

Hyperspectral Image Classification for Mineralogical Identification

William A. Peppin and Richard L. Bedell, Jr.

Abstract

Classification is broadly used in a range of exploration technologies. This paper will summarize standard classification methods and provide a new hybrid method for classifying spectra used in mapping mineralogy with hyperspectral remote sensing data.

Classification methods commonly employed do not allow the user specifically to identify key features that give confidence as to the quality of the classification. Methods that do allow feature selection typically use the position of specific absorption features only. Sometimes these positions are not in themselves diagnostic and other broad feature shapes are often useful in expert interpretation. A new hybrid method is presented in this paper that uses both the position and character of the absorption feature and longer wavelength characteristics such as broad feature shape and asymmetry. Further, this method develops the concept of a “verification image” which, when used with the classification, can give confidence that those image pixels identified contain specific feature characteristics, apart from the classification itself, that gives further support for the classification result.

Introduction

The term “classification” is used in image processing as a statement of odds. In exploration spatially referenced data are used to increase the odds of discovery. Consider a belt of rocks that is 100 x 500 km and is favorable towards exploration. Consider that an outcropping ore deposit is 0.5 x 0.5 km. The probability of finding an ore deposit (assuming it exists) is therefore 0.25/50,000, the ratio of the area of the deposit by the area of the entire exploration region. Assume that the deposit is associated with propylitic alteration that is 10 x 20 km. Now the odds are 0.25/200. Within that favorable alteration is a zone of epidote facies propylitic alteration which is 1 x 4 km and is proximal to the ore. The odds are increased particularly when the exercise is supplemented with geochemical, geophysical and particularly field mapping that identifies potential geologic controls.

The original probability estimated above, 0.25/50,000 is named “prior probability,” defined below. Given the area without any other knowledge these are the odds known absent any new information. Any technique that allows refinement of the prior probability leads to posterior probability, defined below. Bayes’ Theorem allows manipulation of prior and posterior probabilities in a useful way as illustrated in the example below.

In image processing the technique is used by providing known features, e.g., spectra of specific minerals and then letting the classifier make a map of the likelihood of any pixel having that spectral signature. This is known as supervised classification.

This paper will describe methods of classification used in the processing of spectral remote sensing data and present examples using hyperspectral data of a recent evolution of these techniques as applied at Cuprite Nevada.

Bayes' Theorem

Take “prior probability of the occurrence of an event A” as the symbol “P(A)” and “posterior probability of the occurrence of an event B given that event A has already occurred” as the symbol “P(B|A)”. P(A) is the simple odds that event A has occurred. For example if a fair coin is tossed, and if “A” is the event, “a fair coin is tossed once and comes up heads,” then P(A) is $\frac{1}{2}$. If B is the event, “a fair coin has been tossed three times and has come up heads all three times,” then P(B) = $\frac{1}{8}$. Finally, if event C is, “a coin has been tossed twice and has twice come up heads,” then P(B|C) = $\frac{1}{2}$. Thus, prior probabilities, or odds, are to be thought of as theoretical in nature, while posterior probabilities, or odds, are associated with experimental events that have taken place.

Suppose now a gold explorationist looks at a database of geological maps of Nevada showing various minerals on the ground. Looking at the area of the maps which contain successful gold mines, (s)he could raise the following inquiry: what are the odds of finding gold in Nevada, given that a certain set of known minerals occurs on the ground? This problem cannot be addressed directly. However available are: the number of gold-producing sites containing, say, the mineral hematite, “H”, and the number of gold-producing sites “G”. Thus, it is possible to estimate P(H|G) as the simple ratio H/G. But the explorationist is more interested in the inverse P(G|H), that is, if hematite is present on the ground, what are the odds that commercial gold is present as well? Bayes' Theorem provides the means to relate these two posterior probabilities. The problem is illustrated in a way to which Bayes' Theorem can be applied in Figure 1.

Let U be the odds that a certain mineral occurs in Nevada, its “prior probability.” Let G be the odds for the occurrence of gold in Nevada, its “prior probability.” What are the odds that gold is present if mineral U is present? That is, what is P(G|U)? In Figure 1, suppose U is H for the mineral hematite. The rather large region showing hematite intersects the region with gold deposits in a small area $G \cap H$, that is, the region on the figure that is common both to gold and to hematite occurrence. How can P(G|H) be estimated? In theory,

$$P(G|H) = (G \cap H) \div P(H). \quad (1)$$

Why? Because in the expression P(G|H) it is assumed that H is true. Therefore, the total space of possibilities is reduced from the full outline in figure 1 to the region where hematite occurs, H. Then the odds of finding gold when hematite is present is the result of dividing the area of the intersection, $G \cap H$, by the total area of the hematite region H. In just the same way,

$$P(H|G) = H \cap G \div P(G). \quad (2)$$

That is, assuming gold is known to be present, P(H|G) is determined by dividing the area of the intersection by the total area with gold deposits.

In (1) and (2) the area of intersection $H \cap G$ is common:

$$P(G|H)P(H) = G \cap H = H \cap G = P(H|G)P(G) \quad (3)$$

Formula (3) shows how the order of operation in the posterior probabilities can be inverted based on the geometry of the situation. Bayes' Theorem in simplest form isolates the factor P(G|H) as follows:

$$P(G|H) = P(H|G)P(G) \div P(H) \quad (4)$$

Referring to Figure 1, it is possible to consider the probability that gold is present given that any one of the three minerals hematite, illite, or dickite is present. The figure shows schematically that, while hematite is more common, it associates less frequently with gold. Dickite is least common, but frequently associates with gold deposits. Finally, illite occurs in intermediate amounts and is also frequently associated with gold deposits. For each of these minerals, estimates of the amount of gold given the occurrence can be made. Let H, I, D, and G be the prior probability of occurrence of hematite, illite, dickite, and gold, respectively. Using (4) three estimates of the probability of finding gold can be constructed, one for each of the three minerals hematite, illite, and dickite:

$$\begin{aligned} P(G|H) &= P(H|G)P(G) \div P(H) \\ P(G|I) &= P(I|G)P(G) \div P(I) \\ P(G|D) &= P(D|G)P(G) \div P(D) \end{aligned} \quad (5)$$

Notice that each of the terms on the right hand side of equations (5) can be estimated by simple counts, while no such count is available for the terms of greatest interest on the left hand side. Notice also that analysis such as this will disclose immediately which mineral is most relevant to gold exploration. Under broad statistical circumstances, the highest probability in (5) leads to the best choice, which is called Bayes' Rule.

A general problem with this approach is that field observations are inadequate to provide the kind of statistical reliability upon which formulas like (4) and (5) could work. Hyperspectral image classification can greatly expand the statistical database, because it can provide observations over large areas of the ground in a systematic fashion. Such imagery is obtained either by satellite overflight or from airborne platforms. The key aspect of hyperspectral imagery lies in its ability to do detailed characterizations of the ground in terms of mineralogy, even towards differentiating minerals as similar spectrally as illite and dickite given in the example above.

The probability associated with finding ore is an important problem, but these examples are only illustrative. The purpose of this paper is to describe the classification methodology based on hyperspectral imagery, and to show how these techniques apply to mapping pixels of specific minerals to make a mineral map. What follows makes use of the spectral aspects of hyperspectral imagery, versus the spatial aspects as given in the example just described. More detailed analysis of spatial patterns lies outside the scope of this presentation.

An Example of Supervised Hyperspectral Image Classification.

In this and subsequent sections, classifications are given in a number of different ways. Each of these makes use of a methodology called "supervised classification," in which the targets for the classification are known at the start. In "unsupervised classification," here not shown, statistics over the entire image are computed, and then the pixels are placed into a number of groups, chosen by the user, that are statistically distinct. It is then the job of the user to associate meaning with the statistical groups so derived. Since the geologist always has some idea what (s)he is looking for on the ground, this knowledge can be used to develop, or supervise, the targets going into the classification. For this reason, supervised classification is preferred, and unsupervised classification is seldom of value to the geologist doing mineralogical mapping as shown below.

High-resolution imagery taken at Cuprite, Nevada, is used in this illustration. The data were collected by SpecTIR LLC using an hyperspectral imager that collects 356 spectral bands in [400, 2500] nm at about 5-nm intervals. Shown here are only the data beyond 2,000 nm in which

alteration minerals commonly manifest, 72 bands in all. The data are first converted to radiance using dark-current subtraction and gain factors derived from a calibration sphere, itself regularly tested, and then taken to reflectance by means of a flat-field correction from nearby Stonewall Playa. This is a standard methodology used on data from other imagers such as AVIRIS at Cuprite, and provides good reflectance data in the SWIR (2,000 – 2,500 nm). Reflectance data is most directly comparable to measurements made of minerals in the laboratory using high-precision instruments such as the ASD Terraspec Spectrometer (ASD, 2007.) The data are collected from an airborne platform, here at a ground resolution of 1 m as a data structure called an “hyperspectral image.”

An hyperspectral image is a cube of data. The “cube” consists of data pixels, one such pixel associated with each ground location within a geographic area, typically hundreds of pixels wide and thousands of pixel long. At each pixel, the 72 bands beyond 2,000 nm are analyzed. The case illustrated is a small region near Cuprite, Nevada, about 400 pixels wide and 800 pixels long, representing a region on the ground 400 by 800 meters in extent. The “data cube” is then 400 wide by 800 high by 72 deep in this instance, containing 400x800x72 numerical values. The aim is to associate each image pixel with one or more spectral types at some threshold of probability. That is, for each image pixel, the questions are asked: what are the odds that either buddingtonite or alunite are found at that pixel on the ground?

Consider a simple classification image for each of the minerals alunite and buddingtonite shown in Figure 2. In order to create such an image, some standard must be found against which to match the image pixels. Two basic choices avail themselves. The standards can be drawn from a major laboratory spectral library such as maintained by the USGS (Clark and others, 2004) or the standard can be drawn from the image itself. Each choice has advantages, but the latter is almost always preferred, because it will generally give more robust classification, as it uses minerals identified within the hyperspectral dataset. The Hourglass method is commonly used to discover such endmembers (described by Bedell this volume.) Such was done in Figure 2: a pair of image endmembers were obtained and used as the classification standard. The lefthand images show areas of light gray, dark gray, and black as those pixels which are ever more similar to the image endmembers. Lines are drawn from the spectral averages on the right to clarify which areas on the images are represented by the averages. Notice that at the best classification, the spectral averages shown are very similar to laboratory spectra, the topmost trace in the stack. This is the kind of information that is used to assign a probability that the pixels so identified reflect actual minerals on the ground. In this case, the lowermost, light gray areas of the buddingtonite classification are partially mixed with alunite, itself a very bright mineral that tends to dominate mineralogical spectra. Note that the broad buddingtonite minimum near 2140 nm is seen on each of these averages, a uniquely diagnostic feature versus other minerals expected to associate with buddingtonite.

The problem with this image is that the pixels shown in the classification are a subset of all the pixels found by the procedure. Judgment was used to decide which part of the pixels to retain. With no prior knowledge, this selection is ad hoc in nature to those without the experience in the creation of such a plot. Note also that counts of pixels classified as either alunite or buddingtonite form the basis for determining prior probabilities as encountered in Bayes’ Theorem above.

Multimineral Classification.

The example in Figure 2 offers a gradation of possible minerals. Another style of classification image is one in which each pixel is identified as belonging to a single class of several. In this methodology, despite the fact that each pixel might contain a mixture of minerals, it is displayed

as a single mineral only, the one which “dominates,” in some sense, the spectral signature. This method can be used when it is expected that the minerals on the ground are truly distinctly located, which is often true for minerals of different groups, e.g., clay minerals versus limestones, see Figure 3. As in Figure 2, the selections of which pixels to show are based on experience, and are therefore ad hoc to those without experience. The literature has numerous examples which make use of standard processing tools in the creation of such images. A common processing path is to use minimum-noise-fraction/PPI analysis to determine image end members, selection of end members of interest from those that emerge based on a wide range of criteria, and then application of matched filtering or mixture-tuned match filtering to derive classification images as shown in Figure 2. This technology has been implemented for commercial use in the ENVITM software, and an extensive example of use of this technology on minerals, with quite similar spectral signatures, can be found in Harris and others (2005). But here as in essentially all such work, the identifications follow from statistical comparisons, so again the identifications given are based on numerical measures that indirectly assess the fit of each image pixel to the end members. Again, those without experience are left to take the results based on the authority of the provider, unless, as in Harris and others, extensive field investigation is performed to verify the imagery classifications on the ground.

Maximum Likelihood Classification.

It is possible to approach the problem from a formal, statistical sense. In maximum likelihood classification, a search is made of all the pixels which fit the image end member to within some number of standard deviations. Then those pixels are retained in the classification which are more similar to the end members, in this case, the top 5% of the pixels. Results of this classification are shown in Figure 4. As compared with Figure 3, the result is similar, and has the advantage that a real number quantifying the confidence in the identification can be given. The pixels classified as in the top 5% could even be contoured by degree of goodness of fit as was done in Figure 2.

But the basic problem with the classifications shown so far is that the identification of a pixel as belonging to one of the three classes – alunite, buddingtonite, or neither – turns on the value of a single number, a spectral angle in Figure 2 and a maximum likelihood probability in Figure 3. To a non-expert user, these numbers in general mean nothing because there is no information on exactly what aspect of the mineralogical spectrum was most important in placing a pixel in one classification category or another. This issue is addressed by a newer, composite methodology, fuzzy/holistic classification, described in the next section.

Fuzzy/Holistic Image Classification and Verification.

Peppin (2001) has developed a methodology which addresses the issues alluded to in the preceding paragraphs. The method makes use of a combined classification based both on an “holistic” analysis and one that is “feature based.” An “holistic classifier” resembles those discussed in the previous section. It takes a band of wavelengths and uses each of the spectral data points within that band equally to determine a classification fit to an end member. This classifier has been found to give more robust results and fewer false positives than the conventional methods given above. The result of the classification is, like the preceding schemes, a single number, generalized spectral angle, that is used to measure similarity to a target end member. At this point, the new method diverges from those just described.

Another, and wholly-independent method, in which a spectral signal can be compared to a standard is through the process of “feature matching,” and has been developed fully in the

Tetracorder™ methodology of the U.S.G.S. (Clark and others, 2003). In this methodology, certain key spectral features, typically found in absorption features as illustrated in Figures 5 and 6, are identified by an expert user. The characteristics of these features are then extracted, most basic of which are the position and depth of the feature as illustrated by Figure 5. Like spectral lines seen in distant stars, the locations of such features can serve to identify a mineralogical signature; in fact, closely-related minerals may have features quite similar in appearance apart from fairly small differences in the positions of these absorption features. For each feature, three wavelength ranges are specified, of which the last is especially relevant to the problem at hand, differentiating alunite from buddingtonite. This gives the range for “acceptable” feature positions, 2152 – 2184 nm and 2118 – 2143 nm for the major absorption features for alunite and buddingtonite, respectively. The feature is extracted, and a fuzzy truth value is assigned to it based on the feature position. “Fuzzy truth” unlike ordinary truth values can take on a value between 0 and 1, the former for “the feature looks nothing like the target,” the latter for “the feature looks just like the target,” and intermediate values for “the feature looks something like the target.” In this case the fuzzy truth values are taken as 1 provided the feature lies in the specified ranges given above, but then the truth value tapers to zero quickly outside those intervals. In this way, if a feature lies right between the two, at 2148, say, it will have small truth value for either of the minerals. A number of different features are analyzed in this way for the mineral, with fuzzy truths assigned to each feature extraction. Using rules of fuzzy inference, these values are combined into an overall fuzzy truth value for the features found resembling the mineral in question. This information in turn is combined with the previously-obtained holistic classification to give an overall fuzzy truth value for the pixel in question. In this way, information pertaining to the overall shape of the spectrum is combined with information about specific feature characteristics in the production of a final classification (Figure 7, middle image.) But the same problem as before obtains: the classification turns on the value of a single number, the overall fuzzy truth value. How to know what value of fuzzy truth is significant?

The new method presents the concept of a “verification image” whereby some particular spectral characteristic can be displayed as a separate image. Consider, for example, the two absorption features illustrated for alunite in Figure 5 at 2160 and 2320 nm. The 2320 feature should always be seen fairly strongly if alunite is present, along with the bigger 2160 feature. The lefthand image in Figure 7 shows as gray each of the pixels classified as alunite for which the ratio of the depth of the 2160 to the 2320 feature is 2.0 or more, and as black those for which this ratio is less than 2.0. About half of the classified pixels do not meet this test. Therefore, the gray pixels are interpreted as definitely having alunite, while the black ones are possible alunite mixed with other minerals.

Figure 6 shows features, the extraction of which, has proved useful in differentiating areas containing mixed clay minerals, each with strong absorptions near 2200 nm. Shown is an absorption feature (for kaolinite) in which the minimum has been determined (the vertical line) and in which areas left and right of that line have been estimated. Note that in moving upward from the bottom of the feature, the asymmetry starts out as -0.18 and grows to -0.50 and then -0.55. That is, the feature becomes steadily more asymmetric to the left the further removed from the minimum value the calculation is made. This allows character of the feature shape to be incorporated into the analysis. This has been used in the classification figures. The classified alunite and buddingtonite pixels mostly have asymmetries in the preferred ranges, -0.08 to 0.12 and 0.06 to 0.35, respectively: note these two ranges overlap slightly. Thus, most of the pixels on the right side of Figure 7 and the left side of Figure 8 are gray showing that the classified pixels have about the correct asymmetry.

Most interesting is the verification image shown on the right side of Figure 8. Buddingtonite should not have a feature near 2320 nm, as can be seen in the lab spectrum for buddingtonite in Figure 2. Yet most of the pixels in the image in fact show a significant feature at that position. Since alunite is a strong reflector, and since the 2320 feature is associated with alunite, the conclusion is that most of the buddingtonite pixels are partially mixed with alunite.

Note the difference between the results shown in Figures 7 and 8 and the preceding classification images. If an expert insists that (s)he will accept no pixel as alunite unless a sufficiently-strong 2320 feature is present with the usual 2160 feature, reference can be made to the verification image on the left side of Figure 7: a large percentage of all the pixels classified as alunite in fact have this feature fairly strongly. The main point here is to step away from classification that requires the interpretation of a single number for the investment of confidence in the classification given. Rather, assessment of classification makes use of a suite of numbers, one for the overall classification as in conventional methods, and one or more specific feature characteristics – depth, width, asymmetry, curvature – to assist the interpretation based on measurable characteristics from the image pixels themselves. The disadvantage is that the user must be told by an expert which of the feature characteristics are significant in this regard.

The serious investigator would not think of relying solely on image processing to make hard economic decisions in the realm of precious-metal exploration. In this milieu, it is all but essential to follow a campaign of image analysis with well-considered field checking. When field checking spatial data it is important to have an idea as to why the data was classified the way it was. Not only does this give a degree of confidence, but it allows the improvements and misclassification to be addressed in a meaningful way.

Conclusions.

Several methods of supervised classification have been applied to 72-band hyperspectral imagery taken over Cuprite, Nevada in [2000, 2410] nm. The various methods give results that, while similar, are not identical. The test area is one in which the mineralogical signatures are very strong and uncluttered, so good agreement of the different methods is expected. The fuzzy/holistic classifier extends the other methods in providing both classification and verification images. The verification images give specific characteristics about diagnostic features in the target spectral signatures such as an expert might specify to judge the credibility of the classification. As such, they provide explicit and recognizable evidence for that credibility, versus the need to attach meaning to single numbers emerging from most classification schemes. Development and interpretation of these verification images depends on the advice of an expert in mineralogical/spectral associations with mineral-exploration targets. In all such schemes, the use of closely-spaced data from hyperspectral images permits the differentiation of minerals whose spectral signatures might be very similar. In this way, hyperspectral imagery provides a means toward detailed mapping of minerals, including those known to associate frequently with precious-metal deposits. Image processing as described here will never eliminate field checking, but rather serves as a valuable adjunct to geological interpretation.

Figures

Figure 1. Schematic representation of a theoretical gold exploration terrane. Areas are exaggerated for illustrative purposes. The outer boundary delimits the exploration area, and the shaded area on the right hand side is the area containing commercial gold prospects, whose size relative to the whole state is exaggerated to make the concepts clear. Shown are the occurrences of three minerals, which are variably associated with gold deposits depending upon the type of deposit and where they occur. (The percentages are chosen irrespective of the actual numbers, which are unknown.) Consider the mineral illite. The explorationist can determine the probability that illite is found near a commercial gold deposit. This can be done by estimating the ratio of acreage at gold deposits containing illite [region 3 in the figure] to the total acreage containing commercial gold [region 1 in the figure, greatly exaggerated relative to the others for clarity.] The explorationist seeks to know: what are the odds of finding gold if illite is present? That is, (s)he seeks the ratio formed by area 3 divided by area 1. This would be $P(G|I)$ which is unknown. However, $P(I|G)$ can be estimated: count the number of gold prospects in which illite is found and divide by the number of gold prospects. Bayes' Theorem is then used to write an expression for $P(G|I)$ in terms of $P(I|G)$.

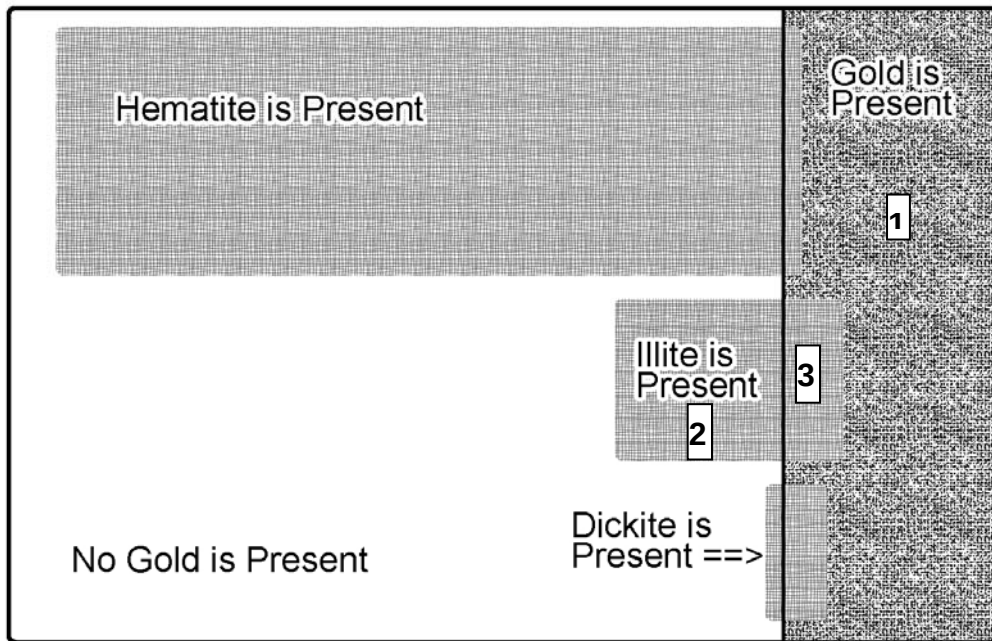
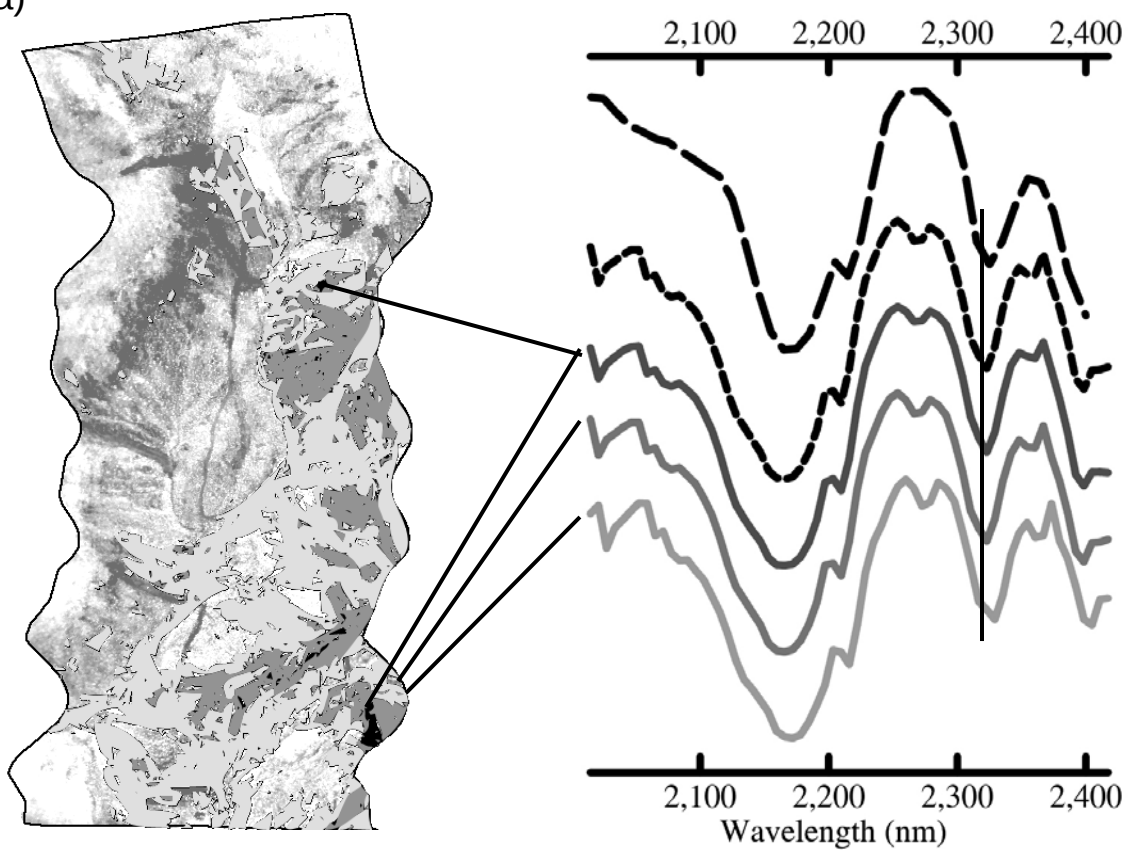
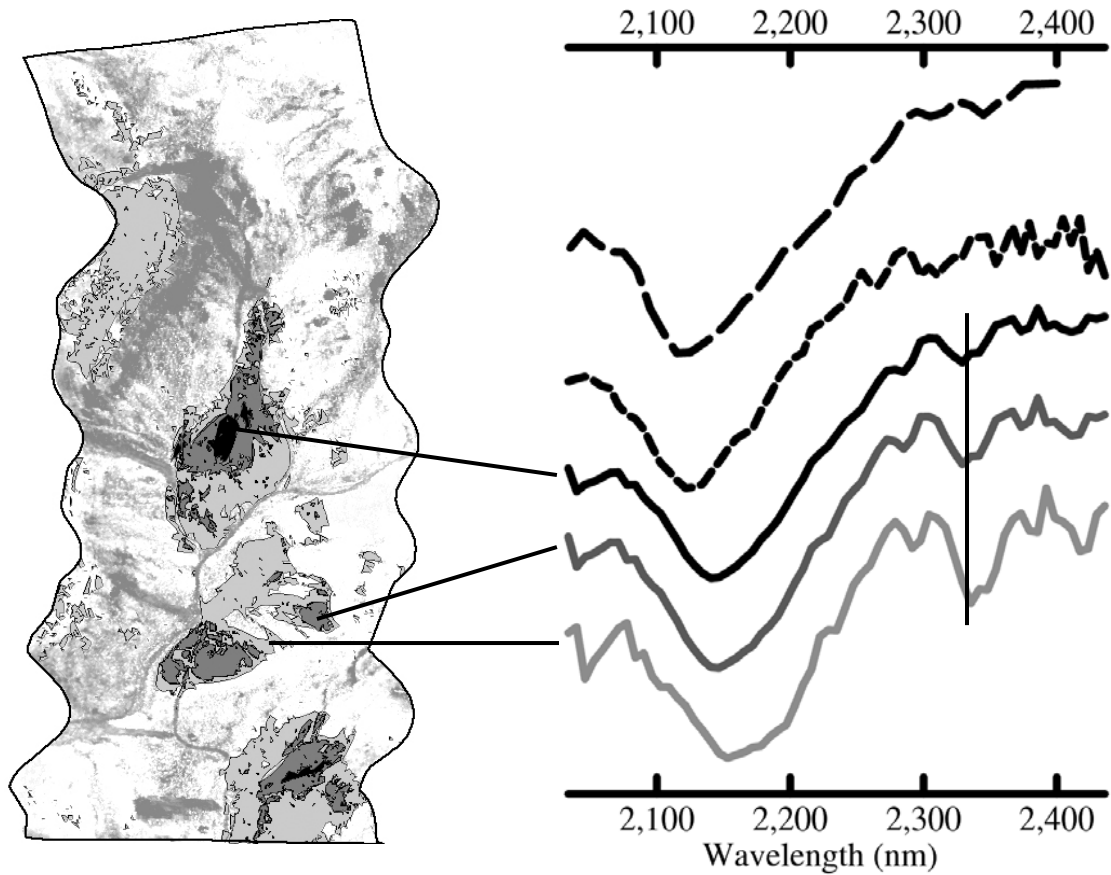


Figure 2. **[next page]** Classification image using end members extracted from this dataset via the hourglass method from ENVITM, elsewhere described in this volume. over Cuprite, Nevada, for the minerals alunite (a) and buddingtonite (b). The left hand of each pair is a classification image, while the right hand of each pair shows a stack of averaged pixel spectra for the regions delimited in the classification image, with ever darker traces for those averages more closely resembling the “image end member.” The top long-dashed spectra are from the USGS spectral library accessible from ENVITM. The second from the top, short dashed, are statistical extremes from the image which most nearly resemble the library spectra for alunite and buddingtonite. These images measure 400 pixels wide by 800 pixels long, representing a region 400 m x 800 m on the ground. At each pixel are shown 66 spectral values spanning (2008, 2410) nm. This type of classification is preferred in those cases in which the minerals of interest occur in mixtures. Note that several areas on the image are common to both of the minerals. The classification is based in each instance on a standard spectral comparator, Spectral Angle Mapper, that matches image pixels to the image end member. Finally, the top traces in each stack are spectra taken from the USGS mineralogical library, which are essentially identical to the end members. Note alunite intermixing in the buddingtonite spectra, the feature near 2320 nm (vertical line,) a major feature of alunite.

2 (a)



2 (b)



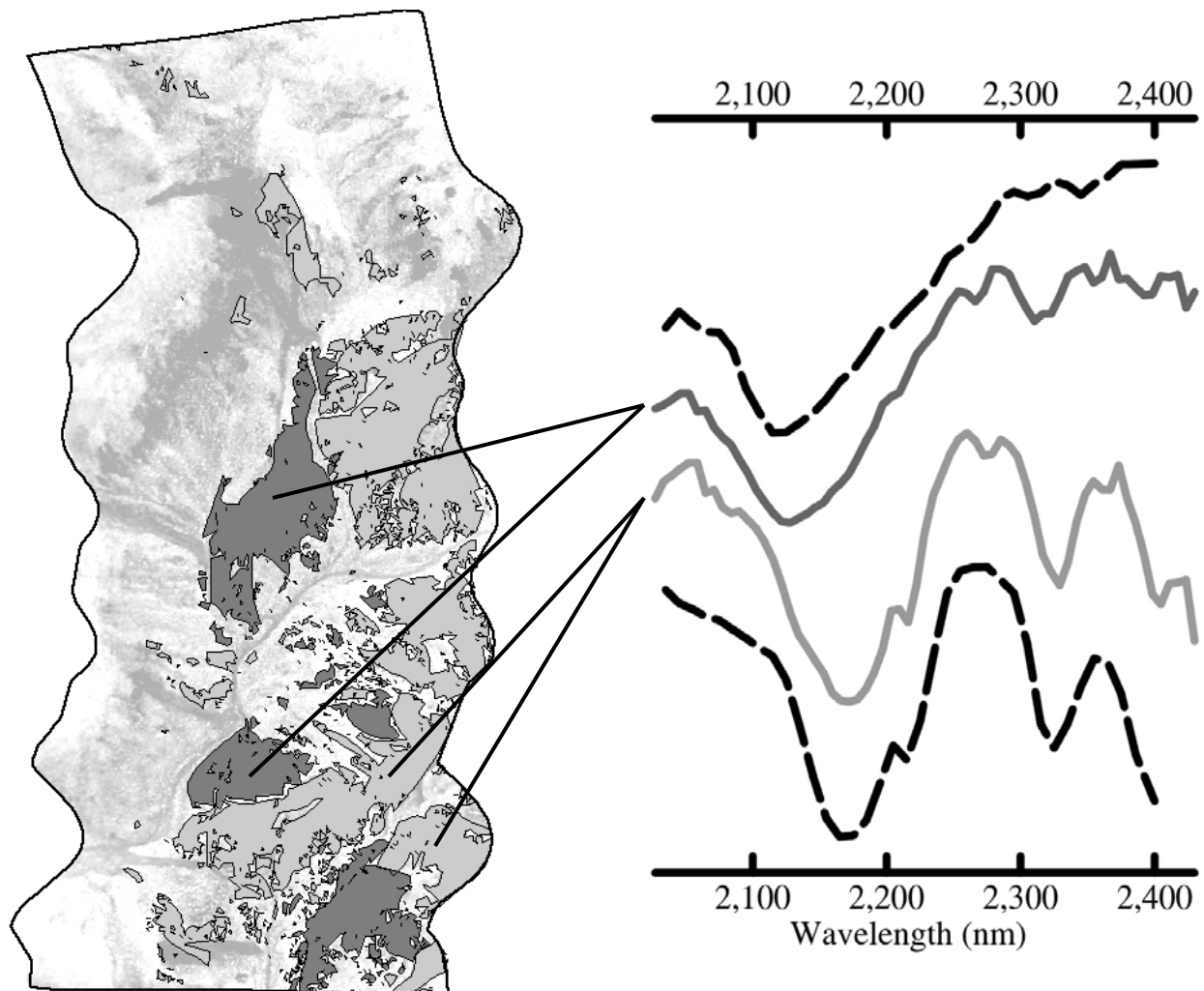


Figure 3. Classification image for a single mineral only, alunite (light gray,) and buddingtonite (dark gray). In this image, each pixel was classified as being definitely alunite, definitely buddingtonite, or definitely neither. The bottom and top traces are the USGS library spectra for alunite and buddingtonite, while the center two traces are spectra averaged over the shaded areas of the figure. This image is much easier to interpret than those in Figure 2, but information about mixing of the pixels is completely absent in this style of classification image.

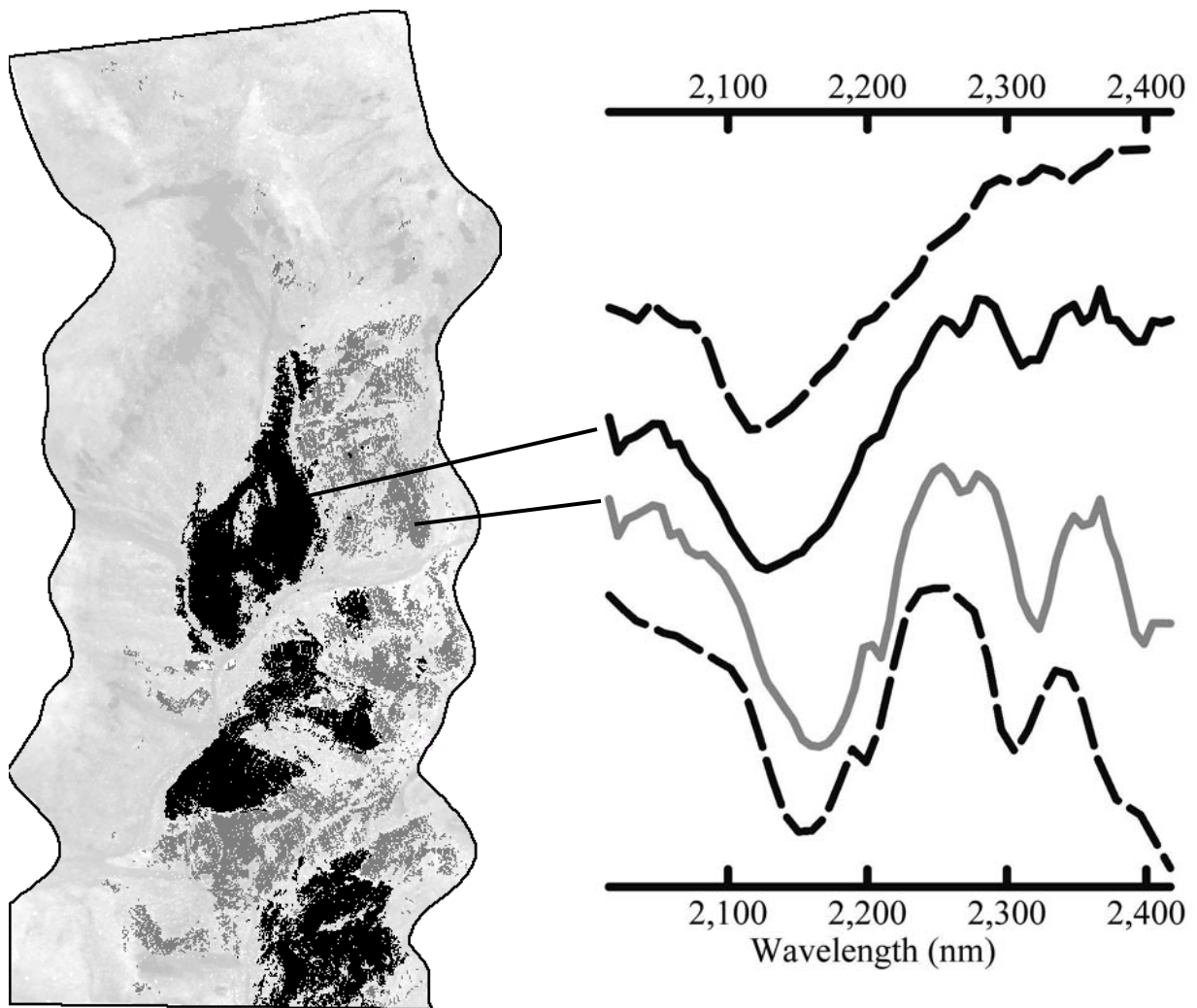


Figure 4. Similar to Figure 3, except that the classification has been done using Maximum Likelihood, in which the pixel statistics are used to create the actual classifications. Here, those pixels are shown which, based on the statistics, are in the top 5% of those in the image which fit the endmembers used in the analysis. The lower and upper dashed traces are the USGS spectra as in Figure 3, while the middle two traces are the average of all classified pixels shown for alunitic (gray) and for buddingtonite (black).

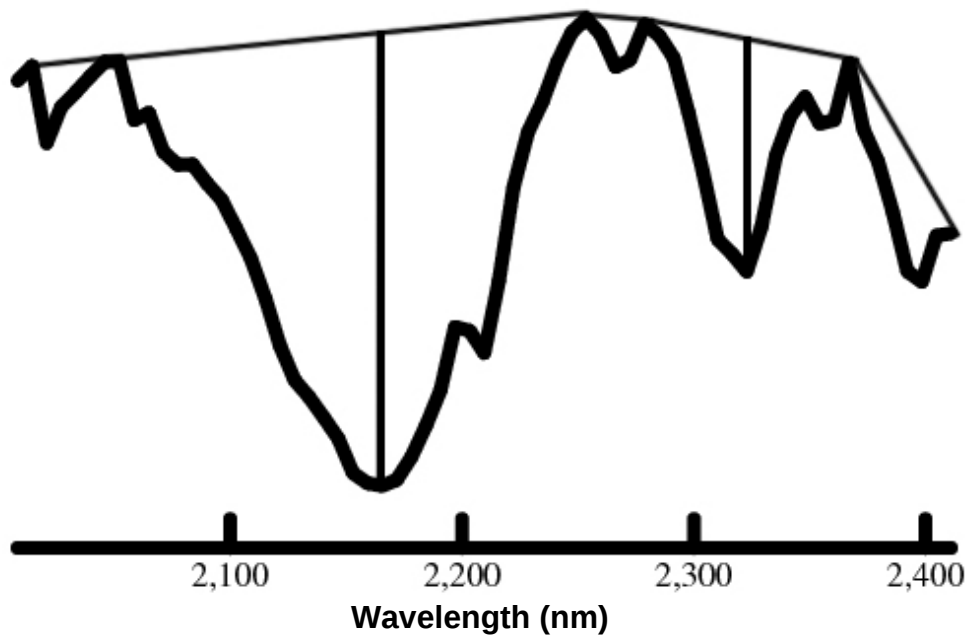


Figure 5. For fuzzy feature extraction of absorption features, a continuum removal process is carried out. The light line above this spectrum here is obtained by an algorithm that effectively draws an elastic rope over the top of the spectrum. This new spectrum is called the continuum. The continuum-removed spectrum, as exemplified for a different case in Figure 6, results by subtracting the continuum from the actual spectrum and then adding a convenient offset to make the result positive. Here, two such features, at 2,160 and near 2,320 nm, occur at locations indicated by the vertical lines. The depths of the features are taken as the greatest difference between the continuum and the bottom of the feature, and the feature minimum position is taken as that point of greatest difference.

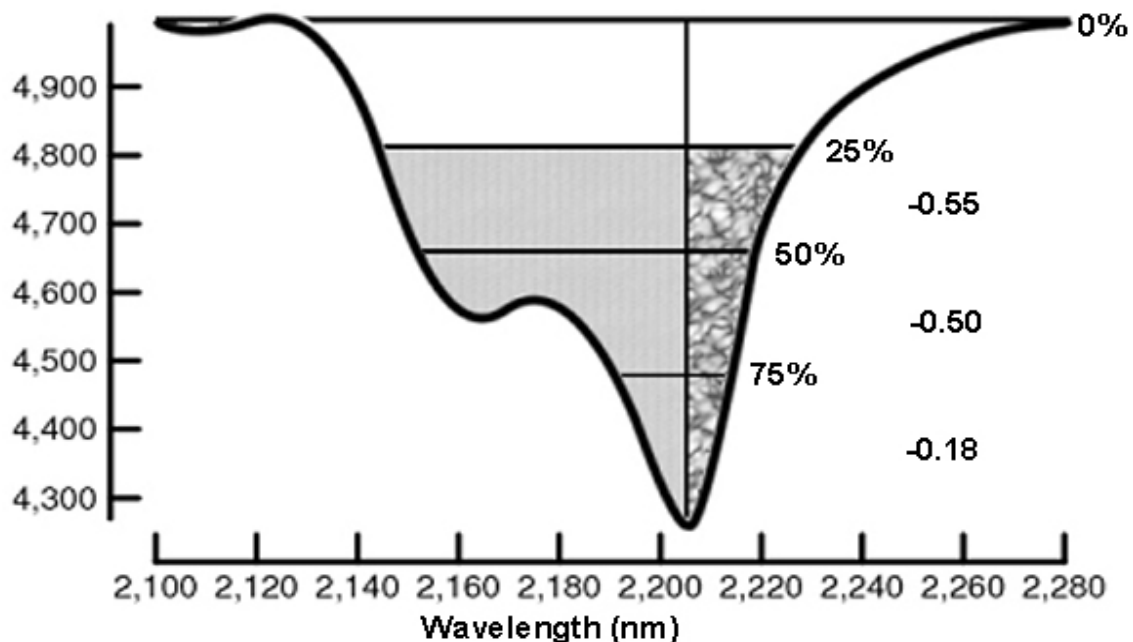


Figure 6. Extraction of feature asymmetry as a function of feature depth. After continuum extraction and determination of the minimum (vertical line), the areas left and right of that line, shaded, are compared as a function of feature depth. If the area left is L , the area right is R , then the asymmetry is estimated as $(R-L)/(R+L)$. A value of 0.0 indicates perfect symmetry, and thus the asymmetry so computed would be zero. Shown are asymmetries computed for the shaded areas between the horizontal lines, here -0.55 , -0.50 , and -0.18 for the areas between 25% to 50%, 50% to 75% and 75% to 100% of the feature depth. The numbers for this mineral show a progressive increase in asymmetry to the left (i.e., more negative values) moving from the bottom to the top of the feature.

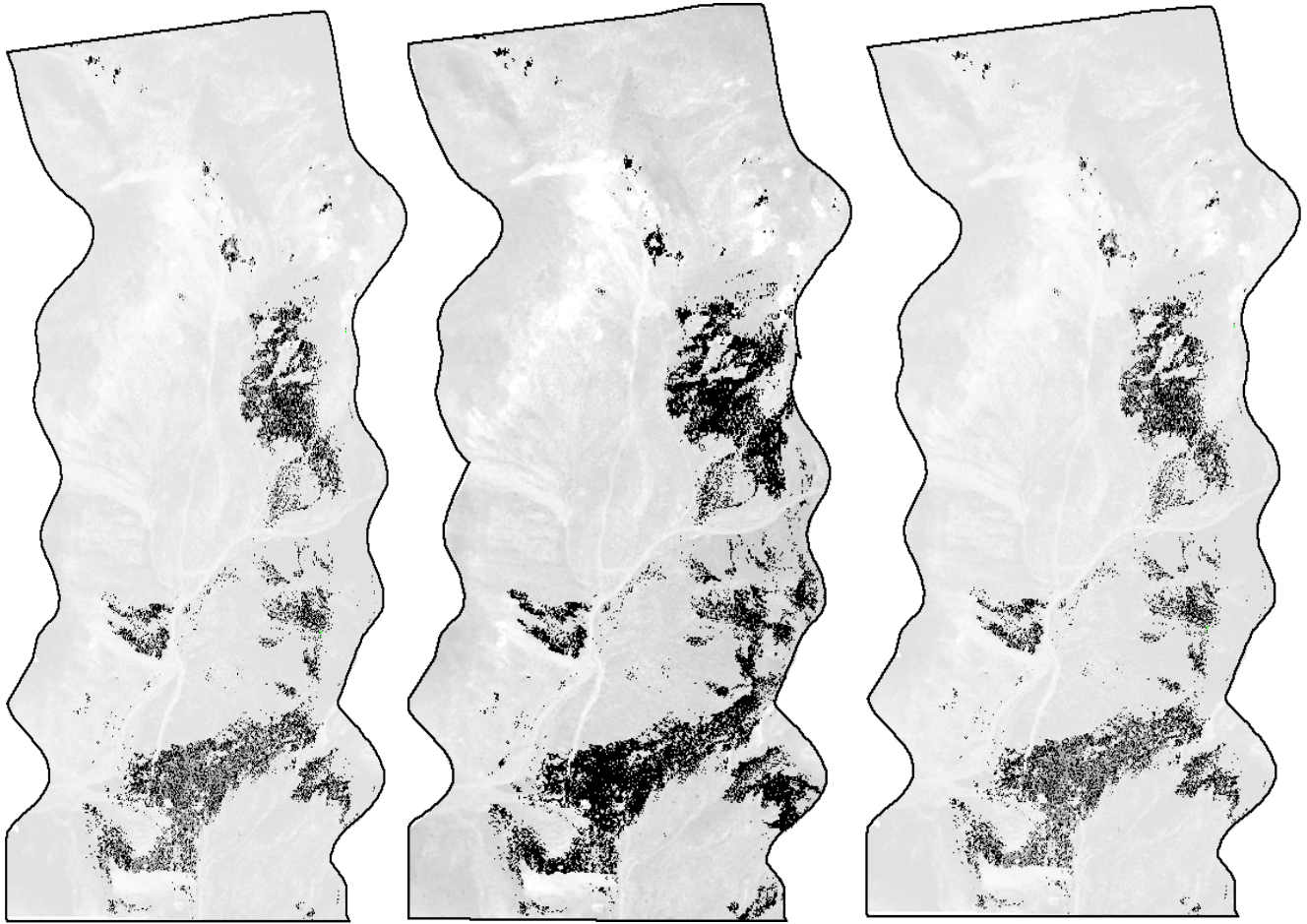


Figure 7. Fuzzy-holistic classification, with verification images, for alunite. Center image: dark pixels are all of those determined to be alunite with “sufficient” fuzzy truth value. Left: verification of ratio of 2160 to 2320 feature depth. Gray pixels: those pixels for which the ratio exceeds 2, preferred; black, those showing a ratio less than 2. Right: those pixels with 2160 feature asymmetry in the range -0.08 to 0.12 , preferred, gray; those outside this range shown in black.

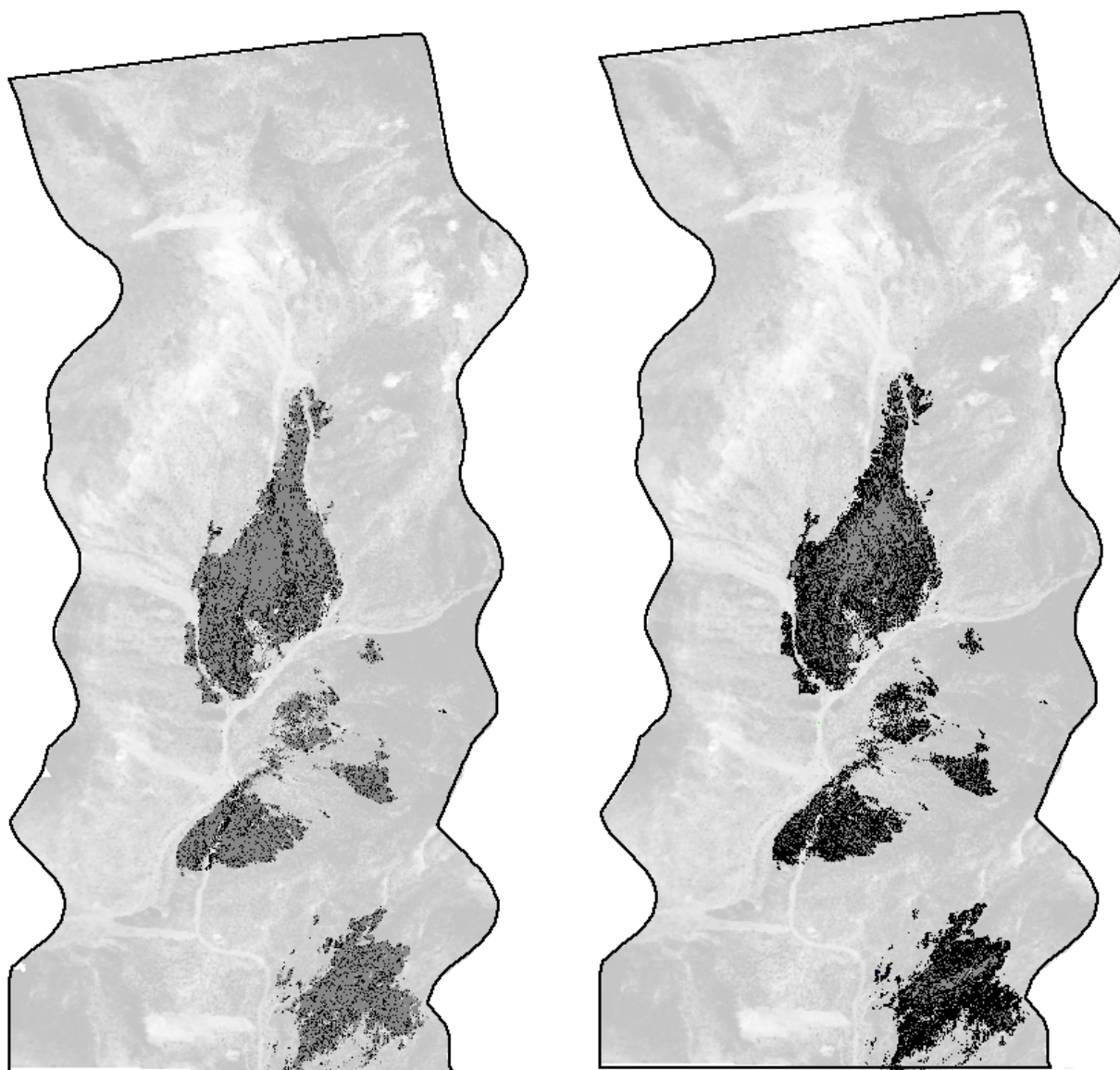


Figure 8. Fuzzy-holistic classification for buddingtonite. Left: asymmetry of major feature at 2,110 nm, the gray pixels with symmetries between 0.06 and 0.35 (preferred), black pixels showing asymmetry outside that range. Right: Depth ratio of the main 2,110-nm feature with a feature extracted near 2,320, the secondary feature of alunite. Gray, those with such a ratio exceeding 2 (preferred), and those with a ratio less than 2 as black. These pixels are probably partially mixed with alunite, which strongly absorbs at 2,320 nm. Note in Figure 2 that the averaged buddingtonite pixels show the 2,320 feature clearly, which indicates that many of the buddingtonite pixels are mixed with varying degrees of alunite.

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