# THE POWER OF REMOTE SENSING CLASSIFICATION FOR ENVIRONMENTAL MONITORING AND MANAGEMENT

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**Abstract:**

Remote sensing, the science of acquiring information about Earth's surface from a distance, has become a critical tool for environmental monitoring and management. Extracting meaningful insights from this vast amount of data hinges on the power of remote sensing classification. This technique categorizes pixels within an image based on their spectral characteristics, allowing scientists to identify and map various features on the Earth's surface. This article explores the capabilities of remote sensing classification in environmental applications. We will examine how classification facilitates the monitoring of land cover change, deforestation, forest health, water quality, and other critical environmental parameters. By enabling the creation of detailed and up-to-date maps, remote sensing classification empowers environmental managers to track changes, assess risks, and develop effective strategies for sustainable resource management.

**Key words:** Remote Sensing, Classification, monitoring, pixel.

## Introduction

The overall objective of image classification procedures is to automatically cate-gorize all pixels in an image into land cover classes or themes (Lillesand et. al., 2015, p 537).

Supervised classification is the procedure most often used for quantitative analysis of remote sensing image data (Richards et. al., 2006, p 193).

In classification based on prototypes, the objective is to make the features so unique and easily detectable that classification itself becomes a simple task (Gonzalez et.al.,2018, p 904).

Image classification is an important part of the fields of remote sensing, image analysis, and pattern recognition (Campbell et.al., 2011, p 335).

Digital image classification uses the spectral information represented by the digital numbers in one or more spectral bands, and attempts to classify each individual pixel based on this spectral information (Canada Centre for Remote Sensing 2020, p161).

Classification of images helps to study the information on the ground more accurately.

**Supervised Classification**

We use a hypothetical example to facilitate our discussion of supervised classifi cation. In this example, let us assume that we are dealing with the analysis of five-channel airborne multispectral sensor data. (The identical procedures would apply to Landsat, SPOT, WorldView-2, or virtually any other source of multispectral data.) Figure 1. shows the location of a single line of data col-lected for our hypothetical example over a landscape composed of several cover types. For each of the pixels shown along this line, the sensor has measured scene radiance in terms of DNs recorded in each of the five spectral bands of sen-sing: blue, green, red, near infrared, and thermal infrared. Below the scan line, typical DNs measured over six different land cover types are shown. The vertical bars indicate the relative gray values in each spectral band. These five outputs represent a coarse description of the spectral response patterns of the various terrain features along the scan line. If these spectral patterns are sufficiently dis-tinct for each feature type, they may form the basis for image classification (Lillesand et. al., 2015, p 539).

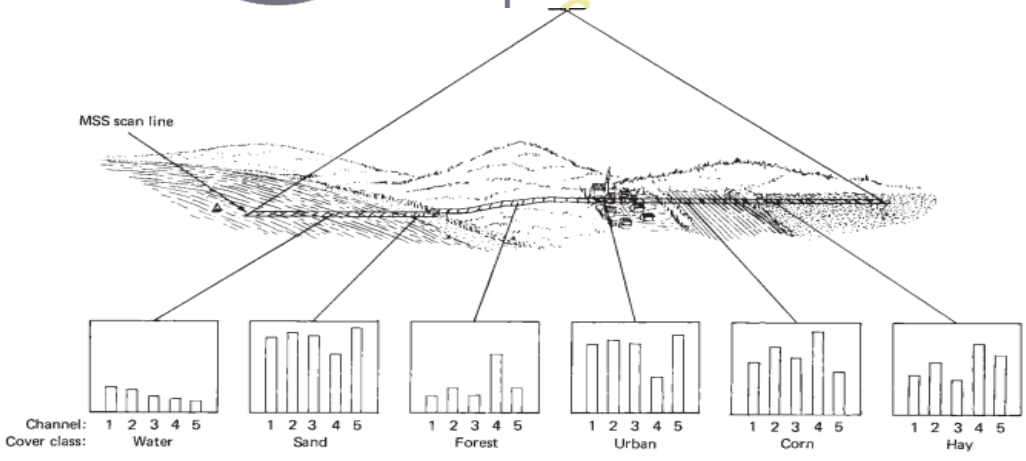


*Figure 1. Figure 7.34 Selected multispectral sensor measurements made along one scan line. Sensor covers the following spectral bands: 1, blue; 2, green; 3, red; 4, near infrared; 5, thermal infrared.*

**The Classification Stage**

Numerous mathematical approaches to spectral pattern recognition have been developed. Our discussion only scratches the surface of this topic.We illustrate the various classification approaches with a two-channel (bands 3 and 4) subset of our hypothetical five-channel multispectral sensor data set. Rarely

are just two channels employed in an analysis, yet this limitation simplifies the graphic portrayal of the various techniques. When implemented numerically, these procedures may be applied to any number of channels of data. Let us assume that we take a sample of pixel observations from our two-channel digital image data set. The two-dimensional digital values, or measurement vectors, attributed to each pixel may be expressed graphically by plotting them on a scatter diagram (or scatter plot), as shown in Figure 2. In this diagram, the band 3 DNs have been plotted on the y axis and the band 4 DNs on the x axis. These two DNs locate each pixel value in the two-dimensional "mea-surement space" of the graph. Thus, if the band 4 DN for a pixel is 10 and the band 3 DN for the same pixel is 68, the measurement vector for this pixel is represented by a point plotted at coordinate (10, 68) in the measurement space. Let us also assume that the pixel observations shown in Figure 2. are from areas of known cover type (that is, from selected training sites). Each pixel value has been plotted on the scatter diagram with a letter indicating the category to which it is known to belong. Note that the pixels within each class do not have a single, repeated spectral value. Rather, they illustrate the natural centralizing tendency yet variability of the spectral properties found within each cover class. These "clouds of points" represent multidimensional descriptions of the spectral response patterns of each category of cover type to be interpreted. The following classification strategies use these "training set" descriptions of the category spectral response patterns as interpretation keys by which pixels of unidentified cover type are categorized into their appropriate classes (Lillesand et. al., 2015, p 541).

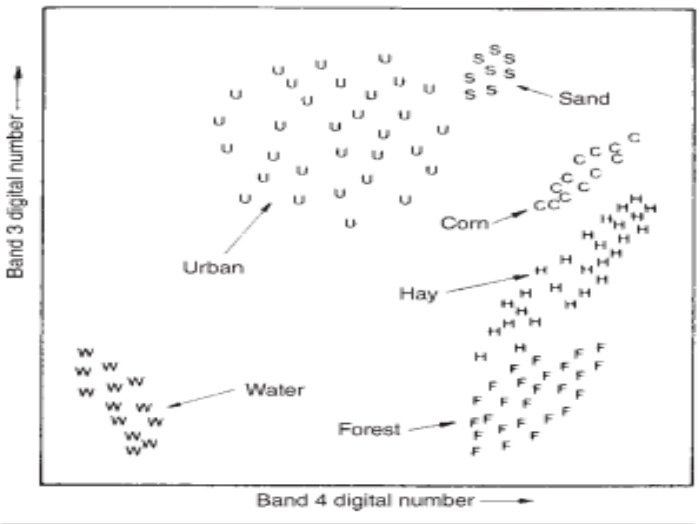

*Figure 2. Pixel observations from selected training sites plotted on scatter diagram.*

**Minimum-Distance-to-Means Classifier**

Figure 3. illustrates one of the simpler classification strategies that may be used. First, the mean, or average, spectral value in each band for each category is determined. These values comprise the mean vector for each category. The category means are indicated by þsymbols in Figure 3. By considering the two-channel pixel values as positional coordinates (as they are portrayed in the scatter diagram), a pixel of unknown identity may be classified by computing the distance between the value of the unknown pixel and each of the category means. In Figure 3, an unknown pixel value has been plotted at point 1. The distance between this pixel value and each category mean value is illustrated by the dashed lines. After computing the distances, the unknown pixel is assigned to the "closest" class, in this case "corn." If the pixel is farther than an analyst-defined distance from any category mean, it would be classified as "unknown." The minimum-distance-to-means strategy is mathematically simple and computationally efficient, but it has certain limitations. Most importantly, it is insensitive to different degrees of variance in the spectral response data. In Figure 3, the pixel value plotted at point 2 would be assigned by the distance-to-means classifier to the "sand" category, in spite of the fact that the greater variability in the "urban" category suggests that "urban" would be a more appropriate class assignment. Because of such problems, this classifier is not widely used in applications where spectral classes are close to one another in the measurement space and have high variance (Lillesand et. al., 2015, p 542).

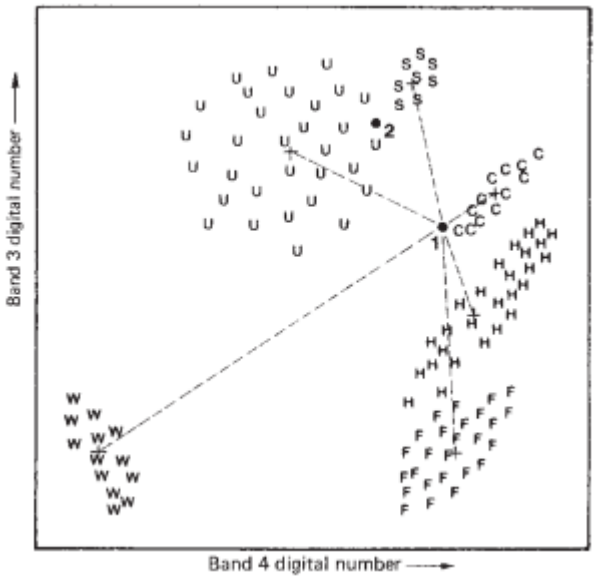


*Figure 3. Minimum distance to means classification strategy.*

**Parallelepiped Classifier**

We can introduce sensitivity to category variance by considering the range of values in each category training set. This range may be defined by the highest and lowest digital number values in each band and appears as a rectangular area in our two-channel scatter diagram, as shown in Figure 4. An unknown pixel is classified according to the category range, or decision region, in which it lies or as "unknown" if it lies outside all regions. The multidimensional analogs of these rectangular areas are called parallelepipeds, and this classification strategy is refer-red to by that tongue-twisting name. The parallelepiped classifier is also very fast and efficient computationally. The sensitivity of the parallelepiped classifier to category variance is exempli-fied by the smaller decision region defined for the highly repeatable "sand" cate-gory than for the more variable "urban" class. Because of this, pixel 2 would be appropriately classified as "urban." However, difficulties are encountered when category ranges overlap. Unknown pixel observations that occur in the overlap areas will be classified as "not sure" or be arbitrarily placed in one of the two overlapping classes. Overlap is caused largely because category distributions exhibiting correlation or high covariance are poorly described by the rectangular decision regions. Covariance is the tendency of spectral values to vary similarly in two bands, resulting in elongated, slanted clouds of observations on the scatter diagram. In our example, the "corn" and "hay" categories have positive covar-iance (they slant upward to the right), meaning that high values in band 3 are generally associated with high values in band 4, and low values in band 3 are associated with low values in band 4. The water category in our example exhibits negative covariance (its distribution slants down to the right), meaning that high values

in band 3 are associated with low values in band 4. The “urban” class shows a lack of covariance, resulting in a nearly circular distribution on the scat-ter diagram (Lillesand et. al., 2015, p 543).

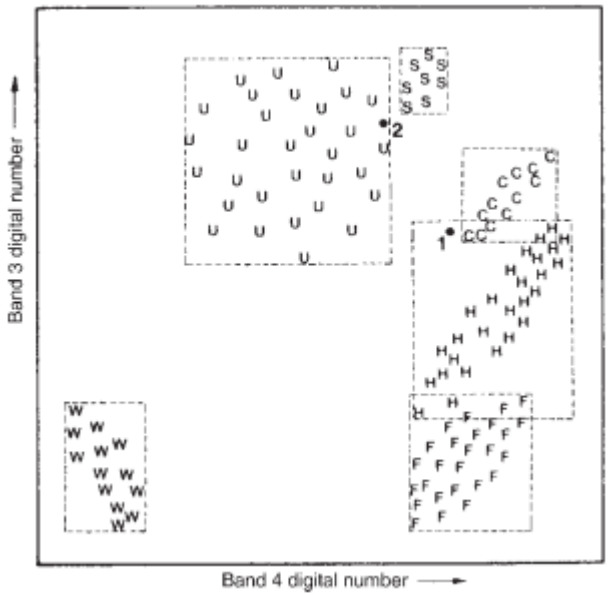


*Figure 4. Parallelepiped classification strategy*

**Gaussian Maximum Likelihood Classifier**

The maximum likelihood classifier quantitatively evaluates both the variance and covariance of the category spectral response patterns when classifying an unknown pixel. To do this, an assumption is made that the distribution of the cloud of points forming the category training data is Gaussian (normally dis-tributed). This assumption of normality is generally reasonable for common spec-tral response distributions. Under this assumption, the distribution of a category response pattern can be completely described by the mean vector and the covar-iance matrix. Given these parameters, we may compute the statistical probability of a given pixel value being a member of a particular land cover class. Figure 5, shows the probability values plotted in a three-dimensional graph. The vertical axis is associated with the probability of a pixel value being a member of one of the classes. The resulting bell-shaped surfaces are called probability density func-tions, and there is one such function for each spectral category (Lillesand et. al., 2015, p 544).

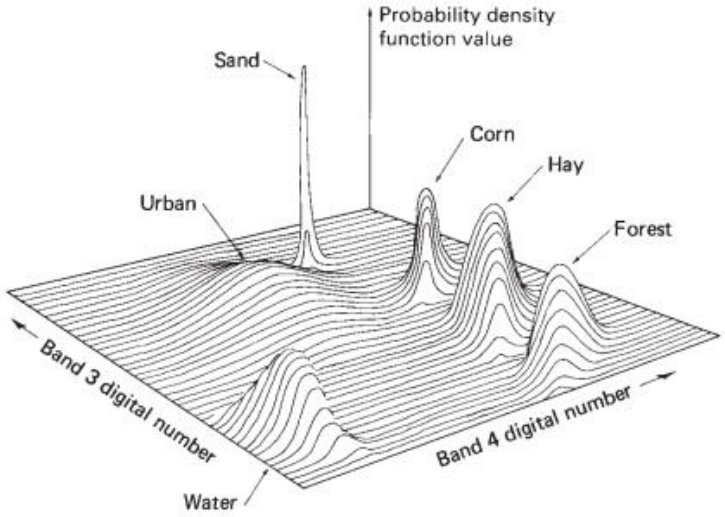


*Figure 5. Probability density functions defined by a maximum likelihood classifier.*

The probability density functions are used to classify an unidentified pixel by computing the probability of the pixel value belonging to each category. That is, the computer would calculate the probability of the pixel value occurring in the distribution of class "corn," then the likelihood of its occurring in class "sand," and so on. After evaluating the probability in each category, the pixel would be assigned to the most likely class (highest probability value) or be labeled "unknown" if the probability values are all below a threshold set by the analyst. In essence, the maximum likelihood classifier delineates ellipsoidal "equi-probability contours" in the scatter diagram. These decision regions are shown in Figure 6. The shape of the equiprobability contours expresses the sensitivity of the likelihood classifier to covariance. For example, because of this sensitivity, it can be seen that pixel 1 would be appropriately assigned to the "corn" category. An extension of the maximum likelihood approach is the Bayesian classifier. This technique applies two weighting factors to the probability estimate. First, the analyst determines the "a priori probability," or the anticipated likelihood of occurrence for each class in the given scene. For example, when classifying a pixel, the probability of the rarely occurring "sand" category might be weighted lightly, and the more likely "urban" class weighted heavily. Second, a weight asso-ciated with the "cost" of misclassification is applied to each class. Together, these factors act to minimize the "cost" of misclassifications, resulting in a theoretically optimum classification. In practice, most maximum likelihood classification is performed assuming equal probability of occurrence and cost of misclassification for all classes. If suitable

data exist for these factors, the Bayesian implementation of the classifier is preferable (Lillesand et. al., 2015, p 546).

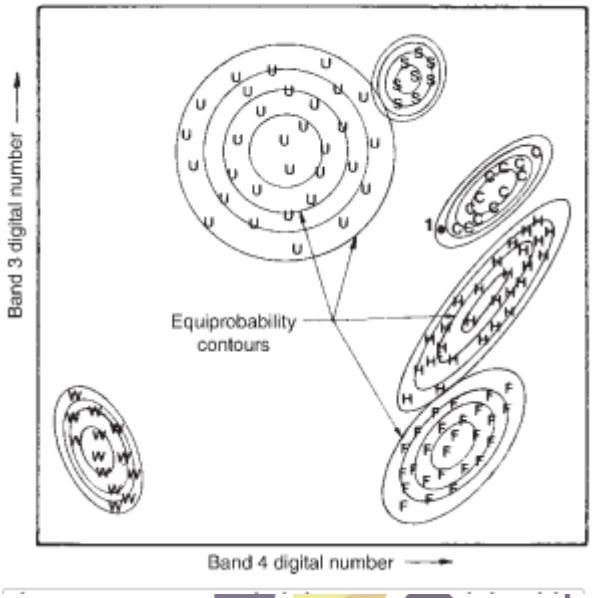


*Figure 6. Equiprobability contours defined by a maximum likelihood classifier.*

Conclusion

Image classification is a powerful technique with myriad applications across various domains, from healthcare to security and beyond. Through our exploration, we've witnessed its ability to accurately categorize and interpret visual data, enabling automation and efficiency in tasks that were once labor-intensive. While significant progress has been made, challenges such as robustness to noise, scalability, and interpretability persist. Continued research and development in areas like deep learning architectures, data augmentation, and transfer learning promise to address these challenges and push the boundaries of what's achievable. As we move forward, it's crucial to not only refine the accuracy and speed of classification algorithms but also to ensure ethical considerations are integrated into their deployment, fostering trust and accountability. Ultimately, image classification stands as a testament to the transformative potential of machine learning in reshaping how we interact with and derive insights from visual data.

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