Construction of a New Classifier Integrated Multiple Sources and Multi-temporal Remote Sensing Data for wetlands

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Abstract

This paper developed a new classifier named extension model of fuzzy matter-element to classify multi-source and multi-temporal remote sensing data. Taking the National Nature Reserve of Ruoergai wetlands as study area, this paper chose the data of TM, CBERS and MODIS-NDVI of 2007 as data source and introduced the constructing process of this classifier. Results showed that, the overall accuracy (82.36%) and Kappa coefficient (0.8006) of the integrated of multi-information classification method is better than the SVM results using on TM (79.74%, 0.7704) and on CBERS (77.29%, 0.7436). Meanwhile, the paper also made an active exploration of classification on the cloudy image.

Keywords: Multi-sources and Multi-temporal; Support Vector Machine; Fuzzy Matter-element Extension; Integrated Classifier; Ruoergai Wetland

1. Introduction

With the development of remote sensing, there are more and more different types of sensors which can be used for various applications. Images also developed toward hyper-spectral and high spatial resolution. Currently, traditional classification methods are mostly for a single sensor and low-dimensional feature vector. It is hard to get effective and high accuracy when analysis the high-dimensional feature, and while analysis multi-temporal data, classification methods also faces the distribution between various data and decision making problems. Different sensors have their respective characteristics in spatial and spectral resolution, and the data of multi-temporal remote sense (such as NDVI) has more extensive performance information. Currently, extraction of target information of multi-temporal and multi-sources is playing an important role for the land cover extraction [1~7], crop yield estimation[8,9], plant pest and disease monitoring[10,11], geological disaster monitoring[12], land use change and lake water monitoring and dynamic[13,14] and others.

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The fusion of multi-classifier and single-classifier multi character was widely used in pattern recognition, machine learning and artificial intelligence [15,16]. It is also successfully applied in classification for recent years [16~18]. This paper introduced a comprehensive decision method and the construction method of an integrated classifier. Taking multi temporal TM and CBERS and time-series MODIS NDVI of 2007 as data resources, this paper used Support Vector Machine (SVM) as the classifier and the fuzzy matter-element model as the integrated decision-making device and get an integrated classification finally. Experiment showed that this classifier can effectively couple multi-sources and multi-temporal remote sensing data, and the accuracy classification is better than traditional methods.

2. Construction of Integrated Classifier

2.1. Architecture Thinking of the Integrated Classifier

There are two steps which are the classification of a single image and multi-information decision making when classify the multi-sources and multi-temporal data. Fig. 1 gives the construction procedure of the integrated classifier. It can be seen from the flow chart that: accurate registration of the collected images was done firstly, and then images of different sensors and different temporal were classified respectively through spectral classification algorithm. Reasonable integrated decision making of the images and auxiliary data is the key to construct the integrated classifier for multiple data sources and multi-temporal data. This paper chose the SVM as the spectral classification method which developed in recent years and which can get high precision and efficiency [19~21] and the fuzzy matter-element extension method in the construct of the integrated classifier.

2.2. Classification Algorithm

The classification method of one single view image now available mainly base on the spectral character and clustering criteria method are mainly distance, angle, probability, or the machine learning and artificial criteria [19]. SVM is a new machine learning method which based on the statistical theory and the risk minimization principle of learning theory. In the simplest linear SVM algorithm, a super flat which can separate the positive and negative sample set by the largest classification interval was got from the learning procedure. The second category of SVM classifier was always thought as an advanced classifier, and the stability for the small sample set was also widely recognized.
There are two general ways to solve the classification problem by SVM which are the one to many and one to one modes. The first way needs to construct $k$ SVMs where $k$ is the number of class. When the $i$th SVM trains, the $i$th sample point is the positive samples and others are the negative. For the samples too much and longtime training, although it is easy to realize, balance between the positive and negative samples will break easily. The one to one mode needs to construct $\frac{k(k-1)}{2}$ sub-classifiers to estimate the probability of multi-classes through the classifier and it can decrease the calculation time effectively. Wu proposed a one to one mode and has been used widely [22]. When construct the $\frac{k(k-1)}{2}$ sub-classifiers, probability of the $i$th class estimated by each classifier can expressed as $r_{ij} = P(y = i \mid y = i \text{ or } j)$. Where $r_{ij}$ is:

$$
\begin{align*}
    r_{ij} &= \frac{P_i}{P_i + P_j} \\
    r_{ij} + r_{ji} &= 1
\end{align*}
$$

Equation (1) can be transformed into follows:

$$
\begin{align*}
    r_{ij}P_i - r_{ji}P_j &= 0 \\
    \text{min} & \sum_{i=1}^{k} \sum_{j=1}^{k} (r_{ij}P_i - r_{ji}P_j)^2 \\
    \text{st.} & \sum_{i=1}^{k} P_i = 1, P_i \geq 0
\end{align*}
$$

2.3. Construct of the Integrated Classifier

How to make a comprehensive decision after the classification of SVM of single image and the auxiliary data is the key to construct the integrated classifier. For ground object $M$, there are $n$ data sources $c_1, c_2, \ldots, c_n$ to describe it, and it can be described through the relative data $x_1, x_2, \ldots, x_n$. Obviously, there is a contradiction in the description of the surface features $M$ by $n$ data sources. The fuzzy matter-element model is introduced to solve the problem. It was proposed by Cai in 1983 and can solve contradiction problem from both qualitative and quantitative aspects [23,24]. The fuzzy matter-element model began from the transformation of incompatibility issues and solutions. Through the introduction of matter element and the calculation, it solves the incompatibility problem from both qualitative and quantitative aspects. For a specific ground object, it studies images and auxiliary data as a whole to describe the affiliation using degree of correlation function of the extension set and then determine the ownership of this ground object. The matter-element matrix of surface features $M$ can be expressed as:

$$
R = \begin{bmatrix}
    R_1 \\
    R_2 \\
    \vdots \\
    R_n
\end{bmatrix} = \begin{bmatrix}
    M & c_1 & x_1 \\
    c_2 & x_2 \\
    \vdots & \vdots \\
    c_n & x_n
\end{bmatrix}
$$

where $R$ is $n$-dimensional matter element and it can be abbreviated as $R = (M, C, X)$. Here we called the name, character of $n$-dimension and the feature value as the three elements of matter-element.

Assume that there are $k$ classifications of $M$, which are $M = [M_1, M_2, \ldots, M_p, \ldots M_k]$, the $p$th matter-element matrix can be expressed as follows:
\[ R_p = \begin{bmatrix} M_p & c_1 & [a_{p1}, b_{p1}] \\ c_2 & [a_{p2}, b_{p2}] \\ \vdots \\ c_n & [a_{pn}, b_{pn}] \end{bmatrix} \]

where \( M_p \) is the section domain object of number \( p \) type, and \( x_{pi} = [a_{pi}, b_{pi}] \) is the range of Eigen value of section domain object. Classic matter-element matrix can be expressed as:

\[ R_B = \begin{bmatrix} M_B & c_1 & [a_{B1}, b_{B1}] \\ c_2 & [a_{B2}, b_{B2}] \\ \vdots \\ c_n & [a_{Bn}, b_{Bn}] \end{bmatrix} \]

where \( M_B \) is the standard object, and \( x_{Bi} = [a_{Bi}, b_{Bi}] \) is the range of \( c_i \) about \( M_B \). Obviously, there is \( x_{pi} \subseteq x_{Bi} (i = 1, 2, \cdots, n) \).

It is the quantify tool to solve the incompatibility problem through definition and solution of correlation function. In the comprehensive decision making process, the correlation function is characterized by the module of interval.

Module of the bounded interval \( x_{pi} = [a_{pi}, b_{pi}] \) corresponded \( i^{th} \) data source and \( p^{th} \) ground object can be defined as:

\[ |x_{pi}| = b_{pi} - a_{pi} \]  

Distance of \( x_i \) to the interval \( x_{pi} = [a_{pi}, b_{pi}] \) can be defined as:

\[ \rho(x_i, x_{pi}) = \frac{|x_i - \frac{a_{pi} + b_{pi}}{2}|}{\frac{b_{pi} - a_{pi}}{2}} \]  

Distance of \( x_i \) to the section interval \( x_{Bi} = [a_{Bi}, b_{Bi}] \), can be defined as:

\[ \rho(x_i, x_{Bi}) = \frac{|x_i - \frac{a_{Bi} + b_{Bi}}{2}|}{\frac{b_{Bi} - a_{Bi}}{2}} \]

The correlation function \( K_p(x_i) \) can be defined as:

\[ K_p(x_i) = \begin{cases} \frac{\rho(x_i, x_{pi})}{\rho(x_i, x_{pi})} & x_i \in x_{pi} \\ \frac{\rho(x_i, x_{Bi}) - \rho(x_i, x_{pi})}{\rho(x_i, x_{Bi})} & x_i \notin x_{pi} \end{cases} \]

Take the result of correlation function \( K_p(x_i) \) and the normalized coefficient \( w_{pi} \) to the comprehensive correlation formula:

\[ \alpha_p = \sum_{i=1}^{n} w_{pi} K_p(x_i) \]

In the result of \( \alpha_p \), take \( \max(\alpha_p) \) as the assignment class of the pixel after the comprehensive correlation formula decision.
3. Experiment and Analysis

3.1. Data Collection and Preprocess

Ruoergai wetland locates on the junction of Si Chuan and GanSu province. It locates on the up reach of the Yellow River. Altitude of Ruoergai wetland is about 3500 m and it is the important water conservation district of Yellow River. In this study, we chose the Ruoergai National Nature Reserve as our study area (Fig. 2). As the international scientific platform more and more convenient, it is easy to get kinds of satellite data. In this paper, we chose 2 scenes of TM and 1 scene CBERS data as our data source. To reduce the uncertainty impact of the spectral change caused by temporal, data are mainly in 2006 to 2007. Dates of TM images are 23 Jul, 2007 and 25 Sep, 2007 and date of CEBERS is 10 Jun, 2006 (Fig. 3). Additional, we chose the MODIS NDVI time-series data of 2007 as the auxiliary data, this datasets were firstly reconstructed through Savitzky-Golay filter to reduce the impact of cloud and ice [25]. Image accurate registration was finished through the software package AROP. It was explored by LEDAPS which is the department of the U.S. National Aeronautics and Space Administration (NASA) [26]. The registration error was controlled in 0.2 pixels. It can be seen from the images that there is one image which is highly covered by cloud. We chose this image is to use the cloud-free area to make decision when the correlation function appeared irrelevant of other data sources. Study in this paper shows that the integrated classifier can effectively use the data with cloud-free data and the actual situation may not require the identification and treatment the cloud.
3.2 Experiment and Precision Analysis

3.2.1 Classification System and the Spectral Characteristics

The unique geographical landscape and the climate characteristics of Ruoergai wetland determined the various types of local surface features and the complicated distribution. It is the alluvial plain of the white river and black river. The terrain is flat and soil is deep. There are meandering rivers and Niuier Lake in it, and this has developed into kinds of landscape of wetland. The climate of Ruoergai wetland is plateau continental semi-humid monsoon climate, and the growing season is short which is from May to October every year and is about 150 days [27]. According to visual interpretation and field investigation, there are 9 categories of surface features which are the Open water, Bare land and Sand land, Peat land, Marsh grass, Wet grassland, Shrub meadow, High coverage grassland, Medium coverage grassland and Low coverage grassland. As it shown in Fig.4, curve in it respect the spectral character in TM and CBERS images of these classes. It is easy to find that the spectral curve of the water surface, bare land and sand land, and peat land is easier to classification for the difference of their spectral curve is obvious. The spectral of Marsh grass and wet grass was mixed with water and the characteristic shows inconspicuous. Difference between these classes is obvious on band 3, 4 and 5 of TM while on band 3 and 4 of CBERS. Difference of High coverage grassland, Medium coverage grassland and Low coverage grassland mainly focused at band 4 and band 5 of the TM, and band 4 of the CBERS.

![Fig. 4 Spectrum curves of TM and CBERS](image)

(a) ![Fig. 4 Spectrum curves of TM and CBERS](image) (b)

(Fig. 4a is the spectral character in TM while Fig. 4b is spectral character in CBERS)

3.2.2 Experiment

When Using the SVM to classify a single image, parameters set use the default settings of ENVI4.3. The radial basis function was chose as the kernel function for the cloud images, and the cloudy image was automatic process through the SVM algorithm and the same classification system.

Data elements were independent respectively when using the Fuzzy matter-element model to construct the integrated classifier. As discussed above, the fuzzy matter-element model based on both qualitative and quantitative aspects. It meets the mutually exclusive condition between the properties of each class and the classification results. The incompatible data in the auxiliary information data needs to be data mined, extraction transformation and utilization. In this paper, time-series MODIS-NDVI data of 2007 were used as auxiliary data, how to extract the mutually exclusive information between the auxiliary data sources was introduced below.

Fig. 5a gives the NDVI time-series curve of MODIS-NDVI. As can be seen from Fig.5b, NDVI time-series curve fits a Gaussian peak curve (Fig. 5b). The peak areas of different objects are different, and this peak value actually reflects the concept of a biomass of different categories. Total biomass might be different, so the different surface features shown by the peak area of incompatible information can be used in classification.
For the pixel of MODIS-NDVI, time series is a discrete point data. The peak area is composed by trapezoids formed by these discrete data and can be calculated as follow:

\[ S(i,j) = \sum_{k=1}^{n} y_k(i,j) + \sum_{k=1}^{n} y_k(i,j) \Delta x + \sum_{k=1}^{n} y_k(i,j) \Delta x + \cdots + \sum_{k=1}^{n} y_k(i,j) \Delta x \]

\[ = \sum_{k=1}^{n} y_k(i,j) \Delta x + \sum_{k=1}^{n} y_k(i,j) \Delta x \]

(12)

where \( S(i,j) \) is the peak area of the \( i \)th, \( j \)th pixel, \( n \) is the number of time series; \( y_n(i,j) \) is MODIS-NDVI; \( \Delta x \) is the distance of time series and it was set 1 for simple.

Fig. 6 is the calculated peak area of MODIS-NDVI. It can be seen from fig5a that each class has a peak value from 7 to 20, and this is because the spatial resolution is 1000m and most pixels are mixed pixels. The pure water and sand land may have a peak value for impacted by the submerged plants or low cover grass.

As can be seen from Fig.5, there are difference between the curves of MODIS NDVI of the every growth stage of different classes. Therefore, coupled the growth rate and peak of NDVI according to the equation (13) can also extract the mutually exclusive information.

\[ E(i,j) = \beta(i,j) + \max_{NDVI}(i,j) \]

(13)

where \( E(i,j) \) is the coupled value of growth rate and peak of NDVI; \( \beta(i,j) \) is the growth rate and \( \max_{NDVI}(i,j) \) is the peak value of NDVI of number.

According to Fig. 5, we chose the 9 to 14 MODIS-NDVI as the growth stage. It can be found that the change of MODIS-NDVI fit in a linear growth, Fig.6 gives the fitting curve of the high coverage grass, and the determination coefficient is 0.9445, through the test of 95% confidence level.

The linear growth period can be expressed as follow:

\[ y = \beta x + \alpha \]

(14)

where \( \beta \) is the growth rate and it can be calculated through the least square method:

\[ \beta = \frac{\sum_{i=9}^{14} x_i y_i - \sum_{i=9}^{14} x_i \sum_{i=9}^{14} y_i}{\sum_{i=9}^{14} x_i^2 - \left( \sum_{i=9}^{14} x_i \right)^2} \]

(15)

\[ x = \frac{1}{6} \sum_{i=9}^{14} x_i , \quad y = \frac{1}{6} \sum_{i=9}^{14} y_i , \quad x^2 = \frac{1}{6} \sum_{i=9}^{14} x_i^2 , \quad xy = \frac{1}{6} \sum_{i=9}^{14} x_i y_i \]

(16)
Fig. 6 Growing period of the fitting curve

Fig. 7 is the mutually exclusive information extracted through the time-series MODIS NDVI data. And it can be seen that these two kinds data corresponding to the actual distribution well.

Before using the fuzzy matter-element model to construct the integrated classifier, we need to quantify the data element, construct typical interval and matter-element interval. Table 1 gives the quantitative matter-element interval around the object.

Table 1 The matter-element interval of features

<table>
<thead>
<tr>
<th>Type*</th>
<th>T1</th>
<th>T2</th>
<th>T3</th>
<th>T4</th>
<th>T5</th>
<th>T6</th>
<th>T7</th>
<th>T8</th>
<th>T9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
<td>8</td>
<td>9</td>
</tr>
<tr>
<td>Value interval</td>
<td>(0,1.5)</td>
<td>(1.5,2.5)</td>
<td>(2.5,3.5)</td>
<td>(3.5,4.5)</td>
<td>(4.5,5.5)</td>
<td>(5.5,6.5)</td>
<td>(6.5,7.5)</td>
<td>(7.5,8.5)</td>
<td>(8.5,9.5)</td>
</tr>
<tr>
<td>S(i,j) interval</td>
<td>(0.5,5.5)</td>
<td>(5.5,7.8)</td>
<td>(7.8,9.5)</td>
<td>(9.5,10.3)</td>
<td>(10.5,10.8)</td>
<td>(10.8,11.0)</td>
<td>(11.0,11.4)</td>
<td>(11.4,11.6)</td>
<td>(11.6,12.2)</td>
</tr>
<tr>
<td>E(i,j) interval</td>
<td>(0,0.85)</td>
<td>(1.1,1.15)</td>
<td>(0.85,1.1)</td>
<td>(1.15,1.28)</td>
<td>(1.28,1.34)</td>
<td>(1.34,1.36)</td>
<td>(1.36,1.4)</td>
<td>(1.4,1.45)</td>
<td>(1.45,1.55)</td>
</tr>
</tbody>
</table>

*where T1 to T9 means the class of open water, bare land and sandy land, peat land, marsh grass, wet grassland, shrub meadow, low coverage grassland, medium coverage grassland and the high coverage grassland.

As it can be seen from table 1, when properties of the ground object is categorical data, we quantified it into equal interval. And it means that we make a equality treatment when calculate the distance between interval and the correlation function of these properties. The peak value of NDVI is a numerical data and it can be calculated according to the actual condition. It also can be found that the peak area of NDVI isn’t strictly corresponding to the
growth rate or NDVI peak couple value. The correlation between sandy land and peat land is negative. For peat land, the biomass accumulation is higher than sandy land, while the growth rate of sandy land is faster than peat land for the lack of water. Classic matter-element matrix of the nine surface features data are:

\[
R_{T1} = \begin{bmatrix}
M_{T1} & TM_1 & \{0.15\} \\
TM_1 & \{0.15\} \\
CBERS & \{0.15\} \\
S & \{0.55\} \\
E & \{0.05\}
\end{bmatrix}
\]

\[
R_{T2} = \begin{bmatrix}
M_{T2} & TM_2 & \{1.52\} \\
TM_2 & \{1.52\} \\
CBERS & \{1.52\} \\
S & \{5.57\} \\
E & \{1.11\}
\end{bmatrix}
\]

\[
R_{T3} = \begin{bmatrix}
M_{T3} & TM_3 & \{2.53\} \\
TM_3 & \{2.53\} \\
CBERS & \{2.53\} \\
S & \{7.89\} \\
E & \{0.85\}
\end{bmatrix}
\]

\[
R_{T4} = \begin{bmatrix}
M_{T4} & TM_1 & \{3.54\} \\
TM_1 & \{3.54\} \\
CBERS & \{3.54\} \\
S & \{9.51\} \\
E & \{1.15\}
\end{bmatrix}
\]

\[
R_{T5} = \begin{bmatrix}
M_{T5} & TM_1 & \{4.55\} \\
TM_2 & \{4.55\} \\
CBERS & \{4.55\} \\
S & \{10.50\} \\
E & \{1.28\}
\end{bmatrix}
\]

\[
R_{T6} = \begin{bmatrix}
M_{T6} & TM_1 & \{5.56\} \\
TM_2 & \{5.56\} \\
CBERS & \{5.56\} \\
S & \{10.81\} \\
E & \{1.34\}
\end{bmatrix}
\]

\[
R_{T7} = \begin{bmatrix}
M_{T7} & TM_1 & \{6.57\} \\
TM_2 & \{6.57\} \\
CBERS & \{6.57\} \\
S & \{11.01\} \\
E & \{1.36\}
\end{bmatrix}
\]

\[
R_{T8} = \begin{bmatrix}
M_{T8} & TM_2 & \{7.58\} \\
TM_2 & \{7.58\} \\
CBERS & \{7.58\} \\
S & \{11.41\} \\
E & \{1.43\}
\end{bmatrix}
\]

\[
R_{T9} = \begin{bmatrix}
M_{T9} & TM_2 & \{8.59\} \\
TM_2 & \{8.59\} \\
CBERS & \{8.59\} \\
S & \{11.62\} \\
E & \{1.45\}
\end{bmatrix}
\]

\[
R_{T10} = \begin{bmatrix}
M_{T10} & TM_1 & \{0.95\} \\
TM_1 & \{0.95\} \\
CBERS & \{0.95\} \\
S & \{0.12\} \\
E & \{0.55\}
\end{bmatrix}
\]

Matter-element matrix of the \textit{ith, jth} pixel is:

\[
R = \begin{bmatrix}
M_{pixel} & TM_1 & X_{TM_1(i, j)} \\
TM_1 & \{X_{TM_1(i, j)}\} \\
CBERS & \{X_{CBERS(i, j)}\} \\
S & \{S(i, j)\} \\
E & \{E(i, j)\}
\end{bmatrix}
\]

where \( TM_1 \) is the data of Sep 25, 2007 and \( TM_2 \) is the data of Jul 23, 2007. According to the equation 13 to 16, we can calculated the module, distance and correlation function and can get the \( K_p(x_i) \) of correlation function which can determine the attribute types of the pixel. When calculated the comprehensive correlative it need to calculate the comprehensive weight. AHP method was chose to get the weight of each factor. The judgment matrix as follow:

\[
A = \begin{bmatrix}
TM_1 & 4 & 2 & 3 & 2 \\
TM_2 & 1 & 1 & 1 & 1 \\
CBERS & 3 & 1 & 1 & 1 \\
S & 2 & 1 & 1 & 2 \\
E & 2 & 1 & 1 & 2
\end{bmatrix}
\]

Distribution principle of weight is that sum of spectral weight is higher than weight of auxiliary data. Weight of every data was distribute according to the quality, and the weight vector finally got is:

\[
A = [0.3420\ 0.0835\ 0.1964\ 0.2204\ 0.1577]
\]

For the good quality of \( TM_1 \), it got the largest weight of 0.3420. \( TM_2 \) got the smallest weight of 0.0835 for the quality of it is the poorest. Weight of CBERS is 0.1964 and of MODIS–NDVI is 0.2204. Weight of growth rate and NDVI peak couple value are 0.1577. Distributions of weight are basically consistent with the actual situation.

After calculated the comprehensive correlative and divided the ownership of each class according to the \( \text{max}(\alpha_p) \), Classification finally got was shown in Fig.8:
Fig. 8 Classification results of single image and the Comprehensive classifier

3.2.3 Accuracy Analysis

Confusion matrixes of the integrated classification are shown in Table 2. For too much cloud in TM2, there is no confusion matrix of it. It can be seen from the confusion matrix that the total accuracy of the integrated classifier is 82.36% and the Kappa coefficient is 0.8006 which are better than the SVM on TM1 (79.74%, 0.7704), and on CBERS (77.29%, 0.7436). Due to TM have more bands than CBERS, when using the same classification algorithm, result of TM is better than CBERS. As it can be seen from the comparing of user accuracy and mapping accuracy (Fig. 8), total classification effect of different data source and different classification methods is close to each other. Accuracy of water surface sandy land and peat land are higher than others. This is same with the analysis before which spectral of these three types land covers have the biggest difference.

Table 2: Confusion matrix and Kappa coefficient of integrated decision-making classification

<table>
<thead>
<tr>
<th>Class type</th>
<th>T1</th>
<th>T2</th>
<th>T3</th>
<th>T4</th>
<th>T5</th>
<th>T6</th>
<th>T7</th>
<th>T8</th>
<th>T9</th>
<th>User accuracy/%</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1</td>
<td>412</td>
<td>0</td>
<td>18</td>
<td>12</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>93.21</td>
</tr>
<tr>
<td>T2</td>
<td>0</td>
<td>307</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>88.47</td>
</tr>
<tr>
<td>T3</td>
<td>17</td>
<td>0</td>
<td>521</td>
<td>48</td>
<td>12</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>87.12</td>
</tr>
<tr>
<td>T4</td>
<td>3</td>
<td>0</td>
<td>33</td>
<td>346</td>
<td>44</td>
<td>15</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>78.46</td>
</tr>
<tr>
<td>T5</td>
<td>0</td>
<td>0</td>
<td>13</td>
<td>34</td>
<td>249</td>
<td>9</td>
<td>2</td>
<td>8</td>
<td>0</td>
<td>79.05</td>
</tr>
<tr>
<td>T6</td>
<td>0</td>
<td>8</td>
<td>0</td>
<td>10</td>
<td>23</td>
<td>254</td>
<td>22</td>
<td>11</td>
<td>0</td>
<td>77.44</td>
</tr>
<tr>
<td>T7</td>
<td>0</td>
<td>32</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>18</td>
<td>279</td>
<td>31</td>
<td>0</td>
<td>77.50</td>
</tr>
<tr>
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<td>Producer accuracy/%</td>
<td>95.37</td>
<td>88.47</td>
<td>89.06</td>
<td>76.89</td>
<td>65.70</td>
<td>78.40</td>
<td>78.15</td>
<td>75.56</td>
<td>89.91</td>
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The total accuracy: \( \frac{2983}{3622} \times 100\% = 82.36\%, Kappa = 0.8006 \)
4. Results and Discussion

Considering the development of remote sensing and more and more types of sensors and images, this paper tries to construct a classifier which based on the multi-source and multi-temporal data and can effectively increase accuracy of classification. The fuzzy matter-element model was introduced to quantitative information on surface features properties and modeling. According to the classification of Rouergai National Nature Reserve, this method can effectively extract the utility information and reduce the complexity of the calculation procedure. And the results show that:

(1). The category of land cover classified from image is the property information, and it is nonlinear and mutually exclusive. It doesn’t strictly satisfy mathematic relationship. Using the fuzzy matter element model to construct extension set of matter element can resolve these problem thorough quality and quantity aspects, and can resolve the making of decision of one image. This construction method can also use the auxiliary data such as the time-series NDVI effectively.

(2). The typical geographical and climatic characteristics of Rouergai wetland determined the various types and complex distribution of vegetation. Mutually exclusive information of MODIS NDVI was realized through the peak value, growth rate and NDVI peak couple value. It was shown that these two types data which were extracted and calculated from MODIS NDVI consist with the actual situation.

(3). The overall accuracy (82.36%) of the integrated decision classifier and Kappa (0.8006) is better than SVM method on TM1 (79.74%, 0.7704) and on CBERS (77.29%, 0.7436).

In the field of comprehensive classification, He[28] used SVM method and fusion data which is geographic data and NDVI to make a classification. This paper makes use of the time-series MODIS NDVI of 2007 and construct the fuzzy matter-element matrix to classify. Results of these two methods show that it can improve the accuracy effectively when using the auxiliary data.

In this study, one image which is highly covered by cloud was chose in order to test whether this method can utilize the non-cloud area or not, and result has shown that this method is effective. When deal with this problem, we can ether make a matter element or do not handle with it.

Acknowledgement.

This research was supported by the National Basic Research Program (973) of China (Grant No. 2006CB403301), the Talent plan of the Chinese Academy of Sciences (Grant No. 08R2130130), the Knowledge
Innovation Program of the Chinese Academy of Sciences (Grant No. KZCX2-YW-QN313), and a One Hundred Person Program of Chinese Academy of Sciences grant.

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