APPLICATION OF MODIFIED COUNTER-PROPAGATION FOR SATELLITE IMAGE CLASSIFICATION

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ABSTRACT:

A supervised category classifier for satellite images by using the Modified Counter-Propagation(MCP) is proposed. The MCP is a neural network which consists of three layers: the input layer, the competition layer and the output layer[1,2,3]. The input and the competition layers form the Self-Organizing Map(SOM)[4,5,6]. The connections of Counter-Propagation[1,2,3] from the competition layer are extended to the output layer. The Landsat image data are adopted as the input data of the MCP, and the output layer consists of the pixel values, which represent categories to be classified. Our result shows that the MCP can classify more accurate and precise than that of the SOM only, especially for the classification of vegetation, farm and wood.

Commission III

KEY WORDS: Modified Counter-Propagation, Self-Organizing Maps, Supervised Classification, Kohonen's Competitive Learning

1. INTRODUCTION

Periodical, precise and broad ranged monitoring of natural and artificial changes of earth surface is now possible especially by sensors on satellites. It is also more important than ever to observe and monitor the earth environment. Sensors on the satellites have been drastically improved both qualitatively and quantitatively in the last decade. Then the classification of land cover by using huge mount of data taken by satellites is one of the main themes of the remote sensing.

The Modified Counter-Propagation(MCP) has been proposed as the supervised version of the Self-Organizing Map(SOM) [1,2,4,5,6] , which is essentially an unsupervised and self-organizing classifier. Adding the third layer as the output layer for the Counter-Propagation, the MCP has the supervising data for the classification. Connection weight vectors between the input layer and the competition layer are multi-dimensional. An element of connection weight vectors between the competition layer and the output layer represents the frequency information of each category. The MCP compresses the category information in the multi-dimensional space to the lower-dimensional competition layer. The MCP can visualize the category distribution onto the output layer, which represents the distribution in the competition layer.

2. MCP FOR COMPETITIVE LEARNING

2.1 Outline of SOM

The SOM is the most familiar neural network for the competitive learning[4,6]. It makes the map of the resemblance of multi-dimensional data by the Kohonen's competitive learning. The SOM is composed of the input layer, to which the input data space $\Re_I^N$ is adopted, and the competitition layer, which is the M-dimensional array of units as Fig.1, where $M<N$ and usually the shape of the array is set M=2. In this work we make the array rectangular. A parametric reference vector

$$W_j = \left[w_{j1}, w_{j2},, \cdots, w_{jN}\right] \in \Re^N$$

is inputted every data i in the input layer and is connected to every node j of the competition layer. The SOM needs no supervising data and the resemblance of the input data can be mapped onto the connection weight vectors W_j.

Input data $X_i \in \Re_I^N$ (i=1,2,…,I, I represents the number of input data) determines the winner unit j, if its distance

$$D_{ij} = \sqrt{|X_i - W_j|^2} \left(X_i \in \Re_I^N\right) \tag{1}$$

becomes the smallest among $\forall j$ for fixed i. Not only the unit which wins but also units in its neighborhood, whose size is determined as

$$N(t) = N(0)\left(1 - t/T\right), \tag{2}$$

learn at the same time by the regression method

$$W_j(t+1) = W_j(t) + \alpha(t)\left(X_i(t) - W_j(t)\right), \tag{3}$$

where

$$\alpha(t) = \alpha(0)\left[1 - \frac{t}{T}\right]$$

and $W_j(t)$ is a reference vector at the t-th iteration and $W_j(t+1)$ is the updated one. Note that $t(=1,2,..., T)$

denotes the learning time coordinate. Each discrete time t, whole input data ($^{\forall}i$) are used for the competitive learning. The output layer has the category information for the classification as the supervising N-dimensional signals.

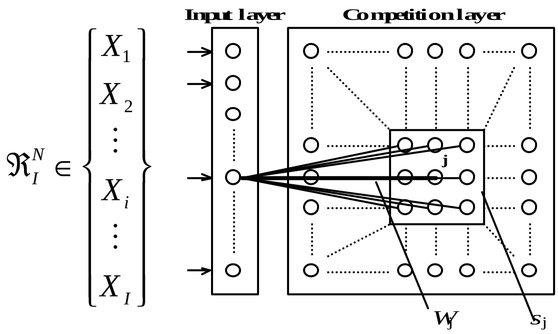

Fig.1 Schematic diagram of SOM

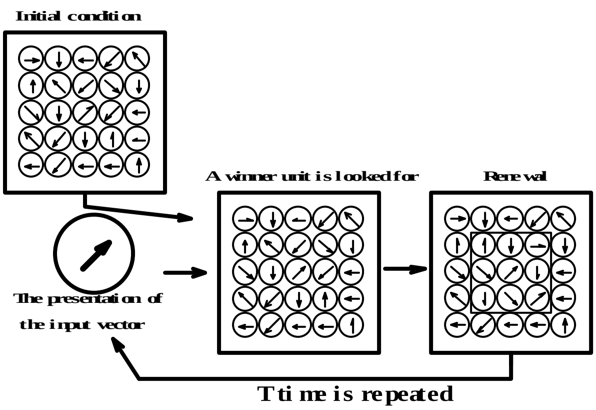

Fig.2 Competitive learning

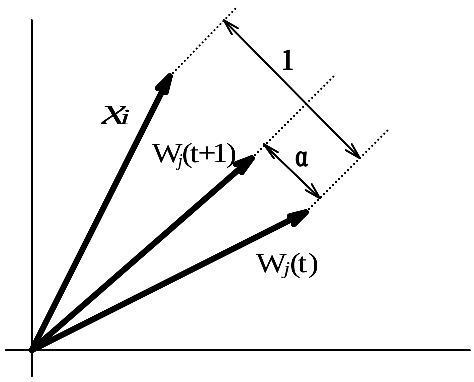

Fig.3 The correction of the connection weight

2.2 Structure of MCP

The MCP is made from the SOM, attaching the output layer which is inputted the element of the output data space $\Re_o^N$. A connection weight vector

$$Z_j = [z_{j1}, z_{j2}, \cdots, z_{jN}] \in \Re^N$$

between the output data space and the unit j in the array has a zero vector as the initial value. Only one element Z_{jk} of Z_j is incremented by

$$z_{jk}(t+1) = z_{jk}(t) + b(t), \tag{4}$$

where $b(t) = b(0) + (1 - b(0)) \frac{t}{T}$ and $b(0) < 1$, if the distance

$$D_{k,j}^{*} = \sqrt{|Y_k - W_j|^2} \tag{5}$$

is minimum during the Kohonen's learning for $^{\forall}k$. Here $Y_k = \Re_o^N$ ($k = 1,2,\ldots,K$, K is the number of categories) represents the k-th characteristic category in $\Re_I^N$. Generally the k-th element of the weight vector Z_j in the neighborhood of the size

$$N_j^{*}(t) = N_j^{*}(T) \frac{t}{T} \tag{6}$$

is also incremented. After the learning, the largest element $Z_{j\tilde{k}}$ determines the most probable category as the $\tilde{k}$-th category for each unit j in the array. Therefore, the reliability of the result can be judged quantitatively by introducing the MCP.

The SOM needs no supervised data Y_k and the result of the classification usually depends on the "visual" judgment at its final stage. We somehow manage to read the category information from the SOM[5]. On the other hand, using the MCP, the classification result of the MCP is more objective and reliable than the SOM, because the qualitative judgment by the relative frequency information of the reference vector Z_j between the competition layer and the output layer is available. The convergence of the competitive learning can be also monitored by the frequency information during the learning. Then, it is necessary to examine supervising data or "code words" carefully

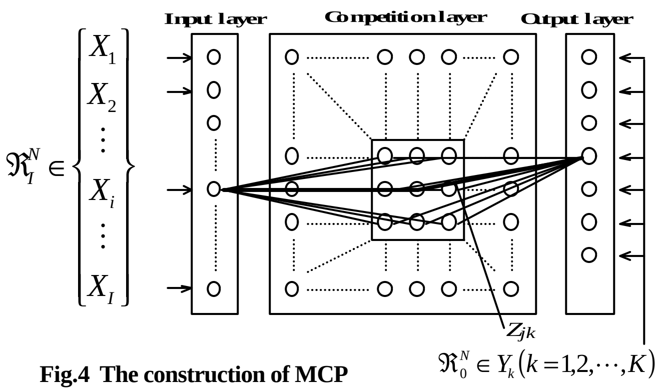

Fig.4 The construction of MCP

for higher reliability of the MCP classification.

2.3 Learning and recognition

The procedure of the MCP has two modes. The learning mode is to make the self-organized map. The recognition mode is for the classification procedure.

2.3.1 The learning mode

Step1. Initialization.

The initial value of the connection weight vector W_j of the input layer and the competition layer is set by random numbers, and the initial value of the connection weight vector Z_j between the competition layer and the output layer is set a zero vector.

Step2. Decision of the winner unit.

Next, an Euclidean distance D_{ij} with the input vector X_i and the connection weight vector W_j is calculated by eq.(1). If this value becomes the smallest among $^{\forall} j$ and for fixed *i*, the unit *j* is a winner unit

Step3. Renewal of the connection weight vector W_j

The winner unit and units in the neighborhood are renewed as eq.(3). A size of neighborhood for the unit *j* is determined by the neighborhood function eq.(2). In this work we make the square neighborhood, whereas the competition layer is rectangular.

Step4. Renewal of the connection weight vector Z_j: Election of the winner init

Only one element of the reference vector $Z_j(t)$ connected to the output unit corresponding to the category *k* is incremented as eq.(4), if the distance $D_{k,j}{}^{*}$ (eq.(5)) is minimum during the Kohonen's learning. The same vote is done inside the neighborhood of the *j*-th unit of the competition layer. Its size is determined as eq.(6).

2.3.2 The recognition mode.

The classification is done by the following process after the learning mode.

Step1. The presentation of the input data to the input layer.

Step2. The winner unit *j* of the competition layer is obtained by the distance eq.(1) for every input data X_i.

Step3. The $\tilde{k}$-th element of Z_j, which has the maximum value, determines the category $\tilde{k}$ that the unit belongs to.

2.3.3 Frequency distribution indication on SOM.

The connection weight vector Z_j between the competition layer and the output layers must be normalized for the classification to make frequency information visualized as

$$h_{jk} = \frac{Z_{jk}}{A_{max}} , \qquad (7) \qquad A_{max} = \max \sum_{k=1}^{K} Z_{jk} , \qquad (8)$$

h_j is the connection weight vector $Z_j(t)$ that is normalized by A_{max}, and *K* is the number of categories in the image. Then eq.(7) can make the visual map of the frequency information. We can see the category-information distribution on the SOM.

3. RESULT FOR LANDSAT IMAGE DATA

Landsat image data are inputted to the input layer of MCP, and the RGB value which represents each category is adopted in the output layer.

3.1 Pseudo-color image and SOM

The Landsat pseudo-color image of Kitaura lake, which is the large shallow lake at Ibaraki prefecture, Japan, is shown in Fig.5. The initial condition of the SOM between the input layer and the competition layers is shown in Fig.6. We choose seven categories ($K = 7$) in the image: 1.Sea, 2.River, 3.Vegetation, 4.Woods, 5.Farm, 6.Soil, 7.City Area. The result of *T*=100 is shown in Fig.7. The learning proceeds from Step.1 to Step.4 in the section 2.3.1. Then the frequency information of each category can be obtained by (7) and (8) as Fig.8-Fig.14. We apply the gray scale to represent the information eq.(7). For example, if $h_{jk} = 1(0)$, the color of the unit *j* for the category *k* becomes black (white).

3.2 Output layer category frequency information.

Fig.15 shows the categories of all units in the competition layer. They are determined by the winner of the election by Step 4 of the section 2.3.2.

4. CONCLUSION AND DISCUSSIONS

The classification result is shown in Fig.16. It is made from the category information of Fig.15. The classification result by the MCP is compared with the result by the SOM[3]. The region growing is applied to determine the category to which each unit in the self-organized competition layer belongs. If the difference between adjacent units after the learning is smaller than some threshold value, they are decided to belong to the same category. Fig.17 is the result of region growing applied to the SOM.

As you see in Fig.17, the boundaries often become open and make too small region for the classification. We have to "fix" the boundaries usually by using "the human eyes" after the region growing. Both Fig.18 and Fig.19 are classified result after "the human eyes correction" by different person. Owing to "the correction", even if the same person corrects the boundaries, the result can be different every time in general.

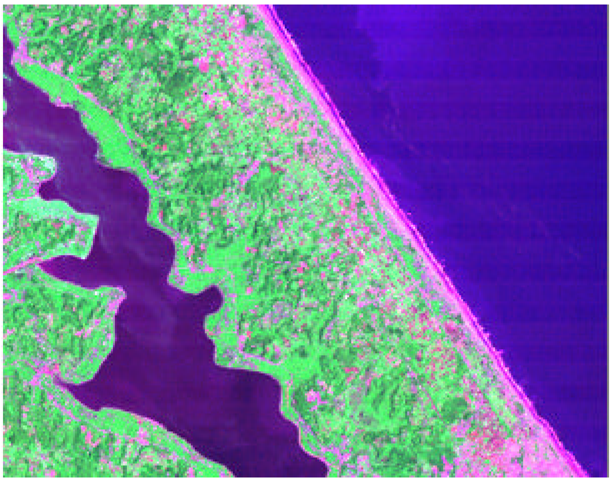

Fig.5 Pseudocolor image of Kitaura lake

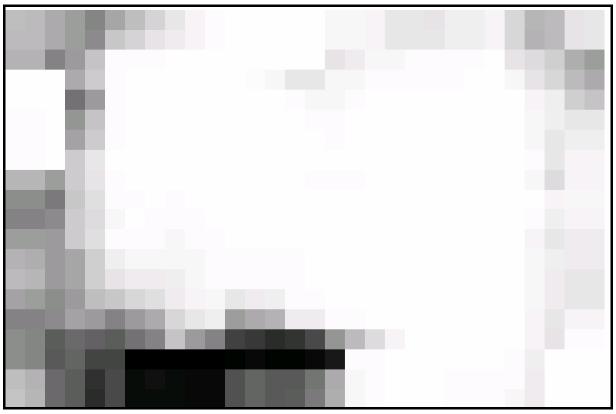

Fig.8 Frequency information of sea

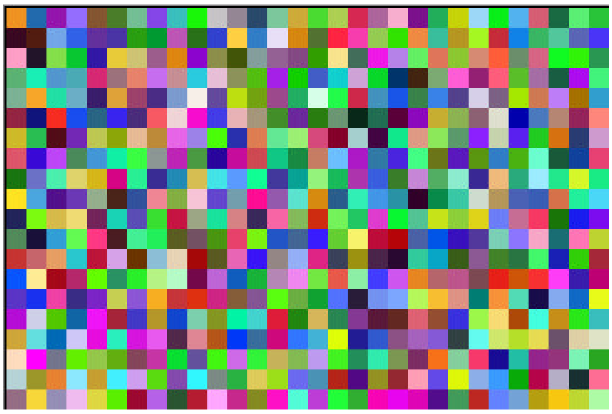

Fig.6 SOM with the initial condition.

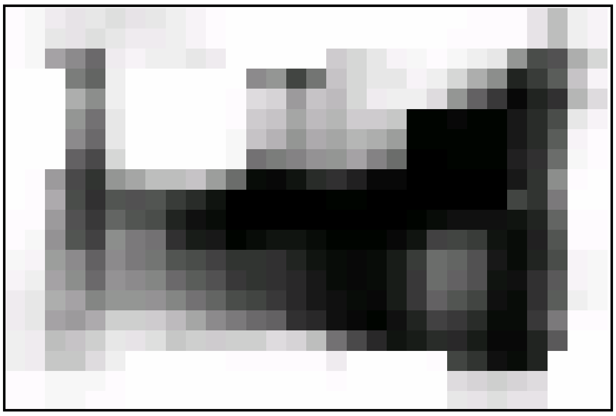

Fig.9 Frequency information of river

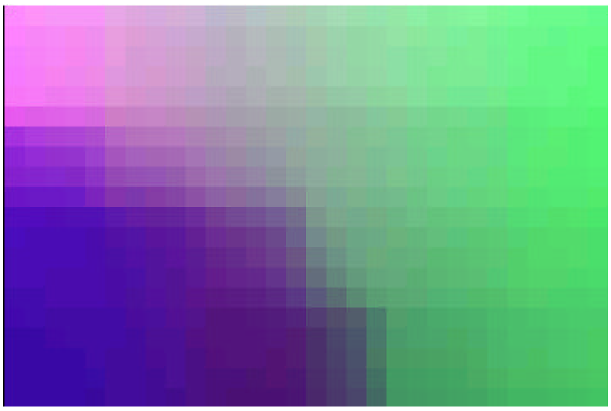

Fig.7 SOM after Kitaura *T*=100 times learning

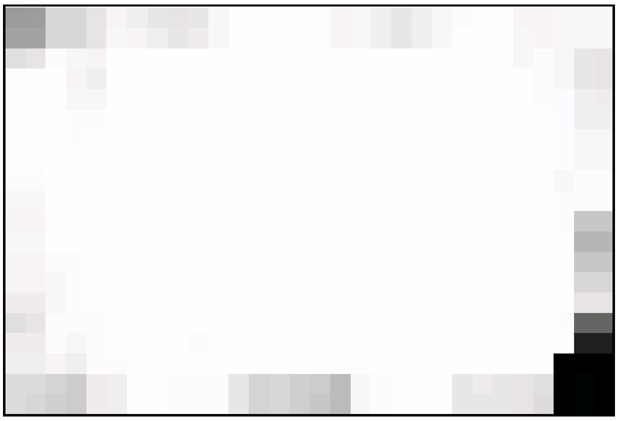

Fig.10 Frequency information of vegetation

In Fig.18 vast area of sea is mis-identified to river. In Fig.19 the area which is actually land is classified to sea or river. Some of the area where soil and city area are also classified to the vegetation and the mis-recognition of the woods are more disastrous. On the other hand, the MCP makes such mis-recognition minimum, especially for vegetation, farm and wood. Therefore the MCP is superior to the SOM and has the qualitative method for the classification (the section 2.3.2).

The classification result by the MCP with the supervised data and the results by the SOM with no supervised data are compared. The MCP can derive more definite and quantitative classification result. It acquires the reliability by adding the category frequency information on the output layer.

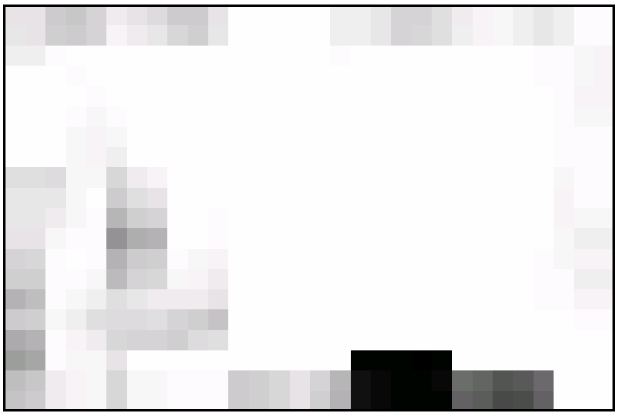

Fig.11 Frequency information of woods

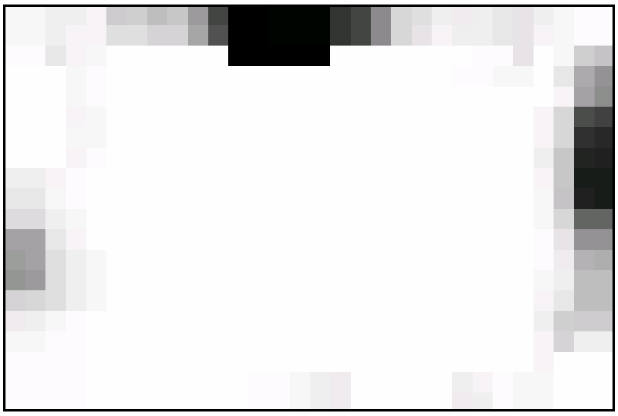

Fig.12 Frequency information of farm.

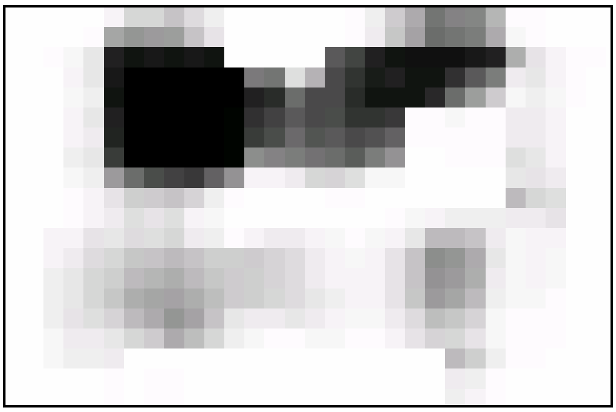

Fig.13 Frequency information of soil

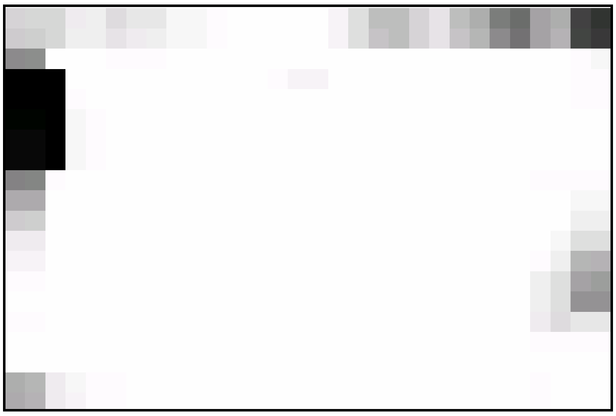

Fig.14 Frequency information of city area

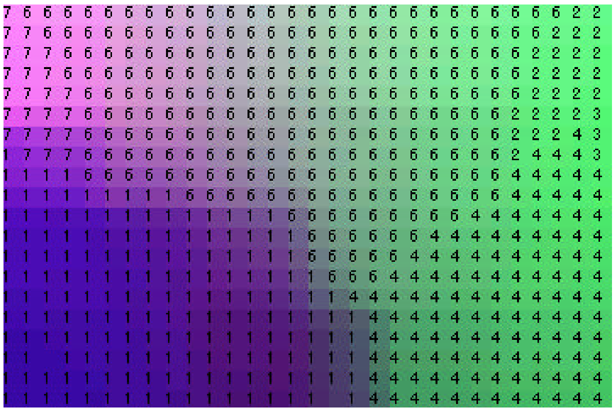

Fig.15 Categories of all units in the competition layer determined by the election.

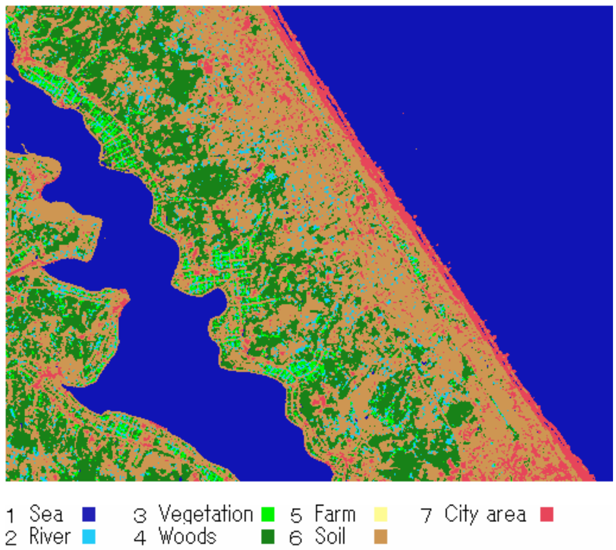

Fig.16 Classified result 1 of Kitaura lake

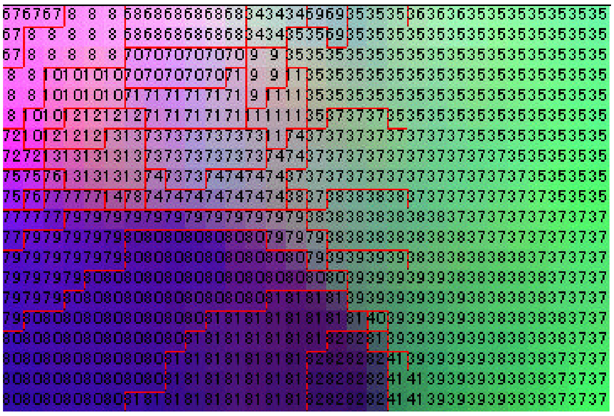

Fig.17 SOM after region growing

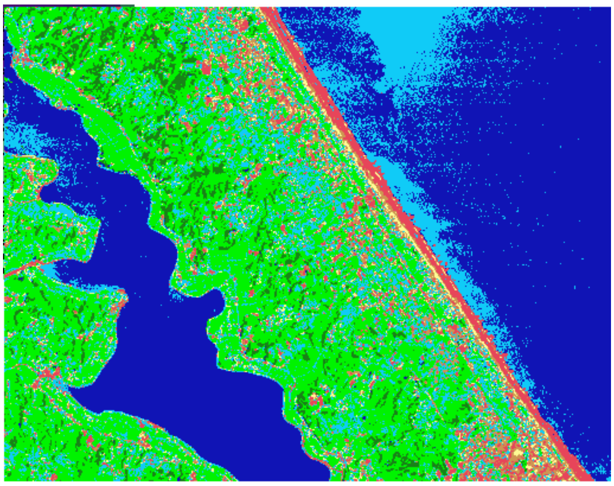

Fig.18 Classified result2

Fig.19 Classified result3

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