspar Pattern-5 and so, this is for this one right here. The blue colour is the measured one and red is basically your modelled spectra. So, both are having the RMSE of four. So estimated abundances, so, 3 to 15% error therefore, these parameters should not be neglected in Geological interpretation.

So, this is from this paper, but as we know that this grain size and geometry plays very critical role. So, it is not only in geological interpretation, but in any other application, the source sensor geometry, grain size so, these plays very critical role they play very critical role and they need to be taken care while measurement. In this slide I want to highlight what is the strength of field spectroscopy or hyper spectral remote sensing technique.

So, the effect of concentration can be seen here. So, this is the suspended sediment concentration measured in the water and corresponding spectra were measured.

(Refer Slide Time: 39:40)



So, you see, this particular colour is showing 500 ppm that means, the water container was having 5 hundred ppm of suspended sediment concentration and then spectra was measured. So, similarly, we have generated for all these different composition right. This work is published in this particular journal right.

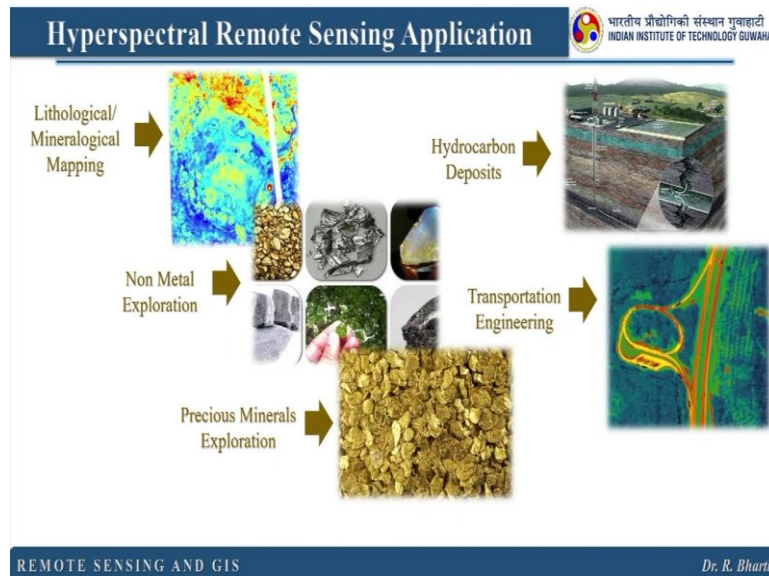
Now, you can access this I have one more figure for you here also you can see in different concentration, how this suspended sediments are behaving and what is their spectral signature right. And we have used this particular information to map this suspended sediment concentration in different classes you can see here the ranges are written right.

So, this is just to give you a flavour how are what is the strength of this hyper spectral remote sensing up to what extent you can use and what are the limitation or what are the different parameters which you need to take care before the measurement right. This is another example from coal. So, here you can see the coal bearing areas exhibit their own spectral signature. And here we have given all the details of this coal spectra right.

So, here you have clay, carbonaceous clay, lignite, how they are different from each other, they are found in the same environment in the same place, but their spectral signatures are different. So, you can use such information to map the way we have mapped the suspended

sediment concentration right. Let us see what are the different potential areas or the potential application of hyperspectral remote sensing data. So, the first one is lithological or mineralogical mapping right.

(Refer Slide Time: 42:03)



Next one is non-metal exploration, then precious mineral exploration, hydrocarbon deposits, you can also investigate this one I will cover some of them in application part. Then transportation engineering you can easily identify which vehicle is parked since may be one week or which is parked just now, what is the road condition? Those information you can derive from this hyper spectral remote sensing.

(Refer Slide Time: 42:32)

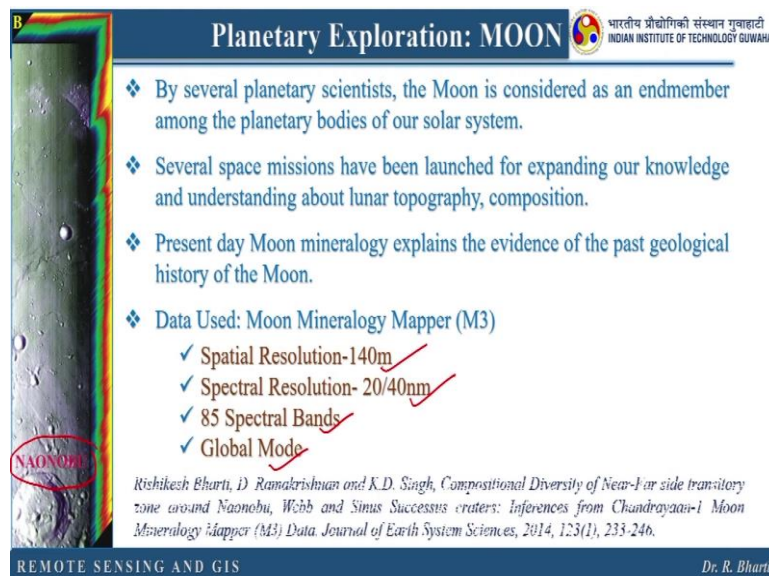


Then crop monitoring, surface deformation, then volcano whether it is active or inactive, what is the stage of this volcano, right? Then land slide mapping, then planetary exploration

and quality control and grade assessment. So, some of these application may not require the data directly from this hyper spectral remote sensing, but one of the parameters which plays very critical role in that application can be derived from this hyper spectral remote sensing right.

Now, let us see how we evolve over the time. So, first for planetary exploration, we started with telescope, then Hubble Space Telescope, then flyby mission, then orbiter mission then landers and rovers, then manned missions. So, this is how we are evolving ourself. So, it is necessary to update ourselves to know the latest techniques and use them in your application. Right. Let us see how this hyperspectral remote sensing data are used in Lunar exploration right.

(Refer Slide Time: 43:58)



Planetary Exploration: MOON

भारतीय प्रौद्योगिकी संस्थान गुवाहाटी
INDIAN INSTITUTE OF TECHNOLOGY GUWAHATI

- ❖ By several planetary scientists, the Moon is considered as an endmember among the planetary bodies of our solar system.
- ❖ Several space missions have been launched for expanding our knowledge and understanding about lunar topography, composition.
- ❖ Present day Moon mineralogy explains the evidence of the past geological history of the Moon.
- ❖ Data Used: Moon Mineralogy Mapper (M3)
 - ✓ Spatial Resolution-140m
 - ✓ Spectral Resolution- 20/40nm
 - ✓ 85 Spectral Bands
 - ✓ Global Mode

Rishikesh Bharti, D. Ramakrishnan and K.D. Singh, Compositional Diversity of Near-Far side transitory zone around Naonobu, Webb and Sinus Successus craters: Inferences from Chandrayaan-1 Moon Mineralogy Mapper (M3) Data. Journal of Earth System Sciences, 2014, 123(1), 233-246.

REMOTE SENSING AND GIS

Dr. R. Bharti


So, by several planetary scientists the moon is considered as an endmember among the planetary bodies of our solar system. Several space missions have been launched for expanding our knowledge and understanding about lunar topography and composition. Present day moon mineralogy explain the evidences of past geological history of the moon, right and here in this particular example.

We will be using this Moon Mineralogy Mapper data that is commonly known as M3. And this is one of the example this is M3 hyper cube right. And this is for this particular area which is known as NAONOBU here, I have used this M3 data of global mode where I had this 85 spectral bands and the spatial resolution was 140 meters. Spectral resolution was 20 or

40 nanometer right that was the spectral resolution. And this work is also published you can refer that for more detail.

(Refer Slide Time: 45:15)

Radiance to apparent reflectance (I/F)



भारतीय प्रौद्योगिकी संस्थान गुवाहाटी
INDIAN INSTITUTE OF TECHNOLOGY GUWAHATI

$$\frac{I}{F} = \frac{\pi \times d^2 \times L_{rad}(\lambda)}{F_{sun}(\lambda) \times \cos(\theta) \times P}$$

where,

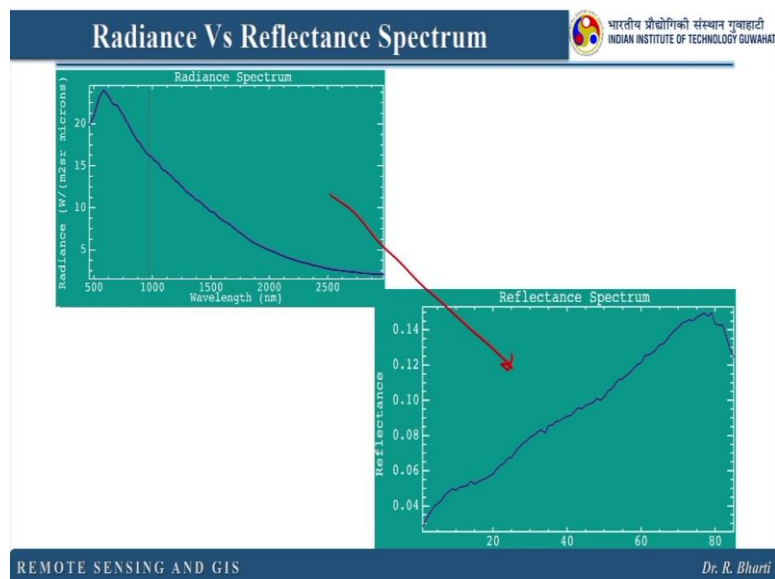
- $\frac{I}{F}$ = Apparent reflectance,
- $L_{rad}(\lambda)$ = Radiance value measured by M³ sensor as a function of wavelength,
- d = Distance from the Sun to the Moon (AU),
- $F_{sun}(\lambda)$ = Exo-atmospheric solar spectral irradiances as a function of λ ,
- θ = Solar zenith angle and
- P = Phase function correction (Unavailable).

REMOTE SENSING AND GIS
Dr. R. Bharti

When we talk about the remotely sensed image and especially for lunar exploration, we need to derive this DN number two radiance, radiance to reflectance. So, how we exactly do that? So, here there is a new term called I/F that is the apparent reflectance. So that is calculated using this particular equation right.

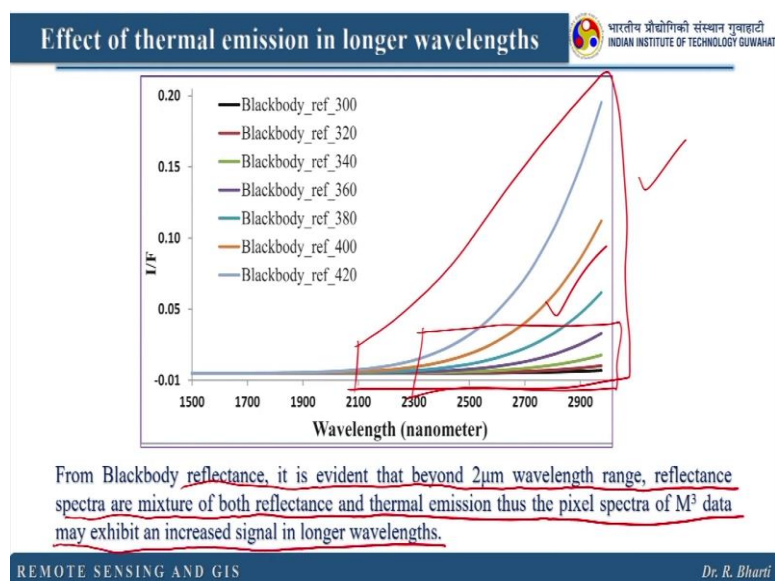
Where I/F is apparent reflectance, $L_{rad}(\lambda)$ is radiance value measured by M3 sensor as a function of wavelength. d is distance from the Sun to the moon in astronomical unit $F_{sun}(\lambda)$ is exo-atmospheric solar spectral irradiance as a function of λ , θ is solar zenith angle and P is phase function correction that is unavailable for this particular data right. But for some of the data sets it is available.

(Refer Slide Time: 46:19)



So, whenever it is available you are supposed to use that. This is the exo-atmospheric solar spectral irradiances which is available in these two links, right. And once you use this solar exo-atmospheric irradiance and that I/F formula, you can see how this spectra is changing from radiance to reflectance right. You can see here the trend has completely changed.

(Refer Slide Time: 46:48)

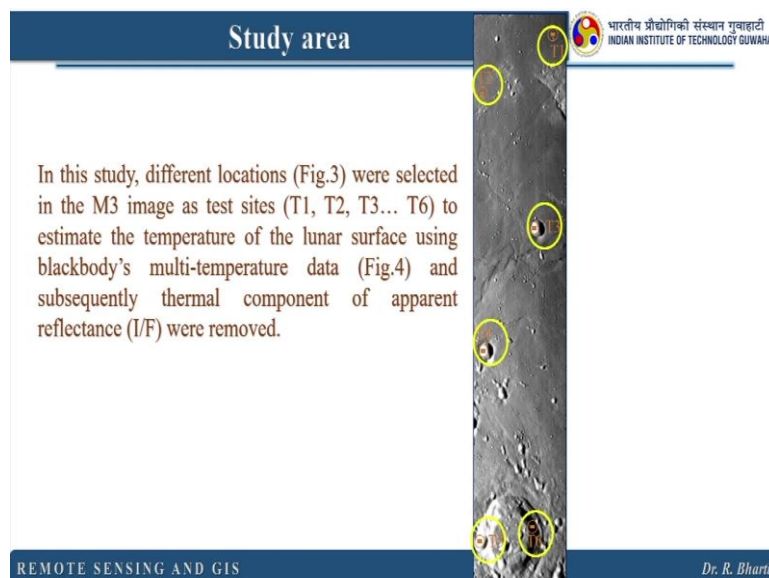


Now, if you remember, I always say that 0.42 to 2.5 micrometre is reflective domain and 3 to 16 micrometre is thermal domain, but what is happening in between 2.5 to 3, this is also allowed by our atmosphere. So, we can measure this particular energy, but why we are not using very frequently because it has effects of both reflectance and emission. So, it is very difficult to separate these two information and derive some meaningful information.

So, here in this case, I have model the black body and calculated the I/F that is the apparent reflectance and you can see from 2100 onwards, you can see there is increase but when we are talking about black body, there will be no reflectance right because everything is emitted. But though we are having this particular data that indicate this particular wavelength region is not free from thermal emission right.

So, from black body reflectance it is evident that beyond 2 micrometre wavelength range, the reflectance spectra are mixed or both reflectance and thermal emission does the pixel is spectra of empty of data may exhibit and increase signal in longer wavelength, right. So, how do we remove this particular information from our M3 pixel spectra, because M3 is also giving you the data till 2500 nanometre, right.

(Refer Slide Time: 48:43)



Study area

In this study, different locations (Fig.3) were selected in the M3 image as test sites (T1, T2, T3... T6) to estimate the temperature of the lunar surface using blackbody's multi-temperature data (Fig.4) and subsequently thermal component of apparent reflectance (I/F) were removed.

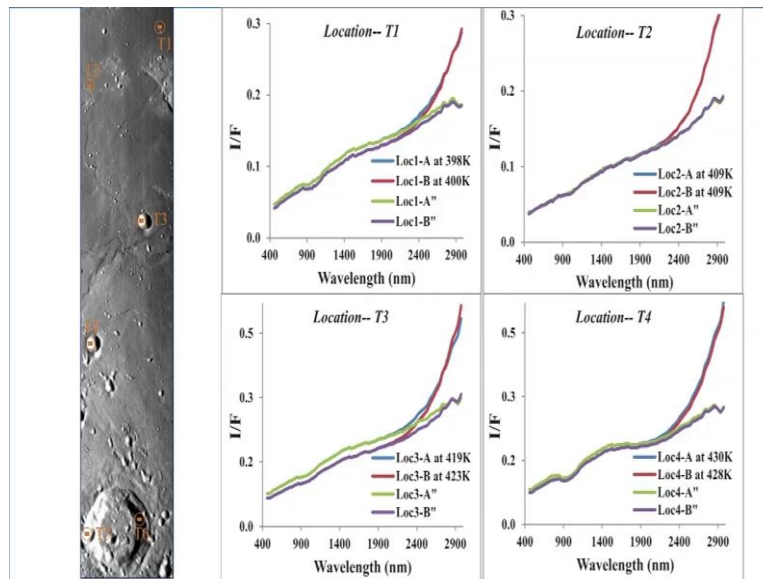
भारतीय प्रौद्योगिकी संस्थान गुवाहाटी
INDIAN INSTITUTE OF TECHNOLOGY GUWAHATI

REMOTE SENSING AND GIS

Dr. R. Bharti

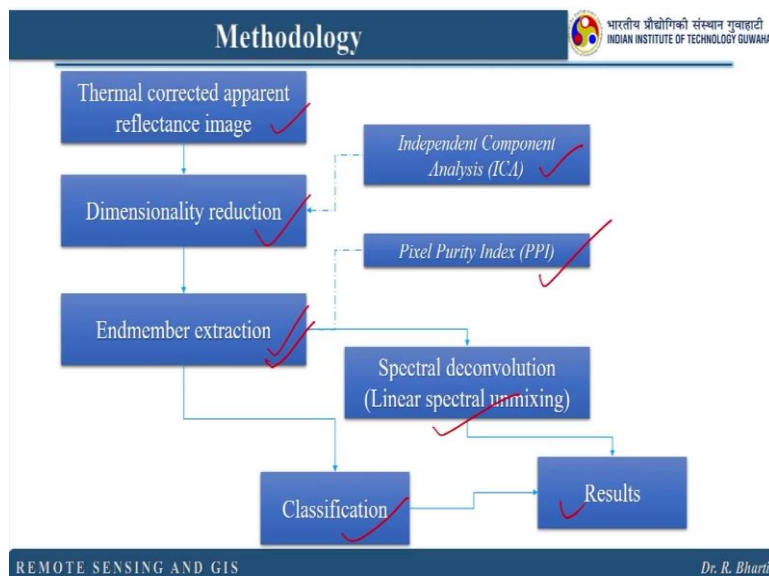
So, in this study different locations were selected in the M3 image as a test site, namely T1, T2, T3, so on T6 to estimate the temperature of the lunar surface using black bodies, multi temperature data and subsequently thermal component of apparent reflectance were removed, you can see these locations were selected for this estimation right.

(Refer Slide Time: 49:12)



Once you have that information, you can see location A at 396 Kelvin, location B at 400 Kelvin, this A'' and B''. So, what is exactly happening here for A and B right, these two temperature data sets are matching. So that means that pixel value or the pixel temperature was here in this range for location T2 again this is 409 Kelvin here 430 and 28 here you have 419 and 423. So, that is how you can derive the information about the temperature and you can correct those temperature in your reflectance spectrum measured or identified using this M3 data.

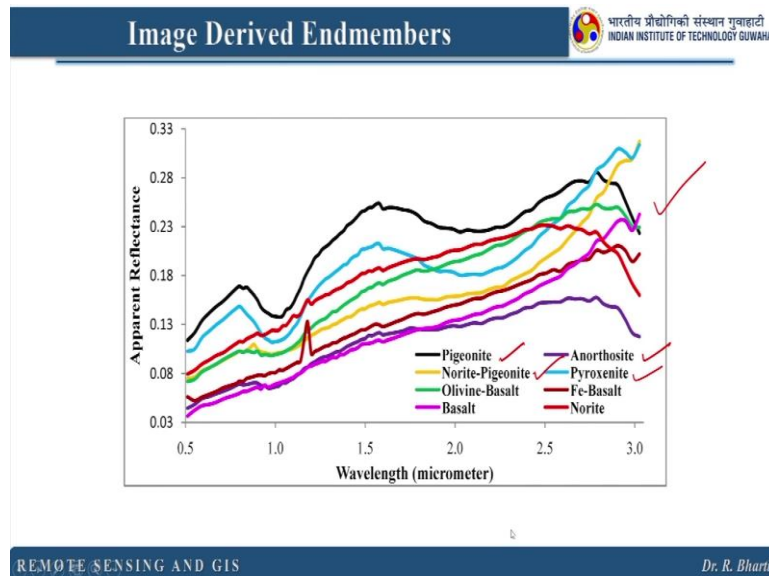
(Refer Slide Time: 50:13)



So in this case, I have followed this particular methodology where thermal corrected apparent reflectance image was used as input, then dimensionality reduction was performed using ICA that is Independent Component Analysis. This is the advanced version of PCA, MNF right. The identified inherent dimensionality of M3 was used to extract the end members and then

we have matched with the library spectrum. And here we have performed the classification and finally, we arrived at the result. So here for this we have used PPI and here for classification we have you SAM.

(Refer Slide Time: 51:05)



So image derived in members were something like this and here I am calling them some with some name right? How so? Because these are the image derived and members. How can I say this is Pigeonite or Anorthosite or Norite-Pigeonite? So, basically here we have matched with the library spectra. This is the moment when you need your library spectra to resolve your end members in different composition right.

(Refer Slide Time: 51:38)

Linear Mixing Model (LMM)

A fully constrained Linear Mixing Model (LMM) (equation 1) was used to identify the minerals and their abundances (Mustard and Sunshine, 1999). This iterative, least square approach (Heinz and Chang, 2001; Yang, 2009) resolves each one of the M^3 endmembers for constitutive mineralogy based on least Root Mean Square Error (RMSE) (equation 2).

$$x = \arg \min_x \|Mx - r\|_2^2 + \beta \left\| \sum_{i=1}^n x_i - 1 \right\|_2^2 + \gamma \left\| \sum_{i=1}^n \text{sign}(x_i)^T x_i - 1 \right\|_2^2 \quad \text{Eq. (1)}$$

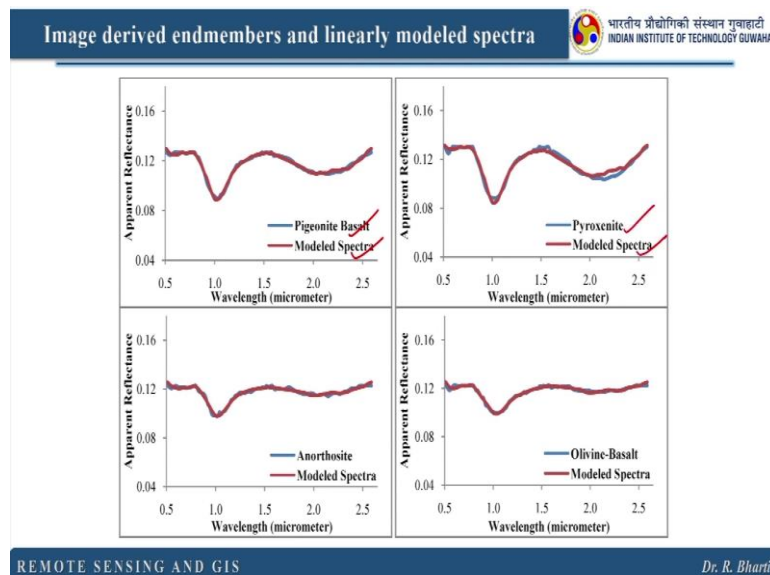
$$RMSE = \sqrt{\sum_{i=1}^n \eta(\lambda)_i^2 / n}, \text{ where } \eta = \sum_{i=1}^n |r_i - M_i| \quad \text{Eq. (2)}$$

REMOTE SENSING AND GIS

Dr. R. Bharti

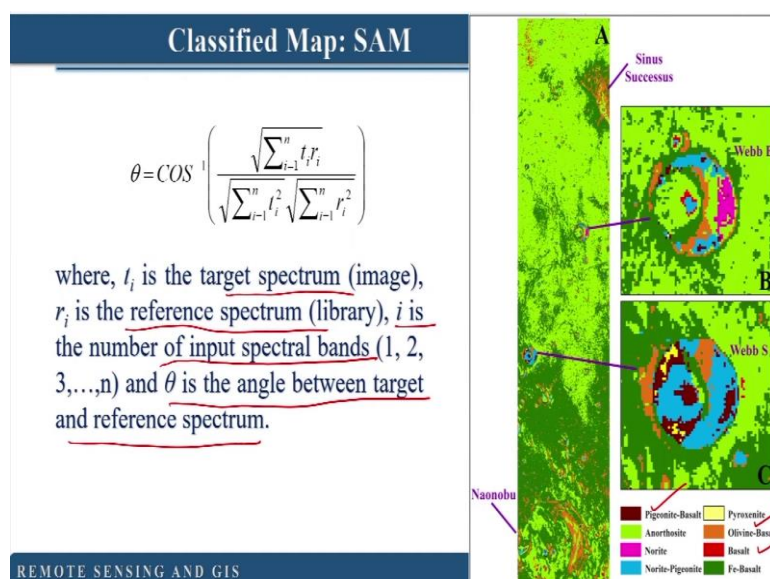
So, here we have used this linear mixing model. So a fully constrained linear mixing model was used to identify the minerals and their abundances. So here is the equation-1. This iterative least square approach resolves each of the M3 endmembers for constitutive mineralogy based on least root mean square error that is equation-2 that is the RMSE right.

(Refer Slide Time: 52:10)



So, now you can see how best fit we got after this linear mixing model. So here the model spectra Pigeonite Basalt right, Pyroxenite modelled spectra, so how these two are matching. So once you do that, then you will end up with the endmembers classified in different rock type, mineral, vegetation or object right. So then you can easily write these names. That is why I have mentioned this in the previous slide. Once you have this information, you can use this end member to classify your image.

(Refer Slide Time: 52:52)



Remember Sam spectral angle mapper where we estimate the Θ between your reference spectra in this case that will be your endmember and the pixel spectra, right? So then we measured this Θ , where t_i is the target spectrum, r_i is the reference spectrum i is the number of input spectral band Θ is the angle between target and reference spectrum.

And that is how we have got this particular output, where you can see all these colours basically represent different types of rock right. So, this is how remote sensing is evolving.

And now we are able to identify the chemical composition of the material in those pixels from space right. So that is all for today. Thank you.