

## REMOTE SENSING FOR NATURAL HAZARD STUDIES

**Course Instructor:** Dr. Rishikesh Bharti  
Associate Professor  
Department of Civil Engineering  
Indian Institute of Technology Guwahati  
North Guwahati, Guwahati, Assam 781 039, India  
e-mail: rbharti@iitg.ac.in  
Website: <https://fac.iitg.ac.in/rbharti/>

---

### **Lec 9b: Remote Sensing Data Analysis-II Part B**

Hello everyone, welcome back to part 2 of Lecture 9. So, we were discussing the image classification in Part 1, and we will continue that discussion here. So, when we talk about classification, image classifiers can be trained in two ways. One is learning techniques; another one is the feature set, So, what is a learning technique? It enables to learn the changes in a system that improves the performance of the same task in the next iteration. So, like driving, cooking, and solving mathematical formulas. So, you might notice that when you drive initially, you might have some problems, but slowly, every time you learn from your mistakes, you improve yourself, and gradually you become a good driver.

Now, similarly for cooking, the more you cook, the more experience you will have, and you will be making tastier foods. This is more relevant when you try to solve numerical problems; slowly, you improve your skills, and eventually, you will be skipping steps in between because you do it in your mind; you do not have to write them down. So, your speed will be very quick in solving a mathematical formula. The same way image classifiers learn in every iteration, they train themselves, and your accuracy will improve. So, there are two major types of learning. So, as we discussed, supervised and unsupervised. Supervised learning requires the information at the beginning of the process from the analyst, and it will be completely controlled by the analyst or the user. Unsupervised, it learns through some standard scientific laws and recognizes unknown patterns using the data statistics correctly. The other one is the feature set based on the attributes of the input data; the pixels are assigned to different classes. So, when you have a very high number of points of information or ground control points from the field, you can directly map them as vegetation, water bodies, or maybe some other class. The supervised image classification is guided by the analyst with his expertise or knowledge. The required number of classes is identified by the analyst, whether you want 5 classes, 10 classes, or 15 classes in your image; that has to be decided by the analyst.

When we talk about unsupervised image classification, classifiers group the image pixels into different classes, identifying them using statistical similarity. If the statistics are the same, if the mean, median, and mode are what you will see, and there are many other ways to do the clustering, then pixels will be assigned to class 1, class 2, or class 3, and there is

one more. Which is hybrid image classification? So, here basically you will go with the unsupervised classification. So, you start the process with unsupervised classification and then subsequently you follow the supervised classification. So, this will be known as hybrid image classification. Now let us understand the training data because when we talk about supervised classification, we must have the training data; otherwise, it will become unsupervised. So, what are the different parameters or cautions that we have to follow? So, we will see some details about the training data. The training data should represent all the desired classes. So, if I want 5 classes, then corresponding to those 5 classes, all the data sets should be captured in the field. It should address the spectral variability means within a class if you have different objects, let us say, vegetation. If you are changing the vegetation species, your area is having 5 different vegetation species. So, you should have the location of those five different vegetation species so that the variation in the DN values or the reflectance falls under one class, which is vegetation. It is based on the field or image information because the training data is completely composed of the location value and the class information. Samples of training data should be geographically well-distributed. So, it should not be clustered into one part of the image, for a bigger class, the training data should be large. So, if this much area belongs to the forest, you have to represent all these pixels. It should be well distributed, and a larger number of points should be there for the forest.

To improve the accuracy of the classification, the training data can be modified. Suppose you have used this set of pixels for the classification training and the result is not very good; then you can go back, modify your training data, and see the result. So, when we talk about the classification techniques, we refer to the supervised and unsupervised classifiers. So, here you can see that in unsupervised classification there are 2 methods that are globally used: the first one is K-Means and the other one is Isodata. In supervised classification, minimum distance to mean, parallel pipe, maximum likelihood, support vector machine, artificial neural network, binary encoding, spectral information divergence, and nonparametric classifiers make this list very long, So here you can use one of them to see how your data is providing you with the input, and then maybe if the results are not satisfactory, you can try some other method, modify your training data, and then you can see the result.

In general, the spectral classifiers are used to classify the hyperspectral data. So, when we talk about high-dimensional data, for example, hyperspectral data, those are the data that have different information; they have high spectral resolution. So, the multispectral classifier, the names that I mentioned in the previous slide, some of which are completely dedicated to multispectral, while some of them can be used with high-dimensionality data. So, here, in general, spectral classifiers are used to classify the hyperspectral data. So, spectral angle mapper, mixed-tune matching filtering, spectral feature fitting, support vector machine, binary encoding, and random forest.

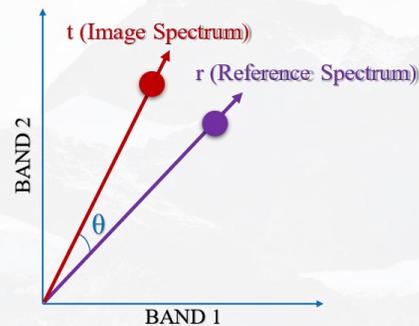
These are popular for classifying the hyperspectral data. So, any one of them, or maybe a combination of them, can be used to classify the hyperspectral data, So, let us talk about the SAM Spectral Angle Mapper. So, here for large dimension data, estimation of band statistics and distance for each pixel is a tedious process. Because when you understand the multispectral classifier, you will understand how tedious it is to find the band statistics and the distance from each pixel to the class mean or category correctly. So, the spectral angle mapper technique is very efficient in handling such large-dimensional data.

## Spectral Classifier: Spectral Angle Mapper (SAM) (1)



$$\theta = \text{COS}^{-1} \left( \frac{\sqrt{\sum_{i=1}^n t_i r_i}}{\sqrt{\sum_{i=1}^n t_i^2} \sqrt{\sum_{i=1}^n r_i^2}} \right)$$

where,  $t_i$  is the target spectrum (image),  $r_i$  is the reference spectrum (library),  $i$  is the number of input spectral bands (1, 2, 3, ..., n) and  $\theta$  is the angle between the target and reference spectrum.



A threshold value is used to specify the maximum acceptable angle for the separation between the pixel and reference spectra.

So, a large dimension means a greater number of bands. SAM is a spectral classifier that determines the spectral similarity based on the angle between the pixel and reference spectra. So, what we will do is try to plot these two into this N dimension. So, suppose this is the target; this is your reference because here we are talking about the reference high spectral resolution. So, we are using the spectral information to classify our data.

It can be from the library, or it can be from the field, or from the lab, So, this SAM treats both pixel and reference spectra as vectors in a space where the dimensionality is equal to the number of bands. Remember I mentioned the Andy plot, which means the Andy is equal to the number of bands. Reference spectra used in SAM can be acquired in the laboratory and field, or can be extracted directly from the image of the endmembers that we discussed in the hyperspectral. So, those end members can be extracted from the image itself. In an n-dimensional feature space, pixel and reference spectra should both have magnitude and an angle.

So, here we will have the magnitude and the angle, at which angle they are different from each other. A small angle between the pixel and reference spectra indicates a high similarity. If they are close to each other with respect to this theta, then they are more

similar in nature. If they are far, then they are not there. High angles indicate low similarity. So, this is a high angle and this is a low angle, here, this particular plot is meant to explain this SAM; here, this  $r$  is the reference spectrum, which is from, let us say, a library, lab measurement, or field measurement. The right data that we wanted to use as our training data for this SAM classifier. Now, when we use this, we try to find this  $\theta$ . So, this  $\theta$  is calculated using this particular equation, where  $t_i$  is the target spectrum,  $r_i$  is the reference spectrum from the library field or lab,  $i$  is the number of input spectral bands, which can be 200 or 300, depending on which data you are using, and  $\theta$  is the angle between the target and the reference spectrum. So, if it is more, they are not in the same class; if they are very close, then they are in the same class, So, a threshold value is used to specify the maximum acceptable angle for the separation between the pixel and the reference spectra.

So, I can put a threshold of 1 degree, 2 degrees, or 3 degrees. So, depending on that, the system or the method will decide whether they belong to the same class or to a different class. So, similarly using this SAM, this image has been classified, and you can see here basalt, anorthosite, norite, pyroxenite, olivine, basalt, and Fe-basalt; those are mapped in this particular image, So, this is a very good method. So, I thought of covering at least one method for the hyperspectral because in the application part we will be referring to this SAM, Now, as we discussed, the ultimate aim of remote sensing images is to provide the input for your analysis, And once you generate the input, you should be very confident, or you should have a value that this input is 60%, 70%, or 90% correct. So, after doing the image classification, the accuracy assessment is mandatory; there is no way out.

So, you have to estimate the accuracy of your output result. The ultimate aim of a remotely sensed image is to produce the thematic map or to be a part of a decision support system; without an accuracy assessment, the result of classification is of zero value to support the results of a remotely sensed image overall, and class-wise accuracy needs to be estimated. So, here we will have class-wise or overall. Class-wise means if my image has 4 classes, let us say this. So, this is forest, water, urban, maybe vegetation, or maybe some other class, bare land.

So, whether my whole classification's overall accuracy is 60%, class-wise my accuracy can be less or more. So, some of the classes may be 90% accurate, some of the classes may be 60% accurate, some of the classes can be 50 percent accurate, and on average, you are getting an overall accuracy of 70% that may be right. We need to have this statistical data about the image classification, and on that basis, we will only say that this particular image, which we have produced using the classification technique, is 60%, 70%, or 80% correct. In general, accuracy can be estimated using ground truth; thus, the ground truth is the pixel whose location values are known. So, we go to the field, we collect the latitude and longitude, and then the class information, and we identify the classified image on the image, and then we see whether the classified classes are correct or not.

So, this set of pixels is known as the test pixel. So, this is one example; here, you can see the satellite images on the left side, and the right side is the classified image, and this is the table. So, this legend can be used to refer to whether this color represents an urban area, a mining area, a rural area, cropland, agricultural land, or fallow land. So, this color code is helping us to understand how much area is covered with a particular class or category.

**Confusion Matrix**

	Ground Truth (Test Pixels)					Total no. of classified pixels	User's Accuracy
	Class-I	Class-II	Class-III	Class-IV	Class-V		
<b>Map (Classified Map)</b>	Class-I	7	1	4	1	1	14
	Class-II	0	8	0	0	0	8
	Class-III	1	0	25	1	1	28
	Class-IV	0	0	1	12	1	14
	Class-V	0	0	1	1	8	10
	<b>Total No. of ground truth pixels</b>	<b>8</b>	<b>9</b>	<b>31</b>	<b>15</b>	<b>11</b>	<b>74</b> <small>Total no. of pixels used for accuracy assessment</small>
<b>Producer's Accuracy</b>							

So, after assessing accuracy, we will state that this particular map is 60% correct or 90% correct. So, once the ground truth for the test pixel has been decided, the classification has been completed into a tabular data format, which is known as a confusion matrix. It is generated to estimate the accuracy. A confusion matrix is also called an error matrix. This table is used to estimate the class-wise and overall accuracy of the classification.

So, class-wise means whether it is for forest, how accurate it is for water bodies, or overall accuracy; the whole classification method is 60%, 70%, or 80% correct. Rows of the confusion matrix are reserved for the information derived from the classified map, whereas the columns are reserved for the ground truth that is from the ground you are collecting the test pixels from. So, those fixed in the columns will show the confusion matrix here. So, here the row is the classified map, and the column is the ground truth. Now, you see we have classified our image into five classes.

## Confusion Matrix

### Producer's Accuracy (Omission Error)

		Ground Truth (Test Pixels)					Total no. of classified pixels	User's Accuracy
		Class-I	Class-II	Class-III	Class-IV	Class-V		
Thematic Map (Classified Map)	Class-I	7	1	4	1	1	14	
	Class-II	0	8	0	0	0	8	
	Class-III	1	0	25	1	1	28	
	Class-IV	0	0	1	12	1	14	
	Class-V	0	0	1	1	8	10	
	Total No. of ground truth pixels	8	9	31	15	11	74 <small>Total no. of pixels used for accuracy assessment</small>	
	Producer's Accuracy							

$$\text{Producer's Accuracy} = \frac{\text{Number in diagonal cell of error matrix}}{\text{Total no. of pixels in column}} \quad \text{Producer's Accuracy}_{\text{Class-I}} = \frac{7}{8} = 87.5\%$$

So, this is class 1, class 2, class 3, class 4, and class 5, and this is the total number of pixels, and here you have user accuracy; here you have producer accuracy. So, similarly, the classified map also has the 5 classes. So, class 1 versus class 1 indicates that 7 pixels are correctly classified as class 1 with respect to ground information. 8 pixels are correctly classified as class 2 with respect to ground truth. 25 pixels are correctly classified as class 3, and here 12 pixels are correctly classified as class 4, and 8 pixels are correctly classified as class 5.

## Confusion Matrix

### User's Accuracy (Commission Error)

		Ground Truth (Test Pixels)					Total no. of classified pixels	User's Accuracy
		Class-I	Class-II	Class-III	Class-IV	Class-V		
Thematic Map (Classified Map)	Class-I	7	1	4	1	1	14	
	Class-II	0	8	0	0	0	8	
	Class-III	1	0	25	1	1	28	
	Class-IV	0	0	1	12	1	14	
	Class-V	0	0	1	1	8	10	
	Total No. of ground truth pixels	8	9	31	15	11	74 <small>Total no. of pixels used for accuracy assessment</small>	
	Producer's Accuracy							

$$\text{User's Accuracy} = \frac{\text{Number in diagonal cell of error matrix}}{\text{Total no. of pixels in row}} \quad \text{User's Accuracy}_{\text{Class-I}} = \frac{7}{14} = 50.0\%$$

So, this is the kind of table you have to generate for your image. And once you add them, this is the total number of pixels that are correctly classified: 74. And when you add this

particular row, we will see it now. So, this is image classification, this particular side is fixed for image information. So, if you see this row,  $7 + 1 + 4 + 1 + 1 = 14$ . So, 14 pixels were classified as class 1 by my classifier. But according to ground information, only 7 are correctly classified; the rest 7 belong to some other classes. So, we can say 50 percent is correctly classified, and 50 percent is wrongly classified. Similarly, for class 2, if I see that 8 is correctly classified, this is coming to 8, For class 3, 25 are correctly classified, and these are wrongly classified.

For 4, it is 12, 1, 1, and here it is 8, 1, 1. Here, when you see the row, you have to see how many pixels are correctly classified and how many are wrongly classified. Now, we will go with the columns. So when we look at this column, the first column says that 7 of the ground truth are matching with class 1, and 1 of them is falling into class 3. So, the classifier has wrongly classified this 1 into class 3, and 7 is correctly classified.

So, similarly, you have to go with all the columns. And then you have to analyze your results. But to say a number, you need to calculate it correctly. So, what will we do? We will go with the producer's accuracy, the number in the diagonal cell of the error matrix, and the total number of pixels in the right column. So, this is the value of 7 out of 8. So, this particular class, Class 1, is having 87.5 percent producer accuracy. That means if I am the classifier and the user, I will say that I have produced an 87.5 percent accurate result for class 1. If I have generated this particular image or if I have generated the classified map, then I will become the producer.

**Confusion Matrix** 

**Overall Accuracy**

		Ground Truth (Test Pixels)					Total no. of classified pixels	User's Accuracy
		Class-I	Class-II	Class-III	Class-IV	Class-V		
Thematic Map (Classified Map)	Class-I	7	1	4	1	1	14	
	Class-II	0	8	0	0	0	8	
	Class-III	1	0	25	1	1	28	
	Class-IV	0	0	1	12	1	14	
	Class-V	0	0	1	1	8	10	
	Total No. of ground truth pixels	8	9	31	15	11	74 <small>Total no. of pixels used for accuracy assessment</small>	
	Producer's Accuracy							

$$\text{Overall Accuracy} = \frac{\text{Total no. of correctly classified pixels}}{\text{Total no. of pixels used for accuracy assessment}}$$

So, as a producer, I have produced a result that is 87.5 percent accurate for class 1. But if you are the user of my results, then you will be calling it in this way. And then the total number of pixels covered in that is right. So, here the accuracy will become less. So, if you

compare the producer accuracy with the user accuracy, the user accuracy is less. So, as a producer, I am saying I have produced a more accurate result, but as a user, you will say no, you have produced less accurate results. So then, the overall accuracy comes. So, this is the sum of all these diagonal pixels and the total number of pixels that are used in this particular accuracy assessment.

## Kappa Coefficient



		Ground Truth (Test Pixels)					Total no. of classified pixels
		Class-I	Class-II	Class-III	Class-IV	Class-V	
Thematic Map (Classified Map)	Class-I	7	1	4	1	1	14
	Class-II	0	8	0	0	0	8
	Class-III	1	0	25	1	1	28
	Class-IV	0	0	1	12	1	14
	Class-V	0	0	1	1	8	10
	Total No. of ground truth pixels	8	9	31	15	11	74 <small>Total no. of pixels used for accuracy assessment</small>

$$Kappa(k) = \frac{(N \times A) - B}{N^2 - B}$$

where, N = Total no. of pixels used for accuracy assessment (74);

A = Total no. of correct classified pixels (60); B = [(8×14)+(9×8)+(31×28)+(15×14)+(11×10)]

So, that will be your overall accuracy. Now, let us talk about the kappa coefficient; this is another way of providing the accuracy value. So, when we talk about the kappa coefficient, it estimates the accuracy of a classified image, which measures the proportion, that is, the percentage. Improvement by the classifier over a randomly assigned ground truth that is your test pixel to different classes is correct. So, here is what we will do: we will try to calculate the kappa coefficient. So, the kappa coefficient, this k (small k), is equal to NxA-B divided by N squared minus B.

So, here N is the total number of pixels used in the accuracy assessment, which is 74, the total number of correctly classified pixels, which is 60, and B is Multiplication of row and column values corresponding to a class or category. So, 8 multiplied by 14 plus 9 multiplied by 8 plus 31 multiplied by 28 plus 15 multiplied by 14 plus 11 multiplied by 10 will give you the B. Now, you use these values here, and then you calculate the kappa coefficient,

So, with this, I will end this lecture, and we will continue this course with Lecture 10, and we will start the next module in the following lecture.

Thank you very much.