Remote Sensing and GIS
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Lecture - 17
Hyperspectral Remote Sensing - II

This is the second lecture on Hyperspectral Remote Sensing. In this lecture, we will see some more details about this hyperspectral remote sensing related to techniques, and related to some advantages, some disadvantages and some limitations. So we will understand slowly all these components in this lecture and in subsequent lectures. So let us go through briefly like what exactly we mean by this hyperspectral remote sensing data and how do we acquire these images from space or from a lab-based instrument.

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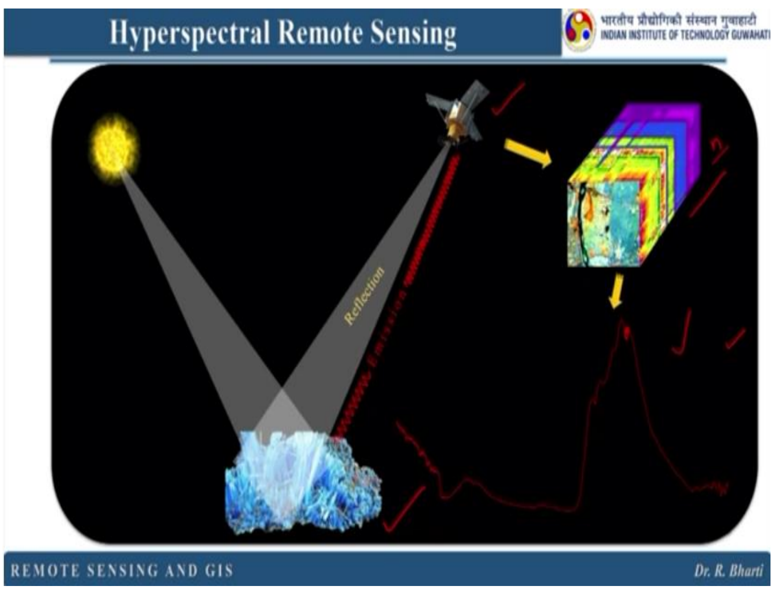

Assuming the case of space-borne sensor, where our sensor is located here and our source is sun. So in this case, what is happening? The sun is illuminating the surface and the target is getting illuminated and it will reflect some of the energy and it will also emit some part of energy and that will be recorded by our sensor in contiguous narrow bands, right, and that will be like this. So here this is the way we represent our hypercube, means hyperspectral data cube.

Why cube we are saying? Because this looks like a cube and here you have n number of bands depending upon the satellite or sensor specification. So it is nothing but the 100s band in different wavelengths, but there is no gap in between, that is why we are calling it contiguous measurement. So here you have continuous and very narrow band width and because of that we could able to generate this kind of a spectral signature.

It can be emissivity or reflection, anything. So now here as we know that these strips are basically resulted by the internal atomic structure and chemical composition. So they actually represent or they actually indicate the compositional diversity of the sample, right. So this is the way we capture our hyperspectral data and analyse our hyperspectral data. So this is the first step towards that, right.

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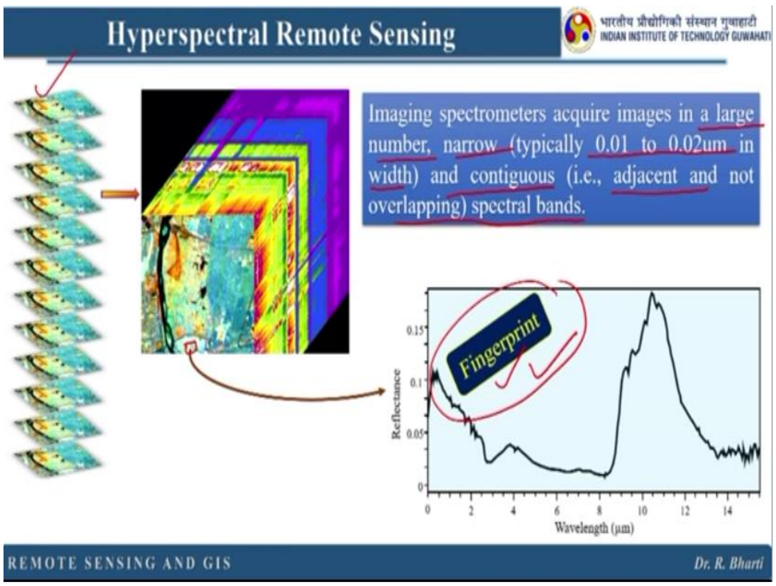

Now here, in imaging spectrometer, what facility we have, we have many number of bands, right in order of 100, then narrow. Narrow means typically 0.01-0.02 micrometer in width. That is your band width and contiguous in nature that is adjacent and not overlapping spectral bands, right. So this is the definition of imaging spectrometer and what exactly they do. So here you have many bands and they are contiguous in nature and this we represent in terms of hyperdata cube.

And subsequently for individual pixel, this is the reflected response, right. Once we have this we can analyse this spectral signature and we can deconvolve it in terms of the mineral or rock or maybe the unique or the pure spectra, right. We will understand slowly what exactly we mean by pure spectra, library spectra, and what is the reference spectra here, right. So as I mentioned earlier also this is actually something like our fingerprint.

It is unique for all of us, so for a given material, the sets of absorption features are also unique. So that's why I am calling it fingerprint of the material, right.

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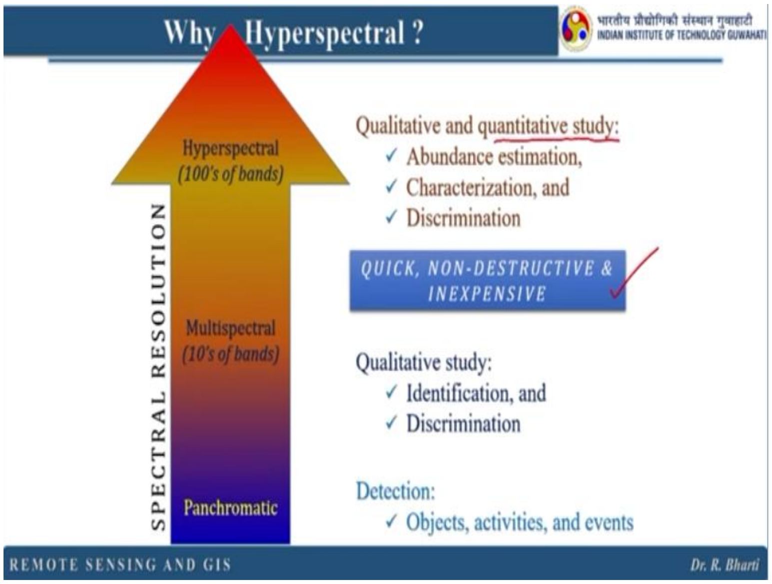

The advantages of hyperspectral data can be understand through this slide. Here I just want to highlight because this is a repetition, so I just want to highlight this part. So this is a quick non-destructive and inexpensive process or technique and which can give you or which can help you to conduct quantitative studies right. So you can identify how much mineral and what are the minerals present in a given rock sample, right.

That much information you can derive from this reflected or emitted energy, which has been captured in the form of hyperspectral data and this is basically we are going to generate the spectral signature from the image and then we will follow the spectroscopy. So we will use the library spectra or the pure spectra, we will generate and then with respect to that, how much it is matching, what is the similarity. So basically we will be doing the spectral analysis.

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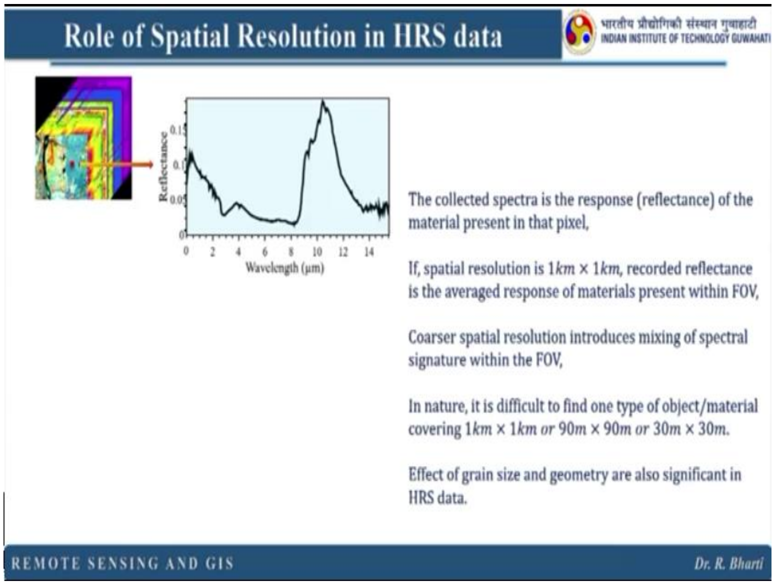

So here one thing we need to understand very carefully, that is role of spatial resolution in hyperspectral data. So it is very important to understand this, that what exactly we mean by this spatial resolution and its implication in hyperspectral remote sensing. So assuming this is our pixel, can you see this red dot? You can see here, right. So this red dot I am considering it as a pixel. So once you have identified your pixel, what you will do?

You will derive the response of that pixel across the wavelength. So here you have all the bands. So whatever value it has got in different wavelengths, that we have used and that we have plotted here, right. This is just for an example. So what exactly we are doing? We are deriving spectral signature of all these pixels, right. The collected spectra is the response of the material present in that pixel on the ground, right.

So if you remember, if this is one pixel from x satellite and it is resolution is 1 kilometer by 1 kilometer from another satellite, you have a pixel which may be 0.25 by 0.25 cm. Then what exactly it says? It says you will get only one averaged value for this pixel in your image, right. here for 0.25 by 0.25 cm, you will again get only one average value in your image. So exactly what we are getting?

We are getting averaged response of material in that particular area in that particular wavelength, right. So here that is why I have written the collected spectra is the response of the material present in that pixel. If spatial resolution is 1 kilometer by 1 kilometer, recorded reflectance is the averaged response of material present within field of view. So field of view means, for that detector how much area it is seeing on the ground, right. So this is the field of view.

So collectively, if you see for image the field of view is something different. For a detector we call it IFOV, right. So here the spatial resolution plays very critical role in this hyperspectral remote sensing. Another coarser spatial resolution introduces mixing of spectral signature within the field of view and how it is happening? Basically let us assume sun is illuminating this particular surface, right. Now here pixel size is something like 1 kilometer by 1 kilometer.

So when it is 1 kilometer by 1 kilometer, what will happen, you will have multiples of object or different material present in this area and whatever if you illuminate them individually, you will get one individual spectra for all these materials, right, but since my pixel size is bigger, which is containing all of them together, what will happen? They will be averaged, right and then ultimately you are getting this kind of spectral signature.

So this again tells you that coarser resolution introduces mixing of the spectral signature within the field of view, right. In nature, it is difficult to find one type of object or material covering 1 by 1 kilometer or 90 by 90 meter or 30 by 30 meters, right. Why, because in nature the objects are changing maybe slowly or maybe drastically, but it is very difficult to find out one type of object presenting 1 by 1 kilometer, right. There may be slight changes.

There may be slight compositional changes, so those thing we are introducing as error in our data. In other words, we have to resolve this ambiguity and we have to deconvolve the spectra into all of them, right. So then only we will be able to conclude with the actual result. Effect of grain size and geometry are also significant in hyperspectral remote sensing data. So suppose, if you take 1 kg of quartz, 1 kg of mica, 1 kg of feldspar.

And if you arrange them in regular manner or maybe in circular manner, right, alternatively, right. In the next case, you mix them randomly and put this, right. In third case, you make squares with alternate material, right and if you acquire the spectra of this, whether they will be same ideally, if you see the same amount of material has been used to generate this pattern, this pattern, this pattern, but if you see there are spectral response, they will be different. So there is a paper where I have demonstrated this problem. So this I will discuss later.

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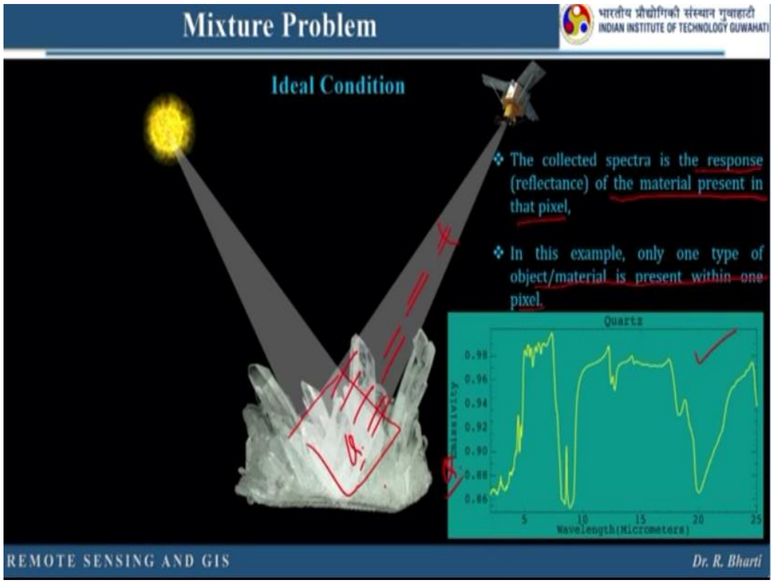

Let us see, what exactly I am calling mixture problem. So in ideal condition, if you see this is a mineral called quartz, right and which has been illuminated by your sun and then captured by your satellite, and then subsequently you will generate a hypercube and then you will get a spectra right. So here in this case, what exactly I am trying to show you, that the complete field of view, right, this complete field of view is basically covering this quartz, right.

There is no other material which is coming into the picture in this particular field of view, right. So they are actually one type of material. So this is ideal condition, where we assume everything is perfect, right. So here if you see the result, it will be only for this particular quartz right. So the collected spectra is the response basically in reflectance of the material present in that pixel. Now the next point is in this example, only one type of object or material is present within 1 pixel.

Let us assume, this is IFOV, not FOV. So in IFOV, you have only quartz or only feldspar, or only mica or only one type of vegetation or one species of vegetation, right. So in that case, life will be very simple and you will get a very good perfect reflected or emitted energy curve. So here you can see this is the response of quartz between 2-25, right. Now based on this, we can easily say that this pixel belongs to quartz.

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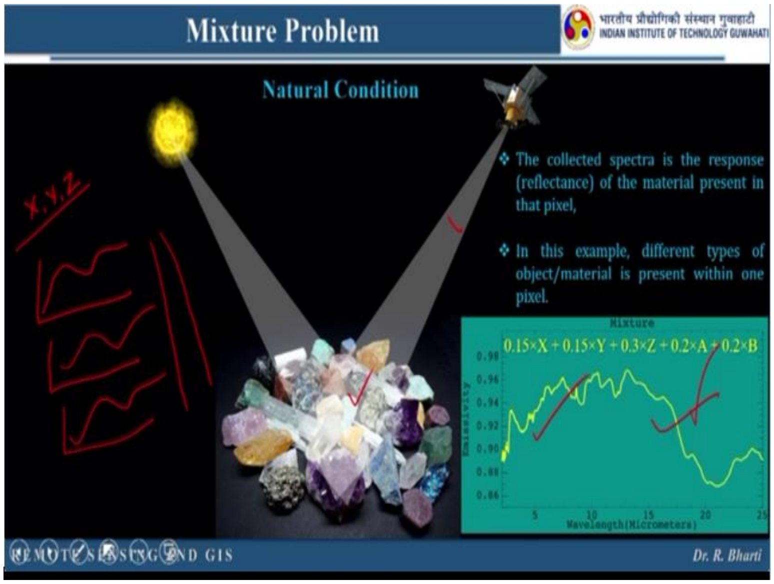

But in nature what is happening? In natural condition, even every 10 cm, 20 cm, 50 cm, or 1 meter, material is changing, right unless until we do not put this same material in that particular area. So if we are doing this hyperspectral remote sensing from space, there the single pixel IFOV, right is covering different types of material here, right. So what will happen, you will get one spectral response of this, another response for this, here for this, here for this, right.

So like that you will have all the unique spectral response of these materials, which are falling in the field of view. But actually we are getting only one value for this pixel, right. So what exactly is happening? We are going to mix this in our one pixel. So the collected spectra is the response of reflectors of the material present in that pixel. Then in this example, different types of object or material is present within one pixel.

So if you see the spectral response, it will be something like this and where if we know what are the materials present within one pixel. Then, if we can add them in some proportion and their spectral signature, you may get this one, right. So assuming here you have x, y and z, 3 types of material within this field of view and you have a spectral library, where you know what is their spectral behavior in given wavelength.

Now if you know that these 3 have been actually reported in this particular pixel, then if you mix them in different proportion, you may match with this particular captured spectra, right. So this is what is happening in the natural condition. So here our life is complicated and the approach, what we used to use for the normal cases where we see that one pixel belong to one particular object, right. Do you remember the classification, but here what we are trying to resolve?

One pixel may have x, y, z material and now we have to resolve this one pixel in terms of x, y and z. So how we can do that, by combining the spectral signature of x, y, z in different proportions, so that it may match with the reported or acquired spectral signature, right. So I hope you have understood this concept. Now the next is linear mixture problem.

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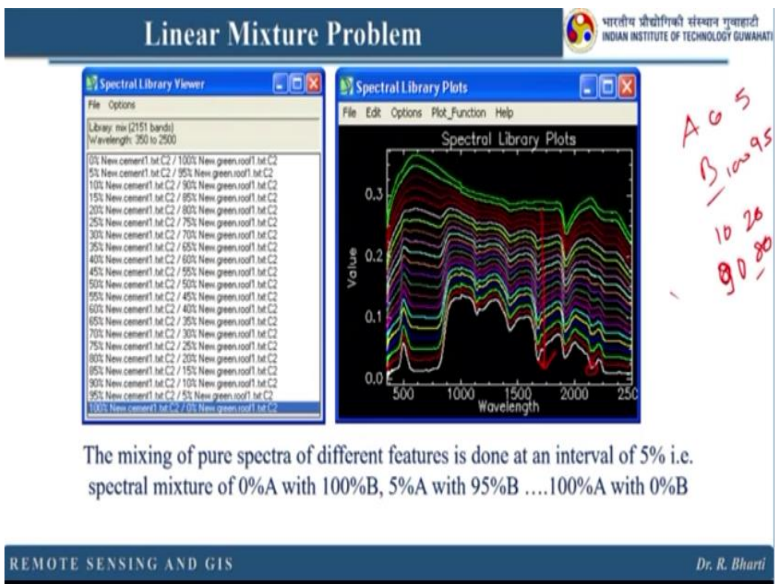

Now you have understood one pixel may have x, y, z material and their spectral signatures are different from each other, but when we do this remote sensing, we get only one value for that pixel, so everything gets averaged, so what we have to do? We have to use the unique or pure spectra of x, y, z. So for x, this is the spectral response right, for y this is the spectral response, and for z, let us assume this is the spectral response.

Now assuming in that pixel, they are basically 33, 33, 33%, right abundance wise. So what we can do is, we can add them or we can give them 0.33, 0.33, and 0.33 weightage and if you add them, it will become 1. So now if you combine them with equal weightage, your resultant spectra will be, right. So here using this spectral matching or linear spectral matching, you can match with the acquired image spectra, right.

So here this is one example where I am showing that you can add these 3 x, y, z into different proportion. So if you use maybe 0%A and 100% B or 5%A and 95%B or you can increase at the interval of 5% or 1%, then it will be for only two materials. So you start with 0-100, then 5-95, then 10-90, then 20-80, like that you will see that different spectra will be generated in different proportion and they will have different characteristics.

So only because we are changing the proportion, so probably what is happening here. The intensity is going to change for the spectral signature, but the position of absorbance or the trough, that will remain same. So here based on the abundance, what is happening, the intensity is increasing from one place to another place. So this is one example in case we are assuming our target is A and B.

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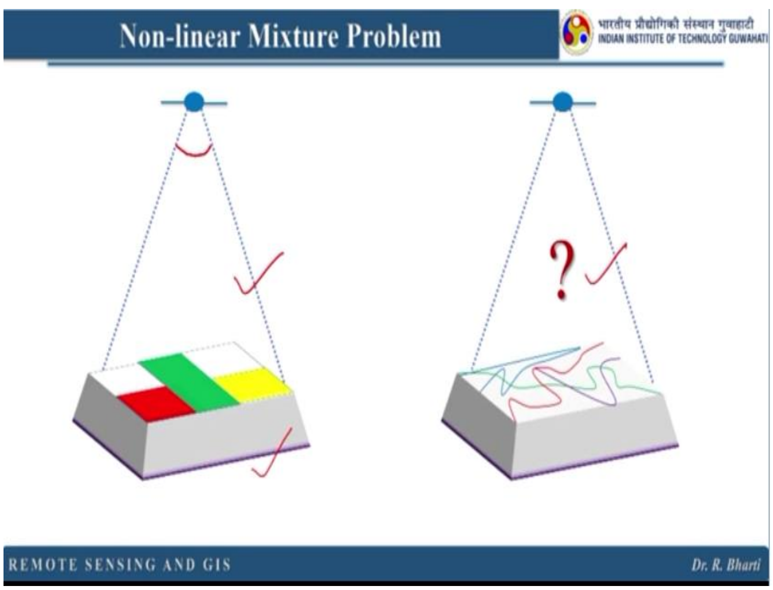

In this slide, actually I want to explain this non-linear mixture problem. So here if you see, here you have four different types of material present within the IFOV, right. So within this field of view or IFOV, you have four different types of material and you know their proportion, they are present in defined proportion and they are actually linearly mixed, right. So then still it is easy to quantify their contribution in the resultant image spectra, right.

But in case if they are not defined and they are actually non-linearly mixed within the IFOV, then what will happen, it will be difficult to quantify their effect on the image spectra, right. So in that case, we need to start or we need to look for the non-linear approaches, right. So in hyperspectral remote sensing, it is very important to have a spectral library where you have stored all the unique spectra or the pure spectra of x, y, z or know material, right.

So here if you see this non-linear and linear mixing. Here what we exactly want to do? We want to deconvolve the image spectra in terms of know materials. So for known materials, how we will know that this is the response of known material, either one has to develop a spectral library where you can find all the spectral behavior of known materials, right. So there are some spectral libraries available, where you can easily find the materials reflected and emitted spectra.

I will explain how to access them and what they are and exactly how they have been developed and what all are freely available to you, right. So let us see more about this spectral library.

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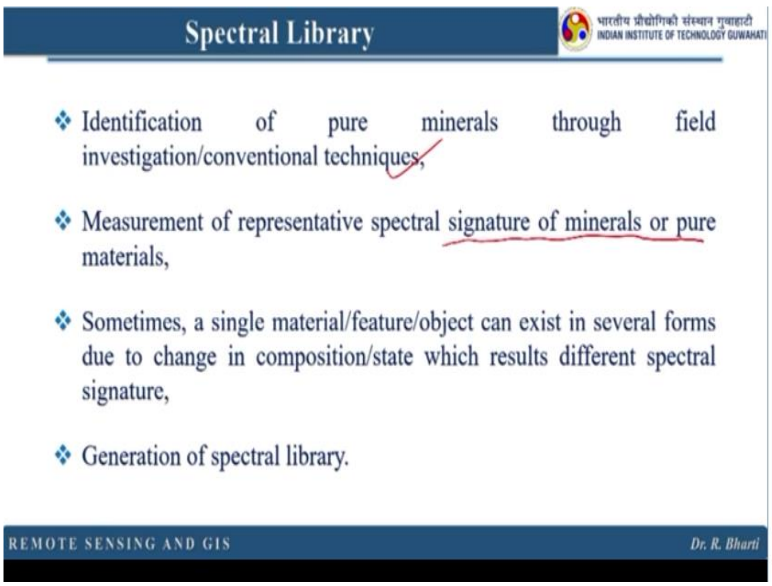

In spectral library, the identification of pure mineral through field investigation or conventional technique is the first step. So here you need to find an unique sample, so let us assume that pure mineral like quartz, mica, feldspar, olivine, so those things are those minerals, you need to make sure that they are 100% pure, right. Then you use the spectroradiometer and generate the spectral response of that mineral and store them somewhere, right.

Now the next is measurement of representative spectral signature of minerals or pure materials. I have already explained this. Now sometimes a single material or feature or object can exist in several forms due to change in composition or state, which results different spectral signature, like water. So water, ice, snow, snowflakes, all of them are having different properties and wavelengths in different wavelengths.

So that is why it is very unique information, that is why it is possible to identify all of them through this space based measurement, right. So once you do that and once you are familiar, like once you are confident that these are the pure minerals or pure materials or objects, then you can generate the spectral signature of them like emissivity or reflected spectra, and then you can save it somewhere and then we can call them spectral library.

So again how to generate this spectral library, what are the components you need to take care, that I will explain you later. Now once you have developed this spectral library, now the next step is spectral analysis. You have already captured the hyperspectral data. You have already developed the spectral library, now what exactly we want to do? We want to match this spectral library spectras and image spectra, to identify what are the materials present within the field of view, right. So this spectral mixture analysis, which is also known as SMA.

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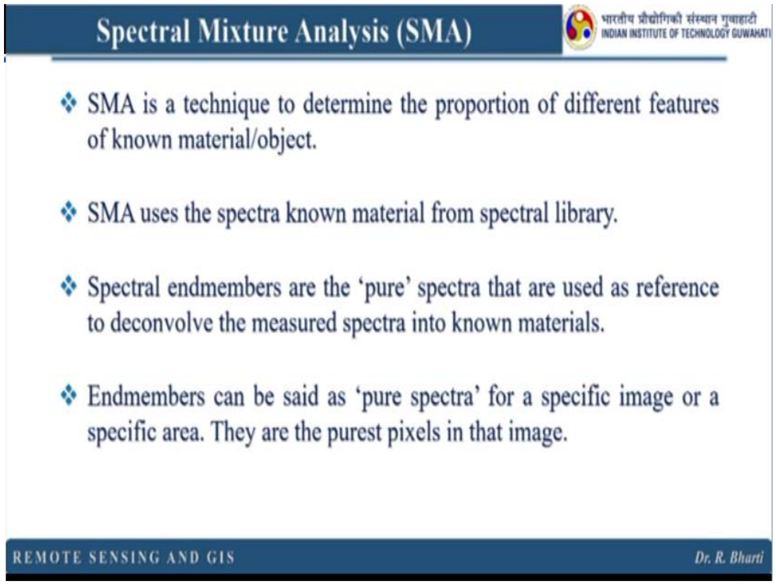

So SMA is a technique to determine the proportion of different features of known materials or objects, right. So here it should be spectra of know materials from spectral library. Spectral endmembers are the pure spectra that are used as reference to deconvolve the measured spectra into known materials, right. Now just imagine if you derive 10,000 by 10,000 pixel spectra and you match 1 by 1, all of them with this spectral library, how much tedious work you have to do right.

So what exactly we are doing? We are trying to match this pixel spectra with the library spectra, so instead of matching all of them, if we can derive or if we can identify endmembers, again, endmembers are pure spectra, does not matter whether it is coming from the library or image. So if we can identify the pure pixel in that image itself, where we expect that only one type of material or with a certain proportion or the known materials are present within that pixel, right.

So if we can get that pixel and if we could able to identify that pixel, then we can classify this whole image with respect to that identified endmember or pure spectra right. Now later on, we can deconvolve or we can do the spectral mixture analysis of the identified endmember from that image, right. So I will explain this using this diagram.

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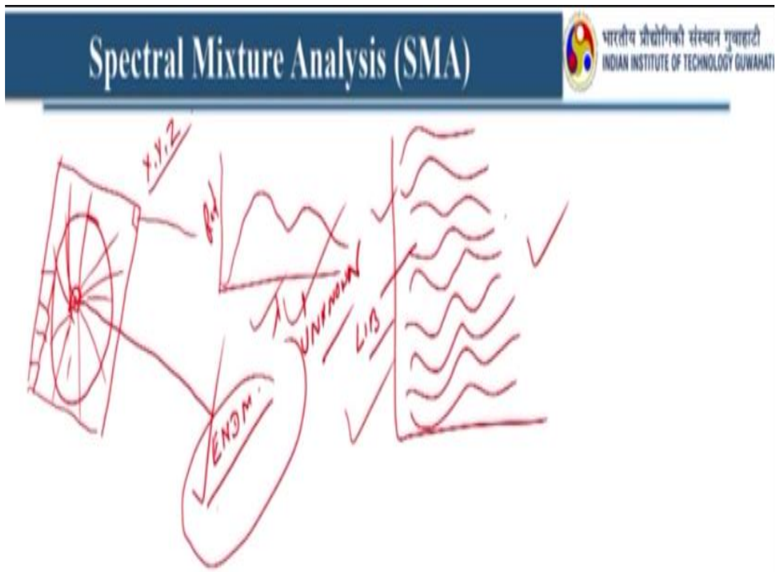

Let us say, you have a hyperspectral image, right and this pixel you want to extract so this is the lambda and this is reflectance. Now what exactly we are trying here? We are trying to resolve this spectra in terms of x, y, and z because we know that x, y, z are present in that particular pixel, but we do not know what is the contribution of x, y, and z, so we need to resolve this in terms of library spectra. So for x, y, z we have the library spectra or the library spectra is having many.

So these 3 are included in this library, right. Now here, if you see this image has been used to generate this particular spectra, which we want to identify, or which we want to study and identify the composition and we have a spectral library here. So either we have to resolve all these pixels in terms of these library spectra or we can go for identifying a pure pixel here, right, which is expected to be pure in nature and then with respect to this, we can see all other pixels, right and we can say that is the composition of this whole image.

So pure spectra is something like your training pixel. So that will be used as reference in your spectral classifier. So why it is spectral classifier? Because we are using the spectral information and spectral matching, so then you will classify this whole image, right. So now here what we have done? We have identified this endmember and this is the library spectra and this is the unknown one. Unknown means, it is from the image.

Now we want to resolve this in terms of this or we want to or we have identified the end member and the whole image pixel will be deconvolved or studied using this endmember right. So this is the way, we look for the hyperspectral data analysis.

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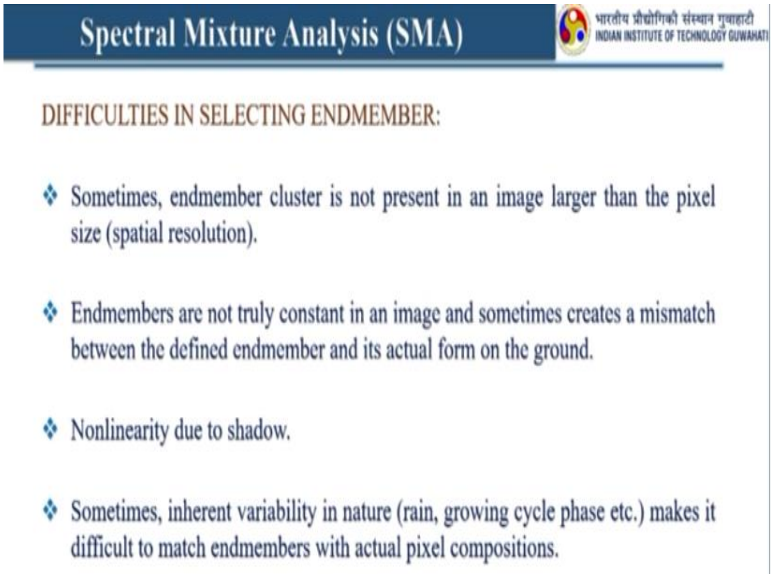

Now what are the problems we face in selecting this endmembers? So sometimes, endmember cluster is not present in an image, larger than the pixel size. So the special resolution will play a significant role here. Endmembers are not truly constant in an image and sometimes creates a mismatch between the defined endmember and its actual form on the ground, right, non-linearity due to shadow, or maybe because of their arrangements.

So sometimes inherent variability in nature like rain, growing cycle phase, etc., makes it difficult to match endmember with actual pixel composition, right. So sometimes you will end up doing qualitative analysis instead of doing the quantitative analysis, right. So these are few limitations, which we have to face in hyperspectral remote sensing. Now what are the assumptions in estimating the composition of pixels we make?

So each pixel contains information about the proportion and spectral response of each component, which is within the field of view. Then, brightness of an image pixel is a linear combination of the percentage of each endmember and brightness of pure sample of the endmember, right. Spectral proportion of the endmember, so proportion of the area covered by features on the ground.

So these are few assumptions we make while doing this while identifying or estimating the composition of the pixel. So most of the pixel contains some measurable amount of endmembers. So this is again, these are assumptions like we assume that it is there, but it may not be. So it depends what assumption you make and what kind of data you have got and whether they are actually supporting each other or not.

I hope you have understood the hyperspectral remote sensing basic part. Now let us see what exactly we are doing when we are going for spectral analysis. So analysis is actually the analysis of your hyperspectral data in terms of your library or in terms of your endmember, right. So let us see this flow chart.

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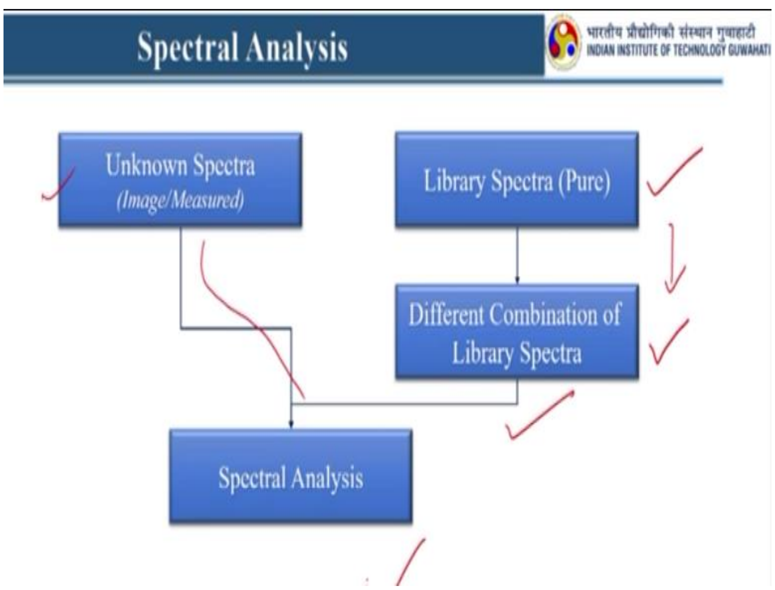

Where this is the unknown spectra derived from your image, right or maybe you might have collected a spectra using a Spectroradiometer in the field. Now you want to identify what is the composition of that spectral signature using this library spectra or is there any other way. So what we will do? We will refer to this library spectra where we have already identified the pure materials and we have generated the reflected or emitted spectras.

Now when we want to deconvolve or when we want to identify the composition of unknown spectra, what we will do? We will mix this library spectra in different proportion. So here we will generate the spectra of different combinations of library spectra right. Now after that we will use this spectra and we will match this unknown spectra, right. So ultimately we are trying to resolve this unknown spectra derived from one image or captured in the field in terms of library information, right.

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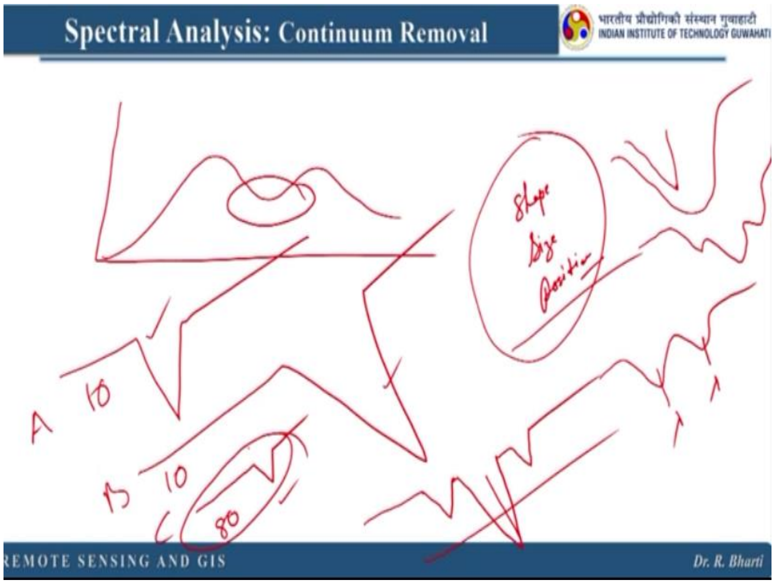

Now if you see the reflected response of any material, so as I told you we always bother about this absorption features, right and the shape, size and position, so shape, size is basically whether it is a very sharp trough or it is a broad trough or it is a doublet, this kind of, right or it is having this kind of feature. So these are related to shape and size. Now what is the position that what lambda value it has got and/or what is the position of these absorption feature in the wavelength, right.

So once we have all these information, we can easily find out what is the material and what is their contribution? Because as I said if you have let us say this is A, for B, it is this one, which is relatively large and for C, it is this one, right. So if I have given 80% weightage to this 10% to this, 10% to this, then your resultant spectra will be, so the first this has got 10%, so this will be like this. This has got 80, so it will be like this. This has got again 10, so it will be like this.

So if you mix them, the more depth will be acquired by the C, why? Because that is having maximum concentration, so that is why the depth, size and position that is very important in this spectral analysis.

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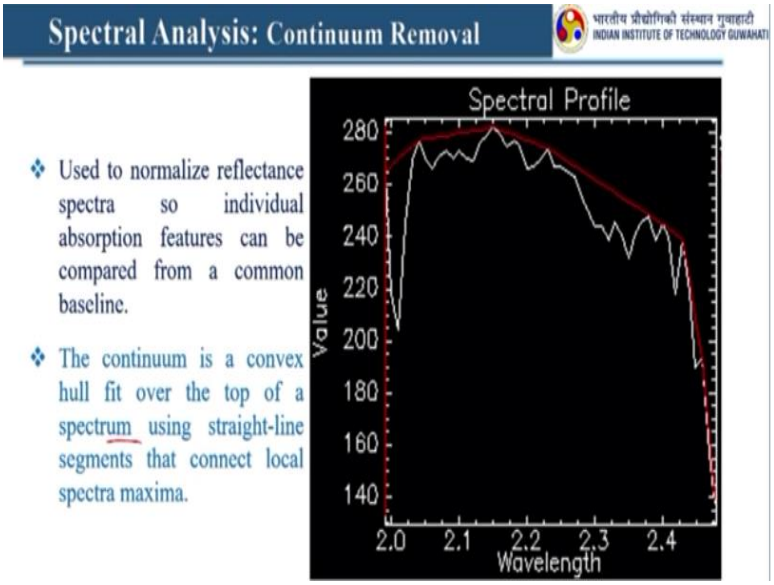

So if you see any spectra, then we need to measure what is the depth and based on this depth, we actually identify their contribution or their composition, right or the amount in the pixel. So here this continuum removal is one of the best technique to normalize this reflectance spectra, so individual absorption features can be compared from a common baseline. The next point is the continuum is the convex hull fit over the top of a spectrum using straight line segments that connect local spectra maximum.

So here to understand this continuum removal, just imagine you have a rubber band, and you are going to fix that rubber band at all the peaks, right. So like you will stitch all these sticks with this rubber band, right. So what will happen, when you stretch them, or when you stretch your rubber band, everything will come to a common baseline, right.

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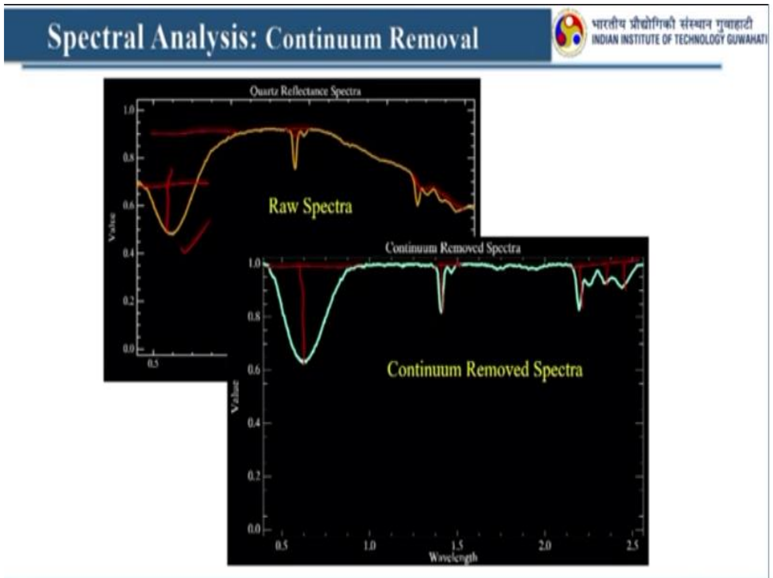

So here I will show you what is the effect of this continuum removal on the measured spectra or image spectra. So assuming this is my input spectra, again this depth whether we should consider from here or from here, we do not know. There is a confusion. Here, again whether I should consider this or this, I do not know. Whether this should be considered or this should be considered, how will you identify that baseline.

So here I am going to fit this continuum removal and then I will see what is happening. So here you see they have been actually brought to this common baseline, right. So in the common baseline, it gives you a flexibility that you can estimate their contribution or their amount present in that pixel. So from here you can easily find out which material is present more, which material is present less by identifying the depth of absorption feature, right.

Now you must be thinking that I have introduced Spectroradiometer, then satellite based hyperspectral remote sensing data generation, but how these 2 are actually related to each other and how they are complementing each other, right. So for that I have a slide, where you can just visualize this scenario.

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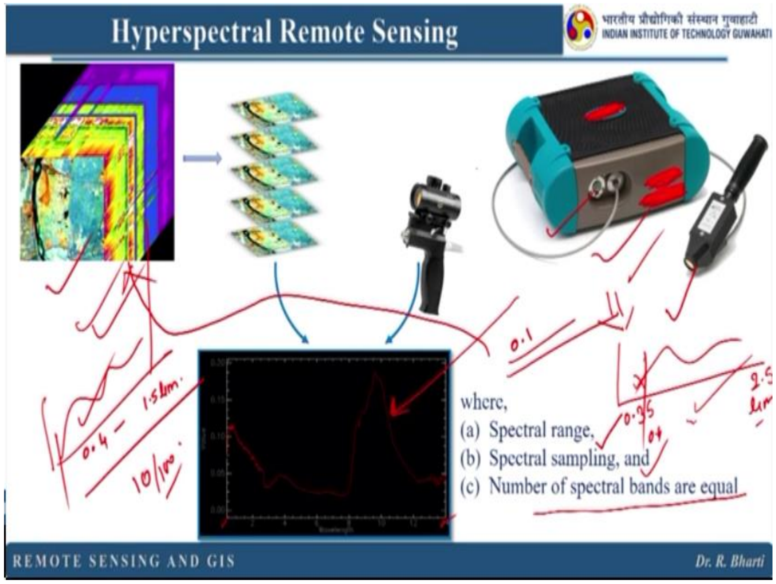

Where you have generated these spectra from this particular pixel and the same time, you have a spectroradiometer, which you can take to your field and you can identify what is the location of this pixel on the ground. There you can use this particular instrument and you can generate the spectra like this. So from space also you have got this spectra for that particular pixel. For that pixel, you have got field data also and how it is going to match with each other.

Because when you are in the field, since the pixel size here is 30 by 30 meter, right and here the field of view of this or maybe this, right, let us assume this is 10 degree, for example. Now to cover this 30 by 30 meter on the ground, because you can easily access or you can easily identify what is the location of this, right and then you can visit that place, then you can design your setup, so you will put it here, let us assume this is the fiber optic cable, right.

And which has got 10 degree of field of view. Now you have to cover this 30 by 30 meter ground, why, because you have to match this information measured from this particular instrument to this image, right. So you have to make sure that you have calculated the height and this angle and you make sure that this pixel size is 30 by 30 meter, because here also you are getting only one spectra for this 30 by 30 meter.

So you have to get only one spectra using this field instrument and for that you have to decide what will be the edge, right. Because this is known, this is 10 degree in this case, this is just for example, right. So when you are using this, you can exactly match the field measured spectra with the space measured spectra. Now again atmosphere will play a very significant role here and then, it will create a problem and these 2 spectras may not match with each other.

So this lab instrument or the field instrument can be used to upscale the field information or lab information to satellite scale, right. This is how we are generating or matching the spectroradiometer and hyperspectral remote sensing data from space, right. In this process, you have to take care of the spectral range, because this spectral range whether it is from 0.4-14 micrometer or it is from 0.4-2.5 micrometer.

So you need to make sure the same range should be there for both space based measurement and your field instrument. Then, spectral sampling, how many times it is going to acquire the samples and what is the band width, right. So those things that a spectral resolution, you need to be very careful, then only this measurement can be used with space measured data. Then number of spectral bands are equal.

Now sometimes it happens that with this field instrument, you may acquire more information than this space based measured data right. So assuming this is instrument, which is capable of giving the spectral response from 0.35-2.5 micrometer, right and this image has been captured or this is hyperspectral image, which has been captured between 0.4 to 1.5 micrometer, right. So this is the wavelength range. So here you have got, here you have got.

Now to match these two, what we need to do? We need to make sure the starting wavelength should be same, so we have to trim here. We have to remove this, right and then it will be 0.4. Now that the next is how many samples are there here in this measurement, in this measurement. So here maybe it might have captured at the interval 0.1 nanometer let us assume, right. But here it may be 10 or 100 nanometer, so what you have to do?

You have to resample this information or this spectra as per the requirement of this image, right. So if it is 10 nanometer interval, then here you have to average 10 nanometer values together and then it will exactly match with each other, right. So that is matching of the other information like what is the band number or what is the spectral range, but the information may not match because one has been captured from the space and one you are capturing in the field, right.

So these two things are completely different from each other, one has been disturbed by our atmosphere whereas the field instrument or the lab instrument may have little bit effects of this atmosphere right. I am going to show you what are the different steps we follow in hyperspectral remote sensing data analysis. So the first step is hyperspectral image. So you need to covert this hyperspectral DN number into reflectance image, right, because reflectance are the unique information, right.

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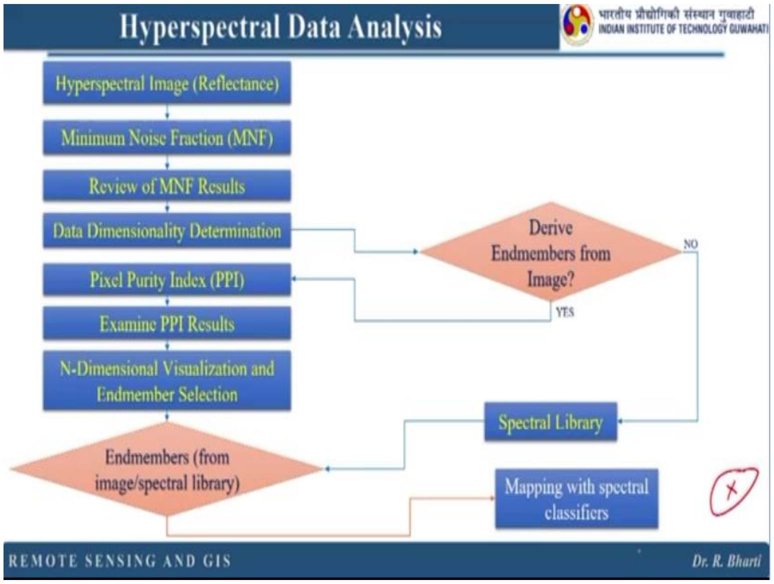

So here, I am considering Hyperion, right. So Hyperion is one space based hyperspectral remote sensing sensor, which is actually capable of giving you 224 numbers of bands in contiguous and narrow bands, right. So here if you see this hyperspectral images, I have written reflectance. So first you need to convert it to reflectance, Why? Because reflectance is unique information and that can be considered as fingerprint. So first we will identify this reflectance value.

So we need to find out how much data redundancy we have in the captured data and that we will remove by analyzing or by using this minimum noise fraction. I will cover this in next few slides. Then once you do that, then you identify using this MNF, you can identify the unique information available in the different band, so by which you can always reduce the data dimension, right. So maybe you might have captured 100 number of bands in hyperspectral data.

But since they are actually having redundant information, what we did? We reduced the number of bands, which had only unique information. So after data dimensionality reduction, what we do? We identify the endmembers that will be from image right. As I told you, endmembers are the pure pixels available within that image and they are unique or they are pure in nature. So they will be considered as library or reference spectra.

And subsequently they will be deconvolved and analyzed in terms of library spectra. So here in case if you want to identify the endmember from image, then it is yes, then for that you need to use this Pixel Purity Index and the next is you examine the result and then you plot them in end dimension and end dimension is basically equal to your input number bands. So whatever number of bands you have identified after data dimensionality, that will be used to visualize this pixels in end dimension and then that will be helpful for identifying the endmembers.

In case, if you do not want to identify the endmembers from image, then what we do, we use the spectral library. In both the cases, it is possible, right. So either you bypass this or bypass this, right. So it is possible. So once I am interested or once I have the field information or the library spectra with me, then I prefer to use this library spectra instead of identifying the pixel spectra, then it will be used here in this image and then I will use some spectral matching and spectral classifiers to identify my target, right.

So I will just summarize this flowchart. Here basically, I want to identify a particular target X, right, but for that we have identified or for that we have captured a hyperspectral data and in this case, let us consider Hyperion data we are using here and we have converted that Hyperion data into reflectance and then afterwards, I have reduced the data dimensionality using minimum noise fraction, then we have two options. First one is to derive the endmember from image.

The second option is to use spectral library spectra as endmember, right. So in case, if I am going with the image derived endmember, then I will be using that image endmember as reference and

I will be using that as input in my spectral classifier to classify my hyperspectral image. In case, if I am not doing that, then I have to use this spectral library spectra as reference spectra and then I will be using some spectral classifier to classify my image into different classes.

Now here in both the cases, ultimately we are using spectral classifiers. So in case, if I am using this endmember from image, then I will get them classified, but we have not classified or we have not studied the endmember. We have classified the whole image into different classes based on the endmembers identified from this image, but still we have to deconvolve or we have to study those endmembers identified from the image, which were used in the classification with respect to your library spectra.

So ultimately library spectra is required to either directly classify the image or indirectly identify the composition of that spectra, which is used in this spectral classifier as reference, right. So in next lecture, I will try to give you some different example, so that this will be more easy to understand, right. So I hope you have enjoyed this lecture. Thank you.