UNMIXING WETLAND VEGETATION TYPES BY SUBSPACE METHOD USING HYPERSPECTRAL CASI IMAGE

Yoshiki YAMAGATA, Yoshifumi YASUOKA

National Institute for Environmental Studies
16-2 Onogawa Tsukuba Ibaraki JAPAN
yamagata@nies.go.jp

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ABSTRACT:

A new approach to unmixing with subspace methods is proposed and an experiment using hyperspectral images was conducted. In subspace method, unmixing is calculated as the projection of each unknown pixel vector on the subspace of each class. This method is more stable than conventional methods against noise in the data and works effectively as a feature extraction and data reduction procedure as well. The performance of this method was tested by an unmixing experiment using a hyperspectral airborne CASI image acquired over the Kushiro wetland in NE Japan. Unmixing for the 7 wetland vegetation classes were calculated using a least squares, quadratic programming, orthogonal subspace projection and the subspace method. Finally, the results of unmixing experiment were evaluated in regard to wetland vegetation monitoring.

1. INTRODUCTION

In wetland landscape, various vegetation types are continuously distributed. Remotely sensed spectral data over wetland areas are spectral mixtures of several vegetation types. These images consist of mixed pixels (Mixel) which have to be analyzed using spectral unmixing procedures to estimate the state of each of the constituents (Settle and Drake, 1993).

Conventional statistical unmixing methods such as least squares use a linear mixel model. In this model, the mixed spectral vector is assumed to be a sum of class spectral vectors which constitute the mixel. By solving this linear mixel model with the pre-determined class vector, an estimate of the fractional area of each class within the pixel.

However, the computational complexity increases substantially as the number of image channels increases and the least squares solution becomes unstable due to the high auto-correlation between the channels. It is necessary to reduce the spectral dimension dimensions of the problem as a preprocessing of unmixing (Malinowski, 1991).

Hyperspectral sensors are a recent development in remote sensing and have been used for environmental monitoring (Kramer, 1992). Hyperspectral imaging is recognized as an effective means for estimating vegetation parameters (Gong et.al., 1994).

To unmix the very large number of channels in hyperspectral imagery, it is necessary to establish an algorithm which can unmix several vegetation types in a fast and stable manner. A number of unmixing methods designed for band selection, feature extraction and dimension reduction which incorporate modern signal processing and neural network methodologies, have been explored recently (Harsanyi and Chang, 1994; Benediktsson et.al., 1995).

Unmixing by the subspace method (Oja, 1984) utilized in this paper is a new approach, based on a fundamentally different principle from conventional methods. The subspace method assigns a different subspace to each vegetation class instead of fitting a mixel model in a pre-determined number of spectral dimensions. Unmixing is then performed by measuring the projection length of mixel vector. In addition, subspace method unifies the process of feature extraction and unmixing, which are usually separate processes in conventional methods.

In this paper, the principle of the new unmixing approach by the subspace method is explained, along with an experimental results derived from Compact Airborne Spectral Imager (CASI) data to compare this new method with conventional approaches.

2. UNMIXING BY SUBSPACE METHOD

2.1 Statistical unmixing methods

Conventional statistical unmixing methods assume that the mixel spectral vector is a weighted mean of the class spectral vector which constitutes the mixel. Within each mixel, there are several mixed classes with area fractions which correspond to the weights of the model. These weights are estimated by the unmixing method.

In a remotely sensed image with p channels K land cover classes exist in the image and area fraction of class $w(i)$ is fi. A linear mixel model assumes that the observed p dimensional vector r is expressed as

$$r = Mf + n = \sum_{i=1}^{K} f_i m_i + \mathrm{n} \qquad (1)$$

Where M is a p x p matrix which has class spectral vectors mi as column vectors, f is a vector which has fi as components, and the $\mathbf{n}$ stands for noise vector.

Statistical unmixing methods include, unmixing by least squares, factor analysis and singular value decomposition (Malinowski, 1991; Settle and Drake 1993). By comparison, unmixing by subspace method does not assume a linear statistical model.

2.2 The Principle of subspace method

The basic idea behind the subspace method is that the class spectral vector lies mainly in a small class specific subspace instead of within the entire dimension of the spectral space. If the class subspace is determined from the training sample of each class, class membership values can be calculated by the projection of the mixel observation spectral vector from the corresponding subspaces from which the training samples were drawn(Watanabe 1969; Kohonen 1977).

There are 3 ways of calculateing the subspace in the subspace method. These are algebraic, statistical and learning subspace method (Oja, 1984). In this paper, a statisitical subspace method called CLAFIC(CLAss-Featuring Information Compression) algorithm is used. This method is known to be fast and effective in the case where the volume of training data is moderate.

2.3 Subspace determination by enhanced CLAFIC method

The CLAFIC algorithm determines the class subspace in order to maximize the projection of the class vector on the corresponding class subspace. However, by maximizing the projections for all classes at the same time, the separation between the similar classes decreases.

In order to avoid this drawback, we have employed the Enhanced CLAFIC algorithm which maximizes the projection on the class subspace to which the training vector belongs and also minimizes the projection on the other subspaces at the same time. In the following, the Enhanced CLAFIC algorithm is described.

In the enhanced CLAFIC method, the class subspace $L^{(i)}$ which corresponds to a land cover classes $w(i)$ $(I=1,\ldots,K)$, is determined so as to maximize the expected projection of vector $\mathbf{x}$ which belongs to the class $w(i)$. It also minimizes the expected projection of vector $\mathbf{x}$ which belongs to the other classes is $\omega^{(j)}$ $(j \neq i)$. The problem here is to determine the subspace $L^{(i)}$ to satisfy these conditions at the same time as formulating the next minimization problem.

$$\sum_{\substack{j \neq i \\ j=1}}^{K} E(x^t P^{(i)} x | x \in \omega^{(j)}) - E(x^t P^{(i)} x | x \in \omega^{(i)}) \qquad (2)$$

where $P^{(i)}$ is the projection matrix to the $L^{(i)}$.

The first term of equation (2) is the expected projection of sample vectors which do not belong to the class $w(i)$, and the second term is the expected projection of vectors which belong to the class $w(i)$. By minimizing term (2), we can determine the subspace $L^{(i)}$ which minimizes the first term and maximizes the second term of (2).

Projection matrix $P^{(i)}$ is expressed using orthogonal normal bases $\{ u_1^{(i)} ,\ldots, u_{p(i)}^{(i)} \}$ of subspace $L^{(i)}$ as

$$P^{(i)} = \sum_{k=1}^{p^{(i)}} u_k^{(i)} u_k^{(i)t} \qquad (3)$$

By substituting equation (3) into (2) and rewriting (2) using base vector $u_k^{(i)}$ (k=1,...,$p^{(i)}$),

$$\sum_{\substack{j \neq i \\ j=1}}^{K} \sum_{k=1}^{p^{(i)}} E((x^t u_k^{(i)})^2 | x \in \omega^{(j)}) - \sum_{k=1}^{p^{(i)}} E((x^t u_k^{(i)})^2 | x \in \omega^{(i)}) \qquad (4)$$

Calculating the expectation first, (4) becomes,

$$\sum_{\substack{j \neq i \\ j=1}}^{K} \sum_{k=1}^{p^{(i)}} u_k^{(i)} Q^{(j)} u_k^{(i)} - \sum_{k=1}^{p^{(i)}} u_k^{(i)} Q^{(i)} u_k^{(i)} \qquad (5)$$

where, $Q^{(i)}$ is the correlation matrix of class ***w(i)*** which is defined as

$$Q^{(i)} = E(xx^t | x \in \omega^{(i)}) \quad (6)$$

By combining (5) with the normal condition of bases $\{u_1^{(i)}, \ldots, u_{p(i)}^{(i)}\}$,

$$u_k^{(i)t} u_k^{(i)} = 1 \ , \ k = 1, \ldots, p^{(i)} \quad (7)$$

Using the Lagrange multiplier method, minimization of (2) is transformed to the minimization of next term (8)

$$\sum_{k=1}^{p^{(i)}} u_k^{(i)t} (\sum_{\substack{j \neq i \\ j=1}}^{K} Q^{(j)} - Q^{(i)}) u_k^{(i)} - \sum_{k=1}^{p^{(i)}} (\lambda_k^{(i)} u_k^{(i)t} u_k^{(i)} - 1) \quad (8)$$

Taking the derivative of this term with respect to the base vectors $u_k^{(i)}$ $(k=1,\ldots,p^{(i)})$, we obtain necessary condition for minimizing solution.

$$(\sum_{\substack{j \neq i \\ j=1}}^{K} Q^{(j)} - Q^{(i)}) u_k^{(i)} = \lambda_k^{(i)} u_k^{(i)} \ , \ k = 1, \ldots, p^{(i)} \quad (9)$$

From equation (9), it is know that the solution base vectors $u_k^{(i)}$ $(k=1,\ldots,p^{(i)})$ of $L^{(i)}$ is the eigen vectors of the next matrix.

$$Q = \sum_{\substack{j \neq i \\ j=1}}^{K} Q^{(j)} - Q^{(i)} \quad (10)$$

In addition, setting the *ith* eigen value of $\boldsymbol{Q}$ as $\lambda_k^{(i)}$, (8) becomes

$$\sum_{k=1}^{p^{(i)}} u_k^{(i)t} Q u_k^{(i)} = \sum_{k=1}^{p^{(i)}} \lambda_k^{(i)} u_k^{(i)t} u_k^{(i)} = \sum_{k=1}^{p^{(i)}} \lambda_k^{(i)} \quad (11)$$

So, in order to minimize (8), we can select the eigen vectors which correspond to the minimum $p^{(i)}$ eigen values as the ortho-normal base of $L^{(i)}$. Here, the dimension $p^{(i)}$ of subspace is the parameter to adjust the mean projection on the classes.

Because the subspace $L^{(i)}$ is uniquely determined from the base vectors $u_k^{(i)}$ $(k=1,\ldots,p^{(i)})$, the above procedure determines the subspaces to minimize the enhanced CLAFIC criterion (2).

2.4 Unmixing by subspace method

Once the class base vectors $u_k^{(i)}$ $(k=1,\ldots,p^{(i)})$ are determined as the eigen vectors corresponding to the eigen values of correlation matrix, projection matrix $P^{(i)}$ is calculated from equation (3). The length of the projection of the observed mixel spectral vector $\boldsymbol{x}$ on the class subspace $L^{(i)}$ is calculated as,

$$x^t P^{(i)} x = \sum_{k=1}^{p^{(i)}} (x^t u_k^{(i)})^2 \quad (12)$$

This projection length expresses how much of the mixel vector belongs to the class ***w(i)***. By a natural extension of the membership values, we interpret this projection as a measure of the class component contained in the mixel vector and have defined the unmixing in each class as the projection on the class subspace calculated by (12).

3. UNMIXING EXPERIMENT USING CASI IMAGE

In order to check whether the unmixing by subspace method works effectively for hyper spectral images, we have conducted an unmixing experiment using a 288 channel CASI (Compact Airborne Spectral Imager) and compared the result with conventional statistical unmixing methods.

3.1 Study site

The spectral image used for our analysis is a CASI image acquired over the Kushiro wetland located in the north east Hokkaido Island, Japan (**Figure. 1**). The CASI spectral sensor can measure a spectrum from 470 to 920nm with a 1.8nm band width. The specification and the data acquisition conditions for the CASI sensor are shown in **Table. 1**. The image was acquired at an altitude of 3,000m by Cesna404 aircraft. The ground resolution is longer (12.6m) in the aircraft flight. Each pixel in the image contains the mean spectral radiance of the ground target..

A selection of 7 bands from the original CASI image (spaced every 40 channels) is shown in the **Figure.2**. The first 4 channels are in visible spectrum and the others are in near infra red. In the center of **Figure 2** is Lake Akanuma and the artificial dike across the area is clearly visible. There are various wetland vegetation in this study area, especially reed, sedge and sedum is overlapping and continuously distributed over the sphagnum moss.

Before the analysis, the CASI image was corrected for the geometric distortion caused by the rolling of the airplane and the digital numbers were converted to radiance values (Babey and Soffer, 1993).

3.2 Unmixing

The spectral characteristics of 7 land cover classes used for unmixing is shown in **Figure 3**. All the classes are wetland vegetation communities except for the road, and water classes. The spectral difference between these vegetation classes is difficult to discriminate using a common remotely sensed image with a small number of bands. So far, research in wetland vegetation classification has not been intensively studied the mutually overlapping and continuously changing vegetation distributions due to the lack of established method (Yamagata, 1995). However from the wetland ecosystem conservation planning and the global warming model perspective, wetland vegetation classification has become an urgent research theme.

3-2-1. Procedure of unmixing

The process of unmixing by subspace method applied to CASI image is as follows.

1) Nine pure pixels (end member points) for each unmixing class were selected as the training data based on the knowledge of field surveys.
2) Using training vectors, the class correlation matrix $\boldsymbol{Q}$ is calculated by equation (6).
3) The eigen value problem using the class correlation matrix $\boldsymbol{Q}$ is solved to determine the subspaces for each class.
4) The projection of pixel vector of CASI image on the class subspace is calculated using equation (12) .
5) The projection (component of unmixing) for each class was normalized to (0,1) and mapped to an image.

3-2-2 Unmixing methods for comparison.

The following 3 conventional unmixing methods are used for the comparison to the new method:

1) Least squares method : Assuming a linear mixing model, area fractions of each class are determined by a least squares model using the training data.
2) Quadratic programming : Adding a condition that the area fractions add up to 1 to a linear mixing model, a least squares solution is obtained by the quadratic programming method.
3)' Orthogonal subspace projection method : First, the projection of the mixel vector onto the orthogonal complement space spanned by the class vectors of the other classes is computed. The inner product of this projected vector and the class vector is calculated (Harsanyi and Chang, 1994).

3-2-3 Results of unmixing.

The result of unmixing by the subspace method applied to the CASI image of Kushiro mire is shown in **Figure 4**. The result of unmixing by conventional least squares, quadratic programming and orthogonal subspace projection methods are shown in **Figure 5, 6** and **7** respectively. Here the unmixed vegetation classes are Yoshi (*Phragmites.*: Reed), Hannoki (*Alnus.*: Alder), Mizugoke(*Shagnum.*: Moss), Isotsutsuzi (*Ledum.*), Suge(*Carex.*: Sedge).

By comparing the quantitative classification accuracy of unmixing by the subspace method with the other methods, and investigating the correspondence between the actual vegetation distribution from field surveys, the following results were obtained:

1) In figure 4, it is seen that the subspace method highlighted the reed contaminated with sedge as Sedge class.
2) With Sedge class, by comparing figure 4 and 6, subspace method delineated accurately the ground pattern of sedge class as well as quadratic programming.
3) Only quadratic programming (Figure 6) delineated the Moss and Ledum class that are spectrally very similar (Figure 3). This result may be due to the constraint of quadratic programming, i.e. it tries to enhance the subtle spectral difference between classes to increase membership difference.
4) Alder class was accurately delineated only by quadratic programming (Figure 6).
5) Water and Road classes were delineated accurately by all methods.

3-2-4 Evaluation of unmixing methods

Based on the results obtained above, an evaluation of the unmixing methods can be summarized as follows[1],

1) Spectrally distinct classes such as road, Water, Sedge (Figure 3) are well unmixed by subspace method (Figure 4).
2) Spectrally similar classes such as Ledum and Moss (Figure 3) are unmixed sufficiently only by quadratic programming (Figure 6).
3) The result achieved by orthogonal subspace projection method (Figure 7) is entirely the same as the least square method (Figure 4).
4) Quadratic programming (Figure 6) shows the most accurate pattern of unmixing across all classes, however it is the most time consuming to implement. The subspace method is a very fast algorithm owing to many fast and stable eigen value problem algorithms. Unmixing is performed by a

[1] Here, these evaluation are all of qualitative nature. This is because the evaluation of unmixing is impossible unless we conduct a through survey of continuous distribution of all vegetation types.

simple inner product calculation which is suitable for parallel processing.

4. SUMMARY

A new approach to the unmixing problem by the subspace method is proposed and applied to wetland vegetation using hyperspectral imagery. Unmixing by the subspace method is superior to conventional methods in numerical stability and computation speed for hyper spectral imagery. The results of the unmixing experiment showed unmixing by subspace is spatially accurate except for the classes that are spectrally very similar. In the near future, the number of sensor channels and the size of image area will rapidly increase. The fast and stable unmixing algorithm based on the subspace method will be most useful for such data. Further, we need to improve the separability between the spectrally very similar classes by developing the present approach.

5. ACKNOWLEDGMENT

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Specification of CASI sensor	
Band width	1.8nm
Number of bands	288channels
Band range	410.3-923.7nm
Image size	39pixel,489line
Dynamic range	12bit
Image acquisition condition	
Altitude	3000m
Velocity	200km/h
Ground resolution	3.7m (along swath)
	12.6m (along flight)
Observation date	31 Aug 1993
Observation time	11:25-11:30am
Weather	Fine

Table 1: Specification of CASI image acquisition

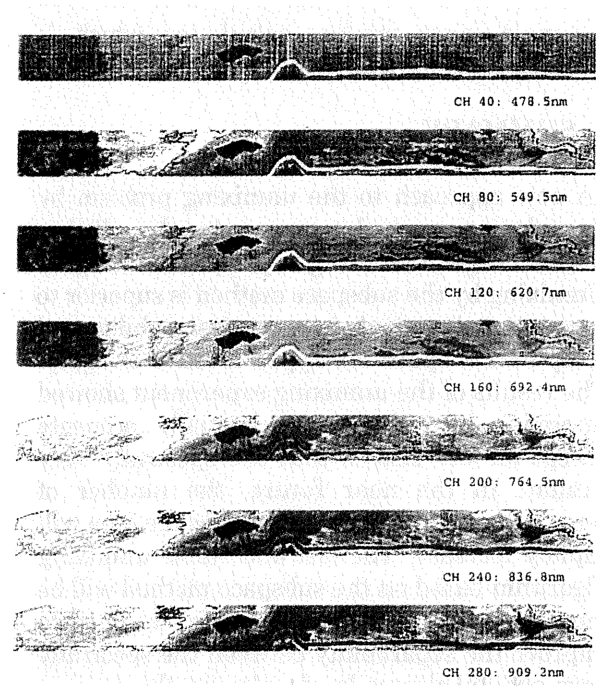

Figure 2: Seven sample channels from the CASI image for Kushiro wetland.

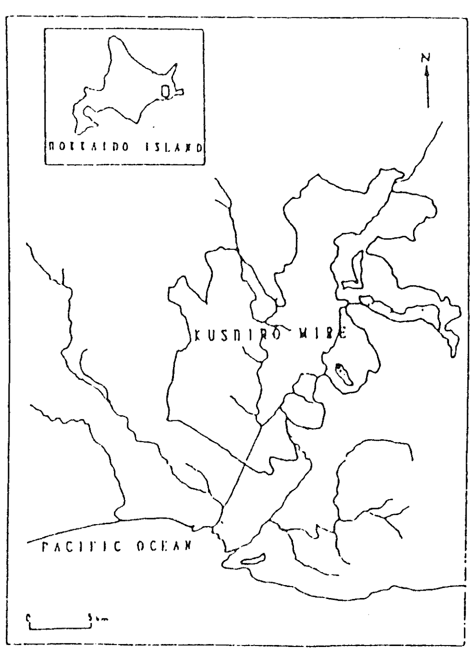

Figure 1: Location map of Kushiro wetland

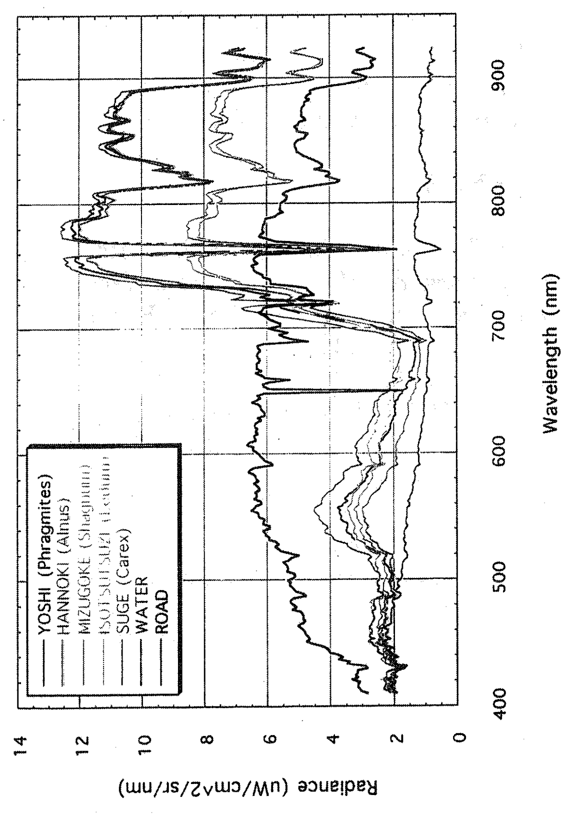

Figure 3: Spectral signature of wetland vegetation communitiy.

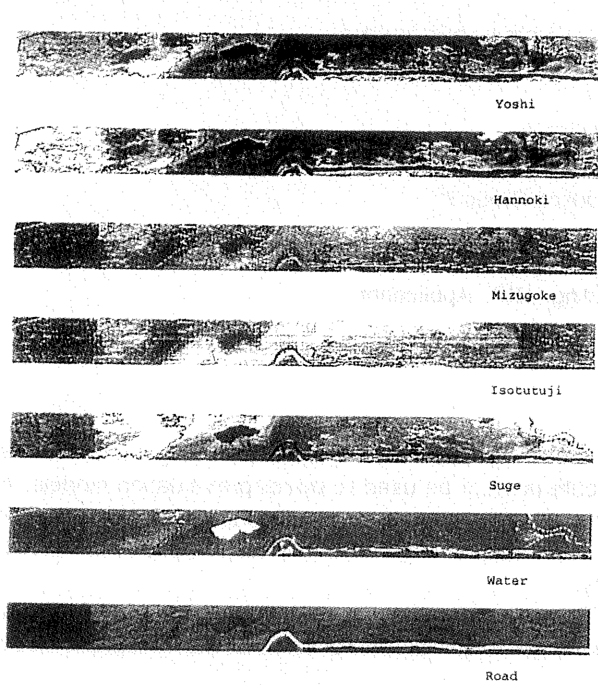

Figure 4: Class unmixing derived from the subspace method, Kushiro.

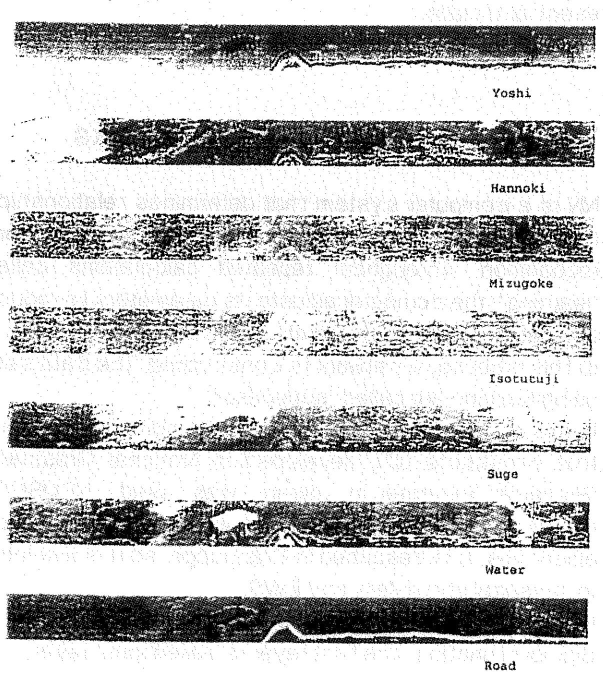

Figure 5: Class unmixing derived from a least squares model, Kushiro.

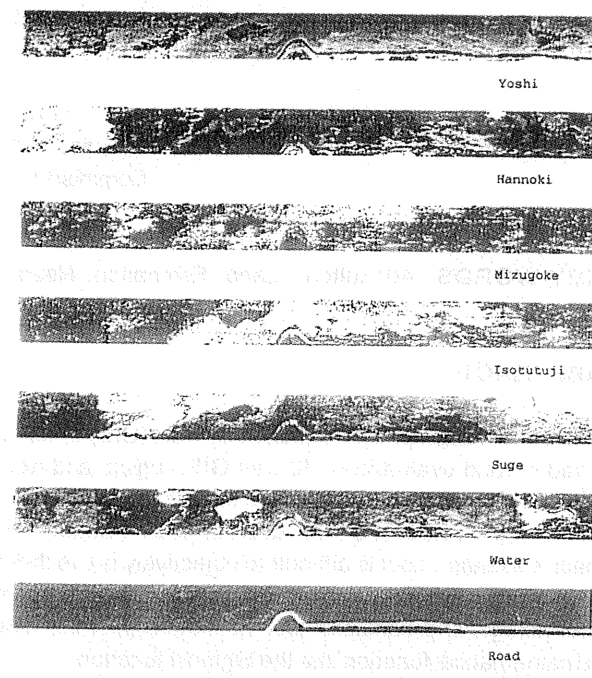

Figure 6: Class unmixing derived from a quadratic programming method, Kushiro.

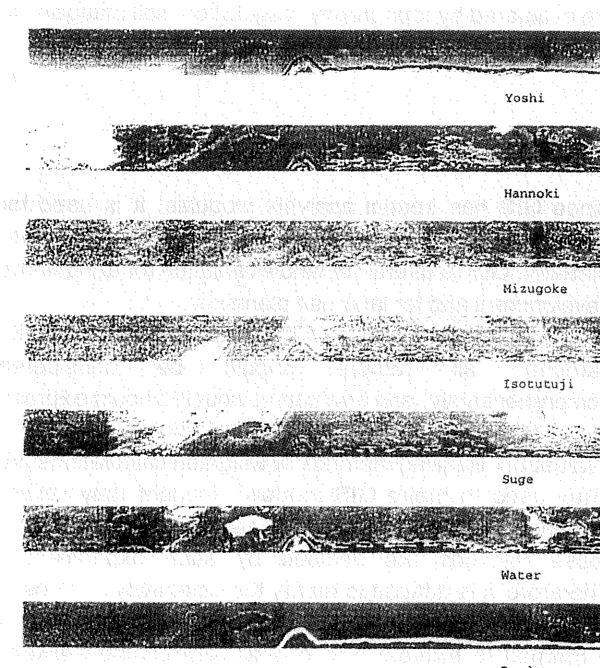

Figure 7: Class unmixing derived from orthogonal subspace projection method, Kushiro