Introduction to Remote Sensing
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Lecture 15
Spatial Filtering, Band ratio and Principal Component Analysis Techniques

Hello everyone and welcome to the 15th lecture of introduction to Remote Sensing Course. In this course we're going to discuss three techniques, and mainly spatial filtering and band receiving and principal component analysis techniques. We will also try to cover the decorrelation stretch which is an offset of principal component analysis technique and there are three techniques mentioned here. The first one is on the indusial channel or bands, and the second band ratio and principal component analysis techniques are performed on multiple bands we say there is a single and this is multivariate analysis, so let's see that what basically is spatial filtering means here, basically.

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The purpose of spatial filtering technique is to improve the again image quality, so that interpretation becomes much easier or even classification becomes much better or accurate. And the concept of special filtering basically came from the electrical or electronics engineering there and they used to have a kind of single dimensional or a slit kind of filtering to pass the signal, certain type of signals and certain to block certain types of signals or noises, so instead of having just one dimensional, here in digital image processing we employ two dimensional filters and it is also called convolution filtering techniques.

Basically they're major if we see the types of these two techniques, then one is the low pass filtering technique which emphasizes the regional special trends or deemphasize the local variability, so that is why it is called low pass filter and whereas high pass filter emphasizes the local special variability and they're just opposite in that sense and then edge enhancement combines both filters to sharp images in that images so edge enhancement is a kind of high pass filter in that sense.

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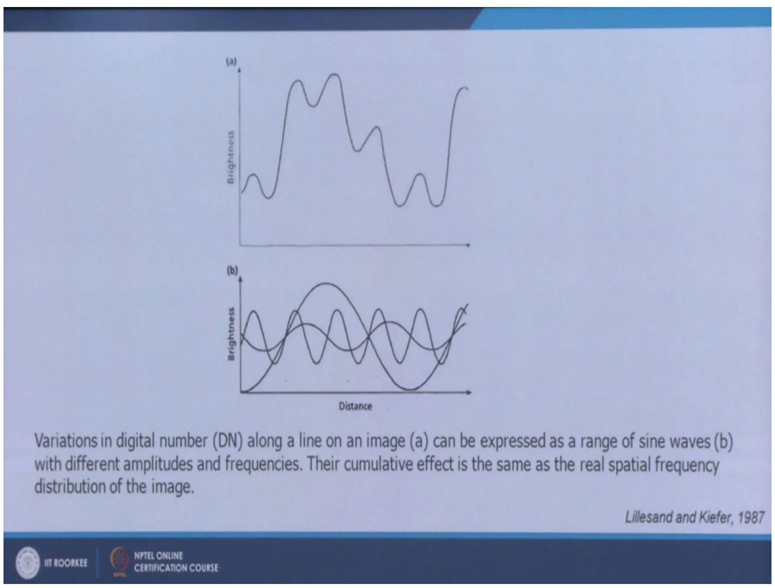

As I was mentioning that we see this way formed and here what we find that here is a combined factor and the various signals are together but these signals through filtering like in electronics engineering people do, can be can be separated out and different wavelength signals can be seen but this is single dimensional thing. In the spatial filtering, what we try to use the two dimensional metrics, a convolutional filter and then try to move throughout the image and try to improve the image as per our requirements.

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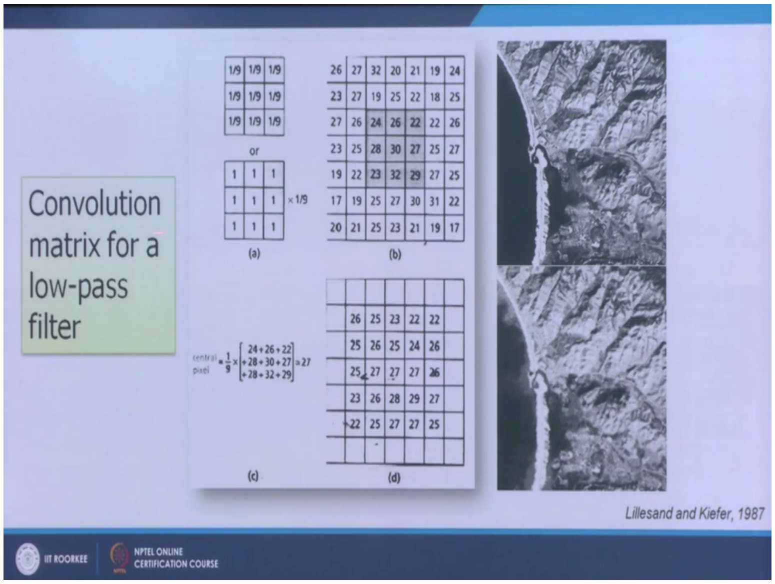

So if we see this, first the low pass filter, i.e. convolutional metrics over this, the size of this moving filter or moving metrics may vary, but it has to be odd number here, it is like in this particular example, it is a 3 by 3 metrics, we can have even 5 by 5, 7 by 7, 9 by 9 but the larger the size is going to be this convolution metrics or a special filter, more the time it would take, more the regional data means more surrounding or neighbouring pixel values will come in calculation and therefore that may not be very efficient.

So initially we can think as a 3 by 3 filter and as the purpose of low pass filter is to deemphasize the local variations which are present and in which and in reverse, we get the emphasis on the regional variations, so that is why it is called low pass filter. Now, we see this is the original image, digital representation of this image is also shown here and when it is subjected to this kind of filtering, then this is how the calculation is done. So, either we can have this kind of thing or having one integer and this is the low pass filter, what it is doing basically, as you can see that, it is making the average of all surrounding 9 pixels and giving the centre value where like here, an average value. So instead of like here, value 30 in original image, that gets 27.

Likewise, the value here 26, it gets 25 so that as you may realize that the difference here between 30 and 26 was 4 after a special filtering, low pass filtering, the difference became only 2. That means the local variations has got deemphasized, whereas the regional variations have become obvious. As you can see that the lot of variations which were present in the image, especially in the built up areas and other part of this image, they have all disappeared and now we see a more regional picture. Though the sharpness has also this is a kind of diffusion filter, so this is how it can be.

Now it is not necessary that all this value should be 1, we can change these values as per our requirements but that is mainly done in case of directional filters which we will see later and this kind of a filtering is very helpful in the mapping, where we don't want to see lot of details, local details, we would like to see the regional details and therefore we apply a low pass filter.

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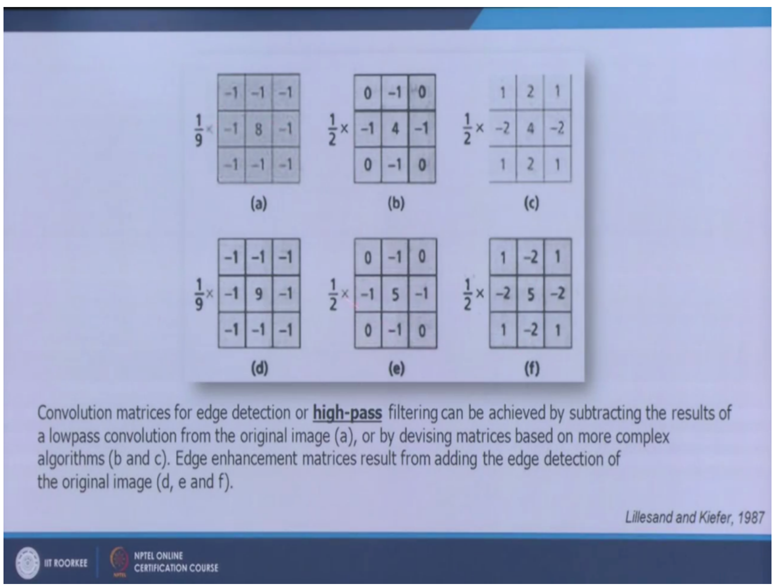

There are several high pass filters can be designed like this as a few examples six examples are shown here that convolution metrics for edge detection, directional particular direction or high pass filtering can be achieved by subtracting result of a low pass convolution from original image and this is by devising metrics based on more complex algorithm like B and C, edge announcement metrics are there, which can be add edge to the these are the directional filters you can realize and that in certain directions, things will so we will see some examples.

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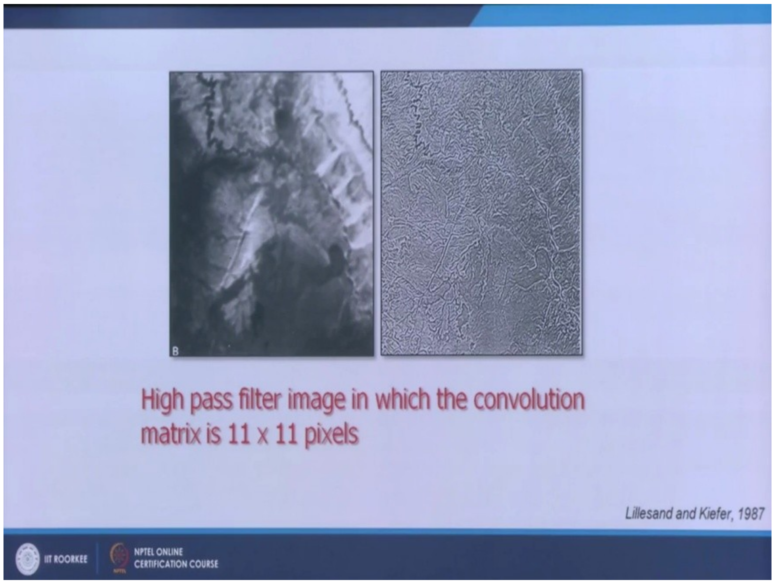

Here, a high pass filter in which the convolution metrics is 11 by 11 pixels, so as I was mentioning this odd number, 3 by 3, 5 by 5, 7 by 7, 9 by 9, even 11 and see these all local variations through this high pass filter. It's not directional, just simple high pass filter of having a size of 11 by 11 pixels, have completely evaporated the regional variations but however it has brought the local variations, has emphasized the local and then if somebody's looking for some linear features, maybe linear meant mapping or for road mapping or any other such features, then this kind of filtering can be very helpful.

All these grey shades and everything has almost disappeared and image has become virtually binary kind of image but your interpretation on linear features or some other features which are having very contrasting surroundings in original image can be emphasized very clearly.

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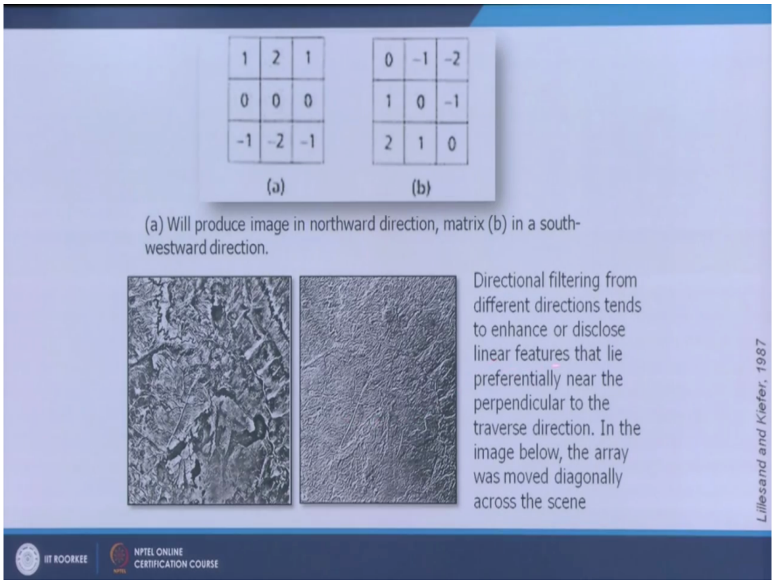

Similarly (uh)if we bring the direction instead of having in old direction the same, like in case of high pass filters here, that like if I take this example, then minus 1, minus 1, minus 1 so in all four directions, the treatment would be same. That means the values from the surrounding pixels will be treated same, but in case of directional filters as you can realize, this example is again from 3 by3 convolution metrics, is that only on one direction, we're using minus values, whereas in opposite, in the northern part, we're using the positive values so what this do, it will produce the image in northward direction which will emphasize the features.

If there are schedules and in northward direction, they will be emphasized and B will produce altogether a different results and it will produce a southward direction. So remember that wherever you are having minus values in opposite direction, the emphasis would be there. Here we're having minus values in southern side, so we will have northward direction things. And this is an example that different directional filtering, the image was the same filtering is done, earlier it was simple high pass, now directional, the peers would be different.

Linear features or which are perpendicular to this diverse direction can be emphasized very easily without much human interventions and then mapping of such things can be done very easily, so that is the advantage of having high pass filter, especially with the some emphasis on certain directions. Now, in this example, in the B example, we're having Southward emphasis, we can have just opposite, so northward north-westward emphasis, we can also change these values, put here so then we will have this north, west, south, east, in all directions and such filtering can be designed and results can be obtained.

Now, we go for the multivariate image analysis and the special filtering as mentioned earlier is always done on the single band, then later on you can combine, even sometimes people also apply this edge enhancement of filtering techniques on a false colour composite as well, so what it would do, if it is not very strong filter, what it will do, it will produce an image, output which would be much little sharper, maybe compared to the original one, so in order to sharpen image, we use this high pass filtering, in order to deemphasize or make more smooth appearance, defuse kind of image, they use the low pass filtering. In various image processing software's or even photo editing software's, you may find a certain options like defusing the image or sharpening the image, so edge enhancement in particular direction can be done and so on.

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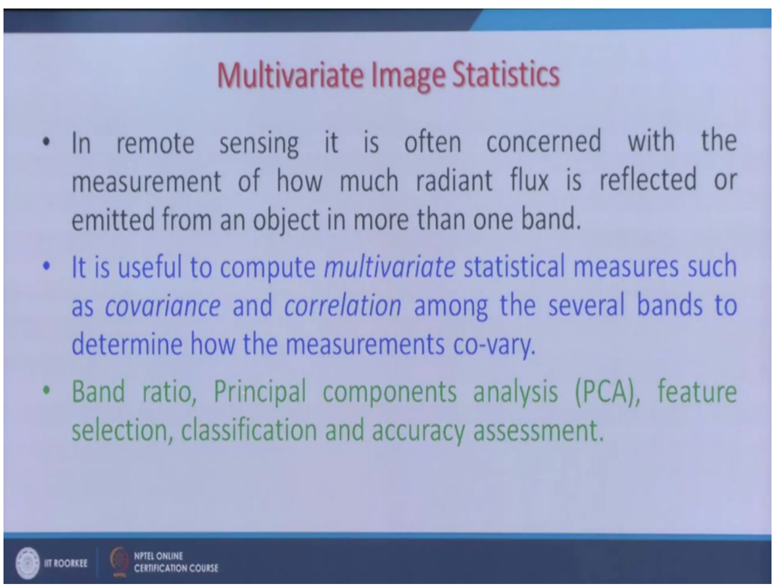

Now in multivariate image statistics, basically as you know that in remote sensing instead of one band, we're generally having multispectral bands, several channels are now available and how to involve many channels in analysis, just depending on three channels for false colour composite and doing everything on false colour composite, we will not be utilizing the entire number of channels which are available, so the best thing is to get involved in this multivariate images statistics or analysis.

As we're concerned with the measurement, how much radiant flux is reflected or emitted from an object and is more than in one band because in one band, we have different reflection of the same object, whereas in another band it's different signatures, so we want to exploit many bands and use in the analysis so that we can produce better results, better classification results as well, so in multivariate statistical, we measure such as covariance and correlation among several bands to determine how measures co-vary.

Basically the purpose here initially is to see how bands are correlated. Let me give you an example, Landsat MSS, initially the band 1 and band 2, they were very highly correlated because the responses of different objects or features which were present on the surface of the earth were sewing almost same responses in the bands. So if the correlation is very high between two adjacent bands or any two bands, then we can choose either one to use in analysis but if there is a lot of difference, then we can use both of them, so for that purpose this multivariate image statistics to analysis is very important.

Two popular techniques are there, one in band receiving, principal component analysis or there are more complex steps are there instead of just simple receiving and we create some induces like normalize difference vegetation index or some other indexes to use multiband data and create some better output. So we will see that how these things can be done.

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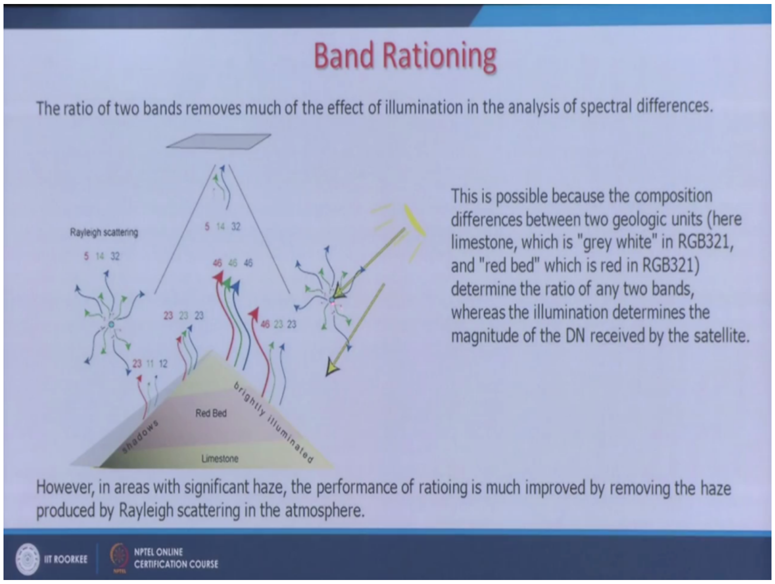

Now, in the band receiving, the ratio of two bands removed, much of the effects of illumination in the analysis of spectral differences. If you are having too much shadow areas and bright areas and shadow areas, you involve two bands and create a ratio, you would find that the shadow effect have reduced and this is what it is… that solar illumination is here, we don't bother much about the scattering which is happening in this atmosphere.

But if the structure is something like this, then this part, the part of this hint is more illumination and whereas other part goes in shadow and in three channels are shown here, examples of three channels in this view graph and they here, the same same same thing is there. But they're also in different signature, so if we start looking well use, 46, 23, 23 for red, green and blue whereas here, because of more illuminations in this part and present of a different maybe rock type all three channels are showing the same signatures, whereas due to the shadow here it has got 46 it is just half say reflection and this is here also, roughly half of on this side.

Now, ultimately it is getting recorded only 5, 14 and 32 so if we perform if we perform band wise in involving two bands, what we would find that this affect of shadow, one surface illuminated, another one is not illuminated or in shadow, this we'll remove and this is possible because of composition difference between geologic units in this example here limestone and red band and which is grey white and in the RGB, i.e. red, green blue, in the combination of 3, 2, 1 and red band which is in RGB 3, 2, 1, determines the ratio of any two bands whereas the illumination determines the magnitude of, and digital numbers received by the satellite. So this is the advantage of having bands.

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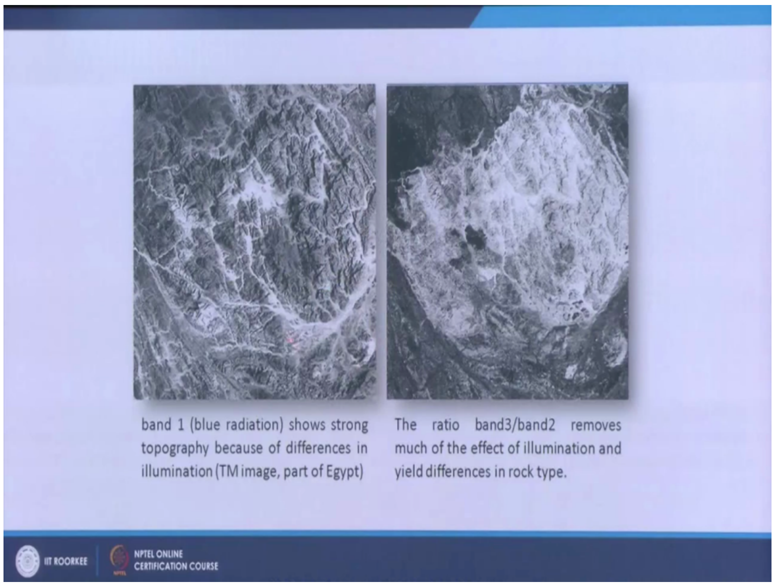

Now, we see the output, here a blue radiation means band 1 and since the strong topography while the strong topography is visible, because of differences in illumination, it's a hilly terrain, rugged terrain and when illumination is there, there will be some shadow in the hilly terrain and that will show the depth perception as well, so if we want to deemphasize the depth perception, then we need to involve some band rationing.

So here in this example, band rationing of band 3 oblique 2 was done and which removed the effects of topography and as you can see that this unit, a litho unit which was basically getting the same signatures in band 1, but in issue of band 3 into which has removed the topographic effects or different illuminations because of shadow and in the rugged terrain and we can now identify that it is a completely different rock unit.

So that is the advantage of having band with the single channel, no matter how many types of main enhancement of filtering we perform but still we may not be able to discriminate between two different lithologies which we have present in this particular example, but if we involve the band rationing, then because of we could remove shadow effects, we could discriminate two major lithological units quite easily.

Same might be in case of forest cover or in two different land uses or maybe in tool soil types. So the similar techniques can be implied but there are not really very sort of that there is no straight forward rules are written, that if we're in this problem, you can take these two channels, make the band ratio and everything we need to, not at all, so it has been it has to perform, it's a kind of hit and try so you perform, you take two bands, make the bands ratio and see whether results are satisfying, serving you a purpose or not, thus, that is one limitation of these techniques.

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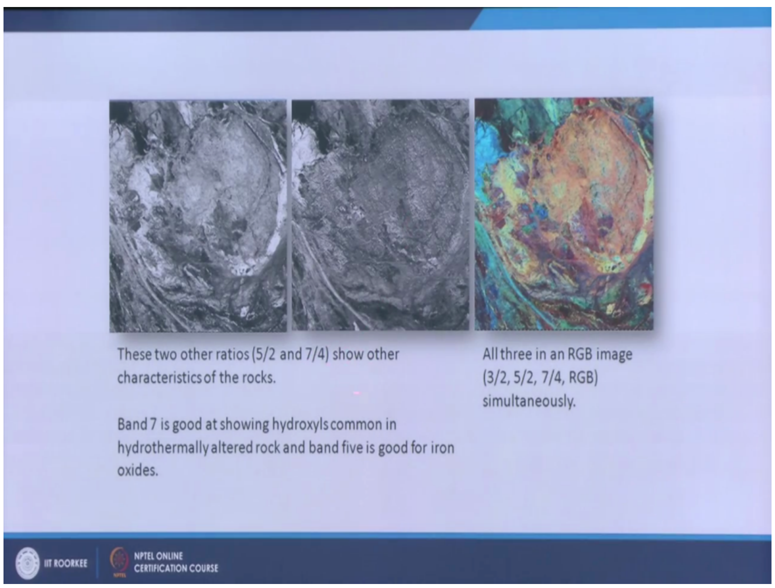

Similarly, if you're having too many bands, you can create the band ratio of several bands at least maybe 6, use them and then later on you can make also colour composites. Those not be a standard false colour composite, but anyway colour composites can be used, so composites of band ratios like example here, that these two colour band receives, this is the band of 5 by 2 and this is the band 7 by 4, an example of a Landsat TM and what we're finding that once when we combine in RGB fashion the ratio of 3 by 2, ratio of 5 by 2, ratio of 7 by 4 in red, green, blue screen, then just compare with indusial ratio and just final colour composite.

It is really giving very good results, even the variations within 1 litho units which were seeing in single band ratio example now have been emphasized here and then you can imagine that what kind of better interpretations of classification can then be performed on such colour composites. Though these are not standard colour composites, but when somebody is looking for mineral exploration or looking for different types of vegetation, different types of sides, different types of lithologies, then we need to try to involve as many as bands.

Here band 2, band 3, band 5, band 4 and band 7, so many bands have got involved, otherwise in the standard colour composite, you would be able to involve only three bands and whereas here we're involving at least 5 to 6 bands. So 5 bands have been involved to create a colour composite, otherwise only 3 can be used. So this example is from to find out the hydrothermally altered rocks and finally it was observed that band 5 is good for iron oxide detections.

But again, if I apply the same band ratio in technique, instead of in this area to another area, then the terrain conditions are going to be different, soil conditions, vegetation conditions and I may not get the same results so again we have to see that which band will emphasize which kind of rocks or materials or alterations according to it we have to adopt these things, so there is no straight forward written rules that if you find this, follow this, no, you have to try different band combinations.

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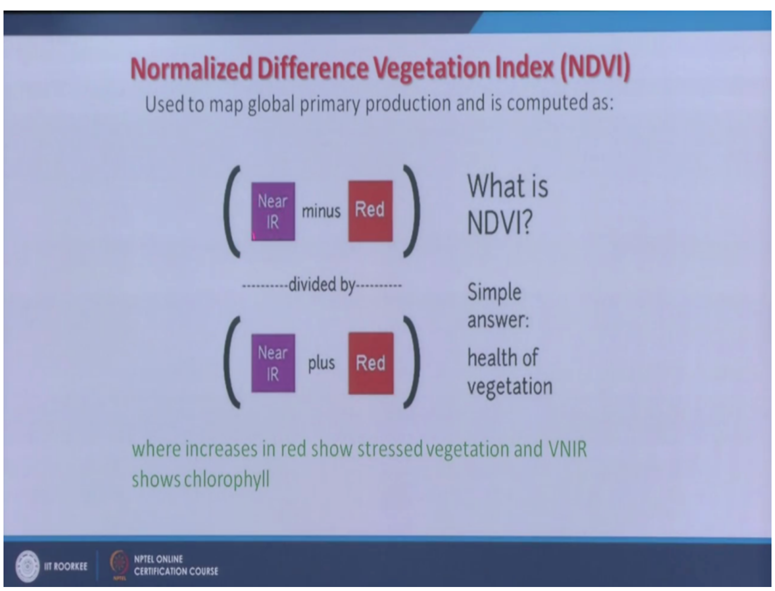

Now, offsete of a simple band ratio is this normalized difference vegetation index because in normal band rationing, there's no normalization and therefore you get a very high value or very low value but in this one you can normalize like in this example, near infrared channel-the red band divide near infrared channel plus red band and this I used to basically for mapping or seeing the changes in the vegetation, i.e. normalized difference vegetation index, this is that we want to see the health of a vegetation.

So by applying this kind of arithmetic on each pixel, involving two bands, one near infrared, because near infrared band as you know the healthy vegetation will have the highest reflection and the red band which is if it is not that healthy, then it will have, so this will create a difference, and then we can normalize it and so whereas increases in red so, stress vegetation and very near infrared shows the chlorophyll.

So this way, we can really map the health of vegetation, even not global scale, if we're using relatively low resolution, low space of resolution, data sets like NOAA AVHRR which is extensively used with of, using the time series data to see that how with global climate change, how the vegetation is changing and where it is changing maximum, where it is changing minimum, so that kind of analysis is possible, involving two channels only but normalizing it so that we can emphasize that where what is happening to the health of vegetation.

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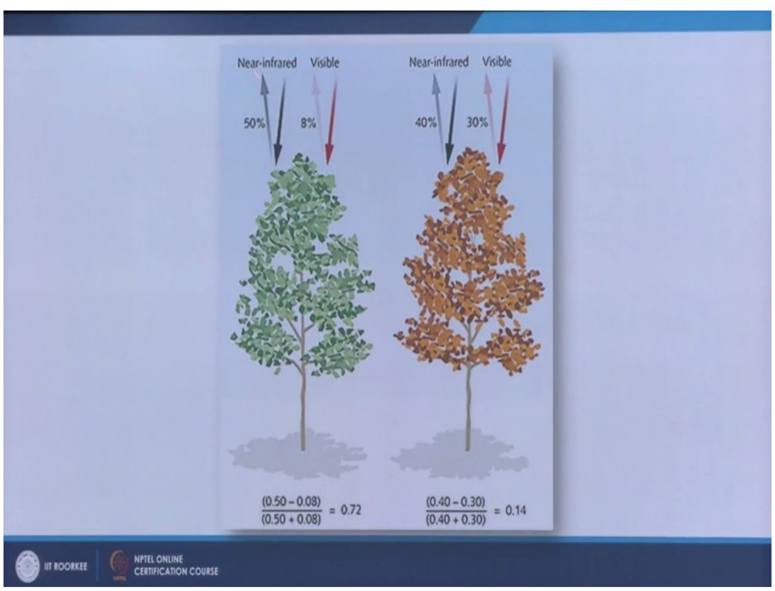

How this works is very simple as I explained that in near infrared and the healthy vegetation will say roughly reflect in this particular example about 50 percent radiation, whereas in visible part of EM Spectrum, it might reflect only 8 percent so if I use the same values and I convert them to percentage, then this is what the NDVI is going to be 0.72, in this particular case where vegetation is healthy.

Whereas in case of a vegetation which is see, this is example, if I take a example of a deciduous trees, then before the fall of these leaves, when they become yellow, the infrared because of chlorophyll content has reduced and the reflection radiation, back radiation or solar radiation may get reduced by 10 percent, whereas in visible part, this may increase very significantly.

So instead of in a healthy vegetation, earlier say for example it was 8percent, now only now 30 percent is getting back to the satellite and whereas in case of infrared, it was 50 percent, now only 40 percent is getting reflect and therefore you see that the the normalized difference vegetation index, i.e. NDVI has reduced to 1.14, so from 0.72 it has reduced to 0.14 that means, just looking the values or assigning some colours or if palette to these values on a map, we can see that where the vegetation is healthy, where is the vegetation is not healthy.

The same technique is also used in agriculture and practices are to assess the health of a crop in a region, in an area, if you're using high resolution images, then even at a level of a firm, it can be assessed, so this is how estimations are done about the production of certain crops in different countries, including in India. Very extensively remote sensing is being used in India, to assess that what kind of crop production is going to be in the Kharif season or Rabi season, so the technique is very simple, you involve a normalize difference vegetation index, NDVI, you use two channels, infrared channels and visible channel and create this normalized index and then you can assess this very nicely.

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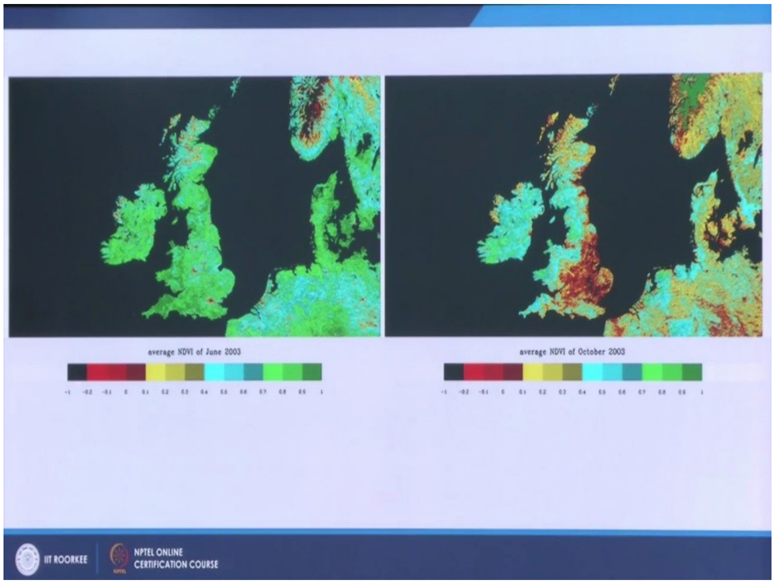

This is the example of giving of some parts of you and UK, United Kingdom, an island and as you can see that in the month of June in 2003, the NDVI was something like this. Then the London is here which is a completely built up area, less vegetation, that is why it is sowing in really in zero or in minus values. Whereas average NDVI for here, in October, 2003 because this is when you’re having maximum greenness, maximum good growth of vegetation and therefore you’re seeing like this.

But when it comes to October just a fall period, then what you’re saying, a large area has become red, that means here the vegetation has changed or so in this way we can assess that where the impact of things are, this is of the same year but if suppose, these are going June, 2072 and June, 2016 then we can know that how things have changed, so if month is same, years are different, then we can see the changes which has occurred, we can involve them since how things have changed, where things have changed and how the things have changed can also be estimated, so this is a very good technique involving minimum two channels and creating indexes, this is simply offsete of band rationing.

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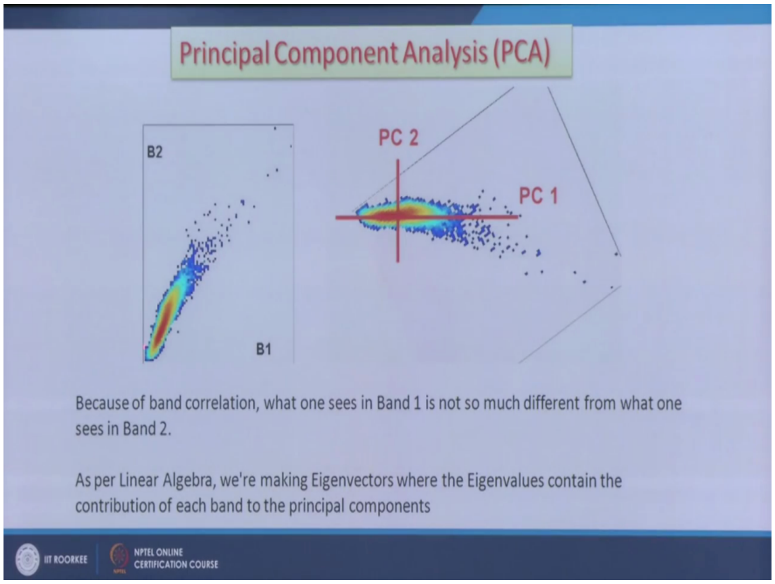

Now, the another very popular technique in digital image processing and that is principal component analysis or in short we call as a PCA ant this is in if you think that there are you have only two bands, here I am taking say example of band 1 and band 2, then I create a scatter plot, then what I see that how when in this plot, I can assess that how these two bands are correlated so what I find that these are highly correlated in this one, but I don't want to use for these two bands for further because if two bands are highly correlated, then no use of using them even in false colour composite or any other class.

We're looking the bands which are less correlated or not correlated at all, so if this is the situation, then I want to use the maximum variations which is available along this direction, so this is what it is done here that these axis are rotated, so this X and Y axis are rotated and they this becomes basically the origin also, shifted, so the maximum variants which are available are will go as a principal component one and then next variations will go in PC 2.

Think that if I involve three bands, then I can have a 3D plot, so there will be another one, which will be perpendicular to this screen and there will be also having variations, maybe little less, so that might become my principal component 3 and the likewise, then I can emphasize or use these variations and can create again colour composites as well, so because of band correlations, one we'd see in band 1 is not so much different, what we'll see in the band 2.

As per linear algebra, we're making Eigenvector, we're Eigen values containing the contribution of each band to principal components. As I have explained that origin is shifted, the axis are shifted and you get principal component 1, 2, and 3. It is a statistical technique which we can perform.

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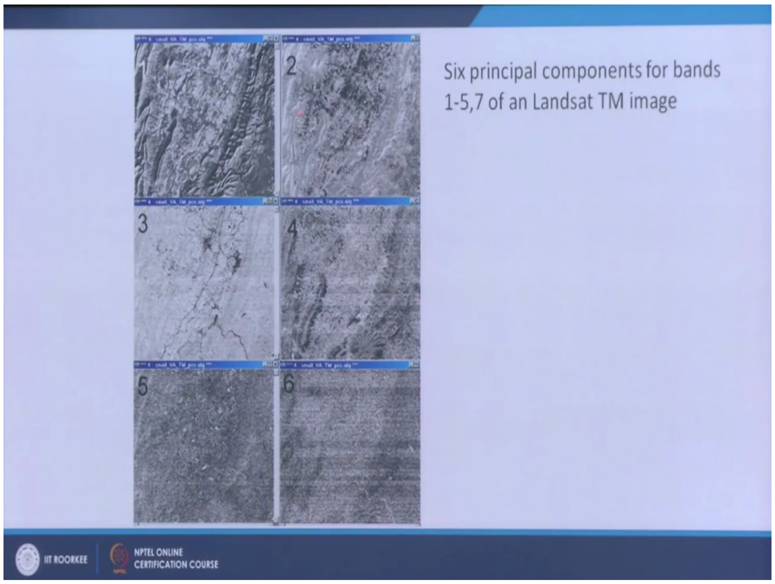

So 6 principal components for band, 1, 1 to 5 and 7 for Landsat images shown here and this is 1, 2, 3, 4, 5 and 6 and 6 is having a lot of noise and 4 is also having some stripping issues none the less if I involve these principal components, then what you will realize that principal component 1 is having the maximum variations and a lot of information can be tried further, can tried from principal component 1 and whereas this principal component 6^{th} which is having only mainly noise so up to 3, principal component 1, 2 and 3 can further use to create a colour composite and that will give you a really good information out of all 6 bands which were involved to create all this.

So 6 bands, through principal component analysis have been reduced to 3 and all the variants which were available in different bands, among different bands have come into the 3 components, the component 1, 2 and 3 and then in later on, as you go further and further, you mainly get the noise, so noise has also been reduced or removed roughly and then you get 3 components, all 3 components are completely different, although same area.

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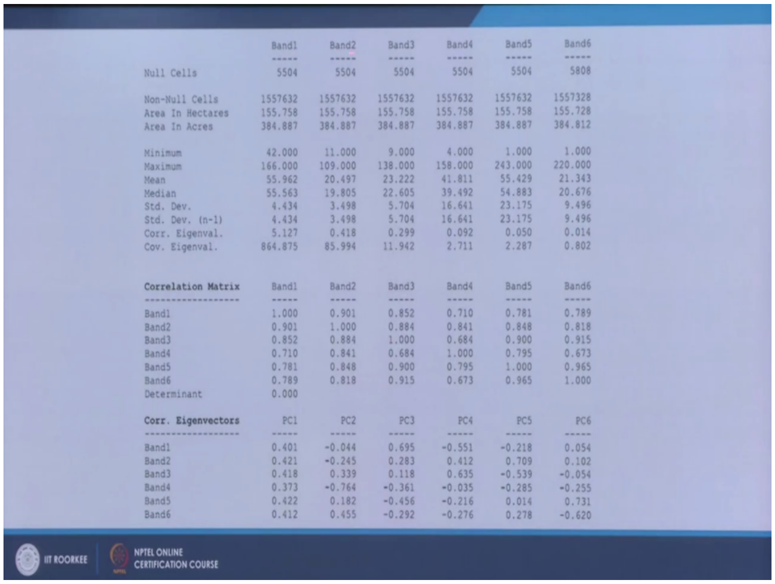

	Band1	Band2	Band3	Band4	Band5	Band6
Null Cells	5504	5504	5504	5504	5504	5808
Non-Null Cells	1557632	1557632	1557632	1557632	1557632	1557328
Area In Hectares	155.758	155.758	155.758	155.758	155.758	155.728
Area In Acres	384.887	384.887	384.887	384.887	384.887	384.812
Minimum	42.000	11.000	9.000	4.000	1.000	1.000
Maximum	166.000	109.000	138.000	158.000	243.000	220.000
Mean	55.962	20.497	23.222	41.811	55.429	21.343
Median	55.563	19.805	22.605	39.492	54.883	20.676
Std. Dev.	4.434	3.498	5.704	16.641	23.175	9.496
Std. Dev. (n-1)	4.434	3.498	5.704	16.641	23.175	9.496
Corr. Eigenval.	5.127	0.418	0.299	0.092	0.050	0.014
Cov. Eigenval.	864.875	85.994	11.942	2.711	2.287	0.802

Correlation Matrix	Band1	Band2	Band3	Band4	Band5	Band6
Band1	1.000	0.901	0.852	0.710	0.781	0.789
Band2	0.901	1.000	0.884	0.841	0.848	0.818
Band3	0.852	0.884	1.000	0.684	0.900	0.915
Band4	0.710	0.841	0.684	1.000	0.795	0.673
Band5	0.781	0.848	0.900	0.795	1.000	0.965
Band6	0.789	0.818	0.915	0.673	0.965	1.000
Determinant	0.000					

Corr. Eigenvectors	PC1	PC2	PC3	PC4	PC5	PC6
Band1	0.401	-0.044	0.695	-0.551	-0.218	0.054
Band2	0.421	-0.245	0.283	0.412	0.709	0.102
Band3	0.418	0.339	0.118	0.635	-0.539	-0.054
Band4	0.373	-0.764	-0.361	-0.035	-0.285	-0.255
Band5	0.422	0.182	-0.456	-0.216	0.014	0.731
Band6	0.412	0.455	-0.292	-0.276	0.278	-0.620

So likewise if we see here in a statistical means for all bands, 6 are here and then there is correlation and covariance metrics, the Eigenvectors can also be assessed here and when you compare band 1 band 1, of course it is going to be band and then you see that band 1 and band 2 are highly correlated but so likewise, you get a statistics as well through which also you can assess about indusial bands, among bands and their statistics as well, so similar kind of test can be created.

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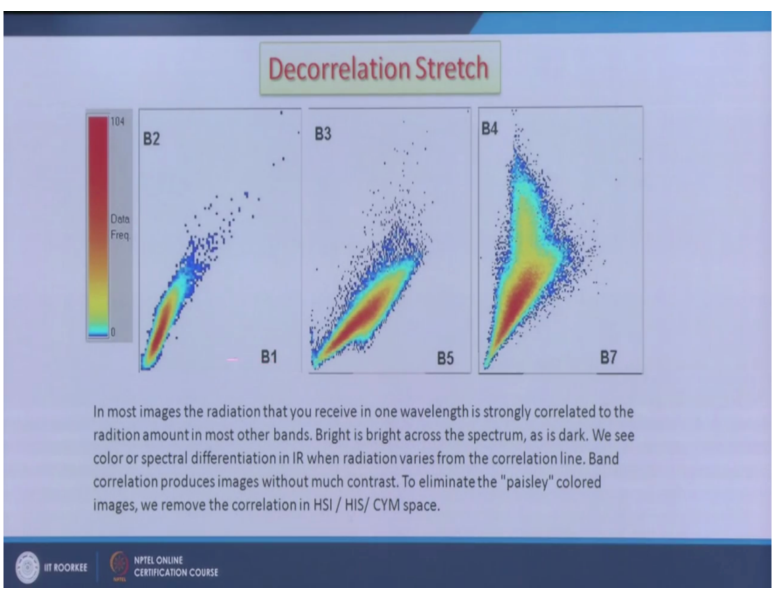

Now, there is one more step in this one, instead of just creating a colour composites, if it performs one more thing, like making a stretching oval indusial components and if there is this if we do it, then this technique is called Decorrelation stretch, so see, the example is, that two bands are plotted here through a scattered plot, band 1 and band 2, it seems they're highly correlated, whereas compared to this, band 4 and band 7, if we have plotted, completely different bands, they're showing a much more variation as compared to band 1 and 2 and in between band 3 and 5 are also showing some variation.

So what we can do, when we shift the origin and axis, same time we can stretch these reasons and we can create more contrast in the images, so in most of the images, the radiation what you receive in one wavelength is a strongly correlated variation among in most other bands, the best example here, band 1 and 2, they're which are highly correlated.

The bright is bright across the spectrum and end is dark, so we see colour or spectral differentiation. In infrared when radiance varies from correlation line, so when correlation produces images without much contrast, to illuminate a paisley colour image, we remove the correlation and then we play in this colour space and this is huge saturation intensity or new intensity saturation of cyan, magenta, yellow colour space and we remove this correlation by stretching indusial components and by which ultimately in a colour composite of destretched or stretched principal component we get a altogether different output and which technique is called decorrelation stretch.

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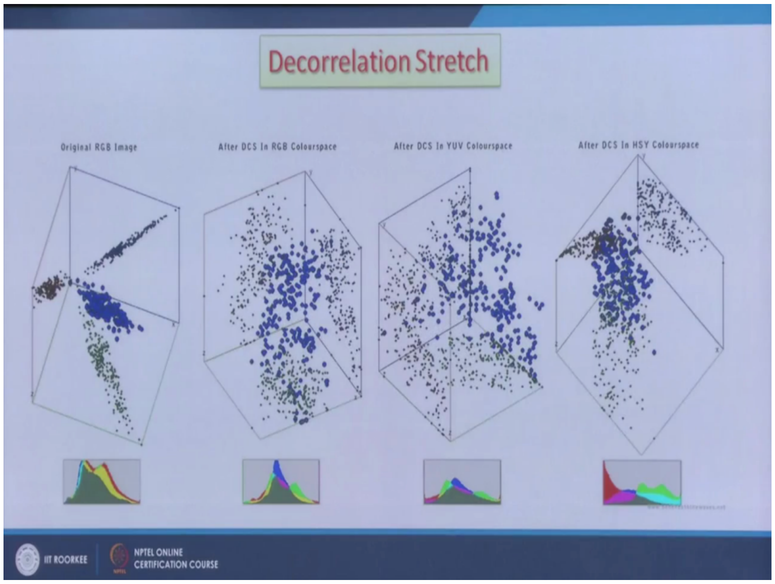

So this is how it is done and then in the original RGB space, different bands are having correlated things, but when after decorrelation stretch, that the DCS in the same colour space and it is now occupying a complete queue and if we play further in colour space, we can send and one can create more decorrelation among these. So this is how the colour space can be exploited to create much better results.

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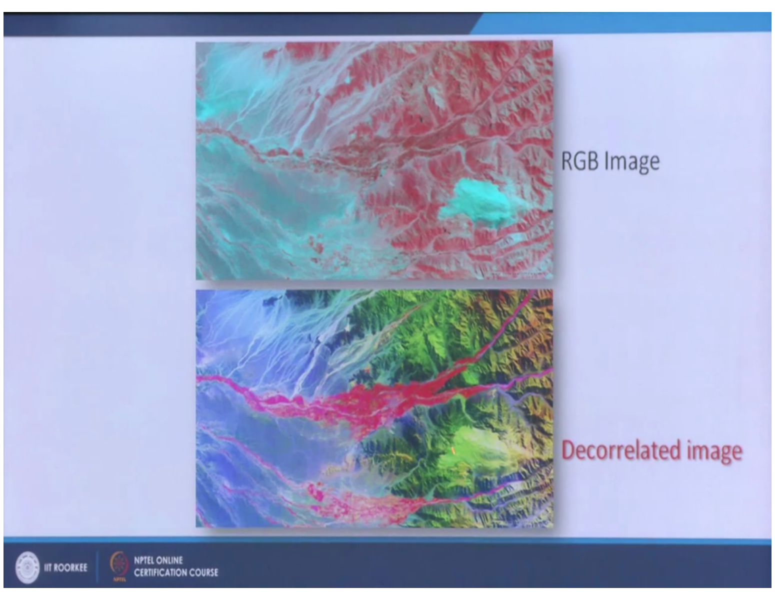

And this is the example here in the real image. This is the original false colour composite which was subjected to decorrelation and so first the principal components, that means they were input, bands were only three and the correlation among these three bands were determined and then principal component analysis were performed, all 3 components came and then using this principal component, they were two stretched indusially and you go back again and put them in same… maybe in same colour skin, so what do you find, that now you can differentiate, this red and that red, in RGB, in simple false colour composite, both are looking red, but here they're looking completely different.

So decorrelation stretch will bring more colours basically in clear image, that means completely less correlation or roughly no correlation and therefore, more colours are there and you may get an image which is easy to interpret, easy to discriminate between two edges and objects as in this example and can become very very useful.

So likewise, multivariate, single channel or single variant or multivariate analysis can be performed using one band in case of simple, spatial filtering or in involving multiple brands like in brand receiving, NDVI and principal component analysis and decorrelation stretch, so NDVI and decorrelation analysis are basically offsets of two basic techniques, one is the band rationing and another one is principal component.

The main purpose of digital image processing is to make image more clear than the original one, to improve the image quality, why to improve image quality? So that my image interpretations becomes much easier and more accurate. If I go and do perform classification, then my classification accuracy should also improve, so that's the purpose of digital image processing to improve the original image to an extent that image interpretations becomes much easier, two adjacent features or objects which are present, normally they're not distinguishable and through normal just normal visualization.

But if I subject these channels, bands, to like decorrelation stretch, then I should be able to see very clearly that how these two features are present, so I should be able to mark them, make them and make my interpretation more reliable. So thank you very much.