Improved Spectral Angle Mapper applications for mangrove classification using SPOT5 imagery

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Abstract

The traditional Spectral Angle Mapper (SAM) is an image classification method that uses image endmember spectra. Image spatial structure information may be neglected, especially in mangrove classification research where there is greater spectral similarity between species. This study combined object-oriented classification to improve the accuracy of the method in mangrove ecosystems. A mangrove area in Guangxi’s coastal zone was chosen as the study site, and spectral feature analysis and ground investigations were carried out, combining pixel purification, training sample set optimization, and watershed image segmentation algorithm to improve the SAM. The improved SAM was used to classify SPOT5 remote sensing image data for a mangrove ecosystem and then classification accuracy was assessed. The results showed that the improved SAM had better classification accuracy for SPOT5 imagery. Accuracy for each mangrove species was greater than 80% and overall accuracy was greater than 90%, which showed that SAM was applicable for mangrove remote sensing. This application potential for classification and information extraction lays the foundation for commercialized remote sensing monitoring of mangrove ecosystems.

Keywords: Spectral Angle Mapper; mangrove classification; SPOT5 remote sensing image data; Watershed image segmentation algorithm; Training sample set optimization
1. INTRODUCTION

Mangrove forests are tropical and subtropical intertidal wetland woody plant communities predominantly composed of mangrove evergreen trees or shrubs (Fan and Wang, 2017). These ecosystems extend from land to ocean, with particular morphological structure and physiological characteristics. They are of great significance for environmental protection, ecological balance, and biodiversity conservation in coastal zones (Zhang, 2001). Due to global warming, shoreline change, and irresponsible development and destruction, however, mangrove ecosystems have been seriously damaged and their monitoring and protection have become top priorities. Mangrove tidal flats have complex topography, there are numerous estuaries and tidal creeks that are often swampy. Field measurements are very difficult and consume a lot of human and material resources. Remote sensing technology has the advantages of large coverage areas, short data update periods, and high spatial resolutions, and has become the primary means for obtaining mangrove information quickly (Li et al., 2008; Hernández, et al., 2005). Correct understanding of the distribution of mangroves, as well as the location and changes in different mangrove species, are important aspects of mangrove protection and management.

Visible satellite remote sensing is the primary data source for mangrove remote sensing classification research, including low- and medium-resolution Landsat TM, Landsat MSS and SPOTXS satellite data (Cao et al., 2011; Zhang, 2011), high-resolution IRS and SPOT5/6 data, and sub-meter resolution IKONOS, QuickBird, and WorldView data (Liu et al., 2007; Li and Dai, 2015; Kuenze et al., 2011; Tang et al., 2015). The use of spectral information to classify mangroves, non-mangroves, and
individual mangrove species has become an important research topic. The Spectral Angle Mapper (SAM) is a commonly used method for image classification using image endmember spectra. This method can eliminate the influence of illumination and terrain to improve feature recognition. It has been widely applied for ground object calibration (Freek, 2006), vegetation research (Zhang et al., 2006), hyperspectral image compression (Qian, 2004), and more. However, multi-spectral images also may also contain identical objects with different spectral signatures, and different objects with the same spectral signature. Therefore, using only spectral information for classification can lose spatial information in the high resolution image. This study combined object-oriented classification with a watershed image segmentation algorithm to improve the SAM. A mangrove area on the coast of Guangxi was selected for study. Based on field measurements of mangrove spectral information and the inversion of remote sensing reflectance, mangrove interspecies classification using pansharpening 2.5m resolution SPOT5 satellite imagery was performed. The classification results were evaluated for accuracy, providing a scientific basis for remote sensing monitoring of mangrove ecosystems.

2. METHODS

2.1. SAM

The basic principle of SAM is to distinguish between categories by calculating the Spectral angle between the pixel spectrum and reference spectrum. The test spectrum is the average spectrum of known points extracted from the image, and the reference spectrum is the standard spectrum measured in the field. Spectra are projected as a vector with direction and length onto N-dimensional space. One classification method is according to the angle $\alpha$ between the pixel spectral vector $X$ and the reference
The SAM formula is as follows:

\[
\cos \alpha = \frac{X_Y}{|X||Y|}
\]  

(1)

Where \(X\) is the pixel spectral vector; \(Y\) is the reference spectral vector; \(\alpha\) is the angle between the spectra, representing the similarity between the spectral vectors, and the smaller \(\alpha\) is the closer the \(X\) is to \(Y\).

2.2. Improved SAM

The traditional SAM first selects training samples, obtains the average value of the training sample spectral vectors, and then classifies them by setting the threshold (Fig. 2). That is, when the spectral angle between the pixel spectral vector and the average spectral vector of the training sample is less than the set threshold, the pixel and the corresponding sample are considered to belong to the same land type. When a certain land type contains more types of features and the spectral composition is more complicated, however, the average spectral vector has limitations and may not necessarily represent that particular type. Therefore, the training sample set is rationally optimized before classification (Fig. 3).
First, a Minimum Noise Fraction Rotation (MNF ROTATION) was performed on the image data. MNF is proposed and modified by Green (Green et al., 1988), that is essentially a principal component analysis with two overlapping processes. The first transformation is used to separate and readjust the noise in the data, and the second step is the standard principal component transformation of Noise-whitened data. The signal-to-noise ratio is arranged from large to small, thereby overcoming the influence of noise on image quality. It can be seen from the eigenvalue graph (Fig. 4) that the eigenvalues of the first three bands were higher, while the fourth band with eigenvalues close to one was mostly noise.

Next, using the Pixel Purity Index (PPI) method, the first three principal components from MNF processing were used as analytical data, and the purest pixel was extracted for various mangrove types in the study area. The PPI was adopted using ENVI 'automated spectral hourglass', that is a new
automated procedure in the hyperspectral analysis process (Boardman et al., 1995) for defining potential image endmember spectra (Bateson and Curtiss, 1996) for spectral unmixing (Lillesand and Kiefer, 2000). After PPI processing, the pixels from different types of mangroves displayed different colors in the PPI window. All pixels of the same color were classified together and defined as representative sample point sets. Ground measurements were used to determine the category attribute of each representative sample point set. Finally, the spectral angle set between the vectors of the pixels in the image and all the vectors for various representative sample point sets was calculated. Comparing the spectral angle set, and the category corresponding to the smallest one was selected as the pixel category attribution. In this way, the SAM optimized by the training sample set takes the particularity of ground spectral composition into consideration and improves the accuracy of the classification.

The SAM is a pixel-by-pixel classification method, and the results are relatively fragmented. Therefore, combined with object-oriented classification, this paper used trapezoidal high-pass filtering to enhance the SAM results and strengthen the texture information. Then the watershed image segmentation method was used to segment the filtering results. Finally, results were formed using the “watershed segmentation” image method. Its purpose is to divide the image into characteristics regions, that is, extract the edges of the objects in the image, i.e. adjoining pixels with similar gray scale values that reflect the degree of the depth of the image pixel color are connected to each other to form a closed contour(Fig. 5), so that it can be reasonably assumed that all points in the closed contour obtained by the watershed segmentation belong to the same category(Shu Su and Yang Ming, 2016). The
classification result of mangroves divided by watershed is shown in Fig. 6. This technique can significantly reduce fragmentation and improve image classification accuracy.

2.3. Data Description

2.3.1 Overview of the study area

The coastal area of Guangxi is located in the northern part of the Beibu Gulf, in the southwestern-most coastal area of China's 18,000 kilometers of mainland coastline (21°24'N~22°01'N, 107°56'E~109°47'E) with Guangdong to the east. It is bordered by the Ximi River estuary west of the Beilun River estuary on the Sino-Vietnamese border. The Guangxi coastal zone has a northern tropical monsoon climate. The annual average air temperatures range is from 22°C to 23.4°C, the annual average coastal ocean surface temperatures range is from 23.1°C to 23.8°C, and salinity range is from 18 to 31 (Deng and Song, 2011). The tidal range in Guangxi is relatively large. The maximum tide tidal range is 7.03 m, the maximum ebb tide tidal range is 6.25 m, and the average tidal range is 2.13 to 2.52 m (Zhang, 2009). Various types of mangrove populations are found along low tide, mid-tide, and high tide belts (Yang et al, 2017).

2.3.2 Sample layout and GCP data collection

On-site field reconnaissance was carried out in the Shankou Mangrove Reserve. According to the
purpose of the study and the actual study area, four sections were defined. In each section, a community survey sample was set up along the inner edge of the mangrove, the tidal creek and the outer edge to monitor the dynamics of the mangrove community. A total of 12 sample plots were surveyed. The plots were 10m×10m, and community type, structure, coverage were collected. At the same time, an INVICTA 210 high-precision GPS/beacon two-in-one receiver was used to measure ground spectral data and collect more than 80 ground control points (GCPs) with a positioning accuracy of 1m.

2.3.3 Spectral measurements and processing

A FieldSpec 3 Pro dual-channel field spectrometer produced by American ASD Company was placed at a distance of 1.5 m above the canopy, perpendicularly facing the target object vertically, or at least maintaining an angle between the probe and the normal of the horizontal plane within ±10°. The FieldSpec 3 Pro dual-channel field spectrometer can continuously measure from 350nm to 1050nm. The weather was clear and cloudless, the wind speed was less than 3m/s, and measurements were mainly concentrated from October 23 to October 27, 2017 between 10:00-14:00. When measuring, shadows were avoided within the field of view of the probe.

The study measured spectral data for several mangrove tree species along the Guangxi coast, as well as data for various non-mangroves adjacent to the mangrove populations, to extract mangrove distribution and classification information. Mangrove species measured included Avicennia marina (Am.), Aegiceras corniculatum (Ac.), Kandelia candel (Kc.), Rhizophora stylosa (Rs.), Bruguiera gymnorrhiza (Bg.), Excoecaria agallocha Linn (EAL.), and Sonneratia apetala (Sa.). Non-mangrove features included Spartina alterniflora Loisel., Manihot esculenta Crantz., and mudflats, and a total of 76 sample data points were collected.
The spectral curve of each measured feature was recorded as $X_i$, $i = 1, 2, 3, \ldots, 76$. Ground object 1 reflectance was calculated using equation (2) (Yu et al., 2006):

$$S_m = \frac{S_t}{S_p} \times R_p$$

(2)

Where $S_m$ is the reflectance of the ground object; $S_t$ is the measured electrical signal value of the target ground object output from the instrument; $S_p$ is the measured signal value of the diffuse reflection reference plate output from the instrument; $R_p$ is the reference plate reflection obtained by laboratory calibration. After obtaining the ASD spectrometer spectral reflectance for each species on site, band processing of measured $R_{rs}(\lambda)$ based on the spectral response function for SPOT5 image data was carried out using the formula:

$$R_{rs}(\text{Band}_x) = \frac{\int_{1000 \mu m}^{1000 \mu m} \frac{R_\nu(\lambda) F_\nu(\lambda) d\lambda}{\int_{400 \mu m}^{1000 \mu m} F_\nu(\lambda) S_\nu(\lambda) d\lambda}}{\int_{400 \mu m}^{1000 \mu m} F_\nu(\lambda) S_\nu(\lambda) d\lambda}$$

(3)

Where $R_{rs}(\text{Band}_x)$ is the reflectance of band $\text{Band}_x$ from the image sensor; $R_{rs}(\lambda)$ is the remote sensing reflectance collected by the ASD spectrometer; $F_\nu(\lambda)$ is the solar irradiance outside the atmosphere at the average distance between the sun and the earth; and $S_\nu(\lambda)$ is the spectral response function of band $\text{Band}_x$.

2.3.4 Satellite data

This study selected six SPOT5 remote sensing image scenes from May to October 2017 with 2.5m panchromatic spatial resolution (0.49–0.69 μm), and four multispectral bands with 10m resolution including Band1: 0.49–0.61 μm, Band2: 0.61–0.68 μm, Band3: 0.78 ~ 0.89 μm, Band4: 1.58~1.78 μm. The data covered the entire Guangxi coast. Remote sensing image data preprocessing mainly includes
satellite data radiation correction, atmospheric correction, orthorectification, and data fusion.

**Radiation Correction:** The multispectral image DN values were converted into radiance data using the absolute radiometric scaling factor for the SPOT5 satellite.

**Atmospheric correction:** The SPOT5 data were atmospherically corrected using the FLAASH atmospheric correction module in ENVI 5.3 software, and the relevant parameters were input to calculate apparent reflectance data after atmospheric correction.

The formula for converting apparent reflectance data into remote sensing reflectance is as follows:

\[
R_s = \rho_o / \pi \tau_o 
\]  
\[
\tau_o = \exp(-\tau_r \cos \theta_o / 2) 
\]

Where \( \rho_o \) is the apparent reflectance; \( \tau_o \) is the diffuse transmittance of sunlight; \( \tau_r \) is the Rayleigh optical thickness, which can be calculated according to the theoretical discrete model; and \( \theta_o \) is the solar zenith angle. As \( \tau_o \) is very close to 1, for the sake of simplicity, it is typically omitted as a factor.

**Orthorectification:** Generally, the RPG file that comes with the image is used to select control points and the SPOT5 sensor model is used to correct it. The total error was controlled within 0.5 cells (a cell is 2.5 m square).

**Data fusion:** A pansharpening fusion method for image fusion was used in this paper. That is the process of integrating a high spatial resolution panchromatic image with a low spatial resolution multispectral image to obtain a multispectral image with high spatial and spectral resolution (Liu et al., 2019). After fusion, the spatial and spectral resolution of the image are improved, and the boundary of the object is more clear.
According to the definition of wetlands in the “RAMSAR Convention on Wetlands” (Valencia, Rodriguez and I.Dario, 2004), combined with the current situation of wetlands in China, the Guangxi Coastal Wetland Research Area (Fig. 7) was defined.

2.4. Data Analysis

The remote sensing reflectance of mangroves along the Guangxi coast and the SPOT5 multispectral band range are shown in Fig. 6. Mangroves had the same spectral curves as other general green plants and exhibited distinct multi-peak and multi-valley characteristics (Xiao et al, 2007). There was peak reflectance of green light between 515 nm and 588 nm, and the reflectance was 9% to 10%.

The reflectance of the red absorption valley between 610 nm and 678 nm is reduced to 2% to 5%; there is a “red edge” characteristic of increasing reflectance from the red to the near infrared region between 700 nm and 740 nm, and the reflectance increased from 5% to 20% to 40%; while between 750 nm and 1000 nm there was a fluctuating near-infrared high-order platform. Reflectance was maintained at 25% to 55%. However, because the mangrove community is located on the water body and a tidal flat, it had higher heat absorption and lower reflectance than the vegetation on land which is especially clear in the infrared region.
There were minor spectral differences between the various types of mangroves, and the wave patterns and trends of the spectral curves of various mangroves were consistent, and peak-to-valley values appeared in roughly the same bands interval, but there were still some subtle differences. In the Band 1 and 2 range, line height changed little. Reflectance values for Am in Band 3 were significantly smaller than that of other mangrove species. Sa values were slightly higher than Am, but also lower than other mangrove types, and values were roughly in the following order: $R_{Bg} > R_{Eal} > R_{Rs} > R_{Ac} > R_{Kc} > R_{Sa}$.

3. RESULTS

3.1. Classification Results

Mangrove species in Guangxi were divided into seven categories in this study, Am., Ac., Kc., Rs., Bg., Eal., and Sa. Combining on-site measured spectral data with precise coordinate information for various types of mangrove boundary points and red tree boundary points, the initial sample set for each mangrove was obtained using the Region Of Interest(ROI) tool in ENVI. Then the training sample set was performed using the improved method above. Finally, the improved SAM combined with watershed image segmentation method was implemented in IDL language programming to classify the image. The final classification results are shown in Fig. 9.
3.2. Accuracy Evaluation

There are many indicators that analyze and evaluate the accuracy of remote sensing classification, among which the confusion matrix and KAPPA coefficient are the most commonly used. Among them, the confusion matrix can see the type and number of the classification and misclassification of each feature, and the KAPPA coefficient represents the proportion of errors reduction caused by the classification compared to the errors caused by the completely random classification. The formula is:

$$\text{KAPPA} = \frac{N \sum x_{ii} - \sum (x_{i+} \times x_{+i})}{N^2 - \sum (x_{i+} \times x_{+i})}$$

(6)

Where $r$ is the total number of columns in the error matrix (the total number of categories); $x_{ii}$ is the number of pixels in the $i$-th row and $i$-th column of the error matrix (the number of correct classifications); $x_{i+}$ and $x_{+i}$ are the total number of cells in the $i$-th row and $i$-th column; and $N$ is the total number of cells used for accuracy evaluation.

Using the field survey results of the study area as reference data, 3556 random samples were selected to create the error matrix and the overall accuracy and KAPPA coefficient were calculated. The error matrix for the unmodified spectral angle classification is shown in Tab.1, and the error matrix for the improved SAM is shown in Tab.2.

Insert Table 1
In Tab.1 and 2, each column represents the predicted class, the column total represents the total number of samples predicted for the category. Each row represents a real category data, the row total represents the total number of real sample of the class. Among them, the bold data indicates the number of cells correctly classified, and Accuracy indicates the proportion of samples that are correctly classified. Precision denotes the proportion of Predicted positive cases that are correctly real positives. Recall denotes the proportion of real positive cases that are correctly predicted positive cases by the predicted positive rule (Powers and David, 2011). As can be seen, the improved SAM had higher accuracy indices than the unmodified SAM. The accuracy for each mangrove species was greater than 80%, and the overall accuracy was greater than 90%. The KAPPA coefficient was 0.8804, which was greater than the minimum allowable discriminant accuracy of 0.7 (Shi et al., 2000). Compared with other related research (Weng, 2006; Liu et al., 2007) based on SPOT5 data and mangrove classification, the accuracy also improved, which further demonstrated the application and potential of the improved SAM in mangrove classification and information extraction.

4. CONCLUSIONS

In this paper, an image classification method based on pixel purification, training sample set optimization, and an image segmentation algorithm for improving the SAM was used to classify
mangrove species in 2.5m resolution SPOT5 satellite images using pansharpening fusion and covering the entire Guangxi coastal zone. Following atmospheric correction of the SPOT5 image, the remote sensing reflectivity was obtained by inversion. Combined with the measured spectral characteristics of mangroves, the training sample set was selected from the reflectance values and optimized. The classified results underwent post-processing, such as watershed segmentation and statistical merging, before classification accuracy was analyzed. The results showed that, first, the improved SAM combined with training sample set optimization takes the particularity of ground spectral composition into consideration. Combined with the watershed segmentation algorithm, the classification results can be post-processed, which can effectively avoid the fragmentation of the results. Together they can improve the overall classification accuracy. Second, the accuracy of each mangrove type was greater than 80%, and the overall accuracy was greater than 90%. In addition, the KAPP coefficient was 0.8804, which was higher than the minimum allowable discriminant accuracy of 0.7. All of the above findings show that the application value and potential of the improved SAM for the classification of mangrove species provide more rigorous technical support for relevant management departments.

Compliance with Ethical Standards

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Conflicts of Interest: They have no conflict of interest.
REFERENCES


### Table 1. Error matrix for the original classification results

<table>
<thead>
<tr>
<th>Types</th>
<th>Am.</th>
<th>Bg.</th>
<th>Rs.</th>
<th>Ac.</th>
<th>EaL.</th>
<th>Kc.</th>
<th>Sa.</th>
<th>Total</th>
<th>Recall (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Am</td>
<td>356</td>
<td>31</td>
<td>29</td>
<td>28</td>
<td>22</td>
<td>20</td>
<td>20</td>
<td>512</td>
<td>69.5</td>
</tr>
<tr>
<td>Bg</td>
<td>12</td>
<td>385</td>
<td>20</td>
<td>13</td>
<td>5</td>
<td>21</td>
<td>18</td>
<td>474</td>
<td>81.2</td>
</tr>
<tr>
<td>Rs</td>
<td>38</td>
<td>21</td>
<td>386</td>
<td>43</td>
<td>35</td>
<td>27</td>
<td>32</td>
<td>582</td>
<td>66.3</td>
</tr>
<tr>
<td>Ac</td>
<td>25</td>
<td>21</td>
<td>16</td>
<td>403</td>
<td>10</td>
<td>21</td>
<td>514</td>
<td>51</td>
<td>78.4</td>
</tr>
<tr>
<td>EaL.</td>
<td>55</td>
<td>21</td>
<td>17</td>
<td>19</td>
<td>315</td>
<td>22</td>
<td>18</td>
<td>467</td>
<td>75.6</td>
</tr>
<tr>
<td>Kc.</td>
<td>11</td>
<td>0</td>
<td>23</td>
<td>32</td>
<td>10</td>
<td>350</td>
<td>19</td>
<td>445</td>
<td>78.7</td>
</tr>
<tr>
<td>Sa.</td>
<td>37</td>
<td>27</td>
<td>26</td>
<td>12</td>
<td>20</td>
<td>33</td>
<td>562</td>
<td>550</td>
<td>72.4</td>
</tr>
<tr>
<td>Total</td>
<td>534</td>
<td>506</td>
<td>517</td>
<td>550</td>
<td>417</td>
<td>500</td>
<td>532</td>
<td>3556</td>
<td></td>
</tr>
</tbody>
</table>

**Precision (%)**

| Am    | 66.7 |
| Bg    | 76.1 |
| Rs    | 77.4 |
| Ac    | 73.27|
| EaL.  | 75.56|
| Kc.   | 70   |
| Sa.   | 76.65|

**Overall accuracy =2602÷ 3556× 100%=73.17%**    KAPPA=0.6868

### Table 2. Error matrix for the improved classification results

<table>
<thead>
<tr>
<th>Types</th>
<th>Am.</th>
<th>Bg.</th>
<th>Rs.</th>
<th>Ac.</th>
<th>EaL.</th>
<th>Kc.</th>
<th>Sa.</th>
<th>total</th>
<th>Recall (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Am</td>
<td>484</td>
<td>0</td>
<td>0</td>
<td>15</td>
<td>0</td>
<td>22</td>
<td>16</td>
<td>537</td>
<td>90.1</td>
</tr>
<tr>
<td>Bg</td>
<td>0</td>
<td>451</td>
<td>17</td>
<td>0</td>
<td>3</td>
<td>0</td>
<td>16</td>
<td>487</td>
<td>92.6</td>
</tr>
<tr>
<td>Rs</td>
<td>0</td>
<td>15</td>
<td>474</td>
<td>11</td>
<td>13</td>
<td>17</td>
<td>0</td>
<td>530</td>
<td>89.4</td>
</tr>
<tr>
<td>Ac</td>
<td>20</td>
<td>10</td>
<td>7</td>
<td>493</td>
<td>0</td>
<td>12</td>
<td>11</td>
<td>553</td>
<td>89.2</td>
</tr>
<tr>
<td>EaL.</td>
<td>11</td>
<td>17</td>
<td>0</td>
<td>7</td>
<td>388</td>
<td>0</td>
<td>8</td>
<td>431</td>
<td>90.0</td>
</tr>
<tr>
<td>Kc.</td>
<td>8</td>
<td>0</td>
<td>15</td>
<td>15</td>
<td>0</td>
<td>449</td>
<td>0</td>
<td>500</td>
<td>89.8</td>
</tr>
<tr>
<td>Sa.</td>
<td>11</td>
<td>13</td>
<td>4</td>
<td>9</td>
<td>13</td>
<td>0</td>
<td>468</td>
<td>518</td>
<td>90.3</td>
</tr>
<tr>
<td>total</td>
<td>534</td>
<td>506</td>
<td>517</td>
<td>550</td>
<td>417</td>
<td>500</td>
<td>532</td>
<td>3556</td>
<td></td>
</tr>
</tbody>
</table>

**Precision (%)**

| Am    | 90.6 |
| Bg    | 89.1 |
| Rs    | 91.7 |
| Ac    | 89.6 |
| EaL.  | 93.0 |
| Kc.   | 89.8 |
| Sa.   | 88.0 |

**Overall accuracy =3207÷ 3556× 100%=90.2%**    KAPPA=0.8854
Figure legends

Fig 1 SAM schematic diagram

Fig.2 Basic process of SAM
Fig. 3 Basic process of Improved SAM

1. SPOT5 Satellite data acquisition
   - Image preprocessing
   - Radiation Correction
   - Atmospheric Correction
   - Orthophoto Correction
   - Data Fusion
   - Data Mask

2. Field data Collection
   - Spectral data acquisition
   - Control data Collection
   - Spectral data processing
   - Spectral feature analysis
   - Sample spectral datasets

3. Training sample selection
   - MNF
   - PPI, Purified endmember
   - Calculate and compare spectral angle sets, and select the final training sample

4. Preliminary classification result

5. Improvement step 2: watershed segmentation

6. Result analysis and accuracy evaluation

7. Mangrove classification based on Improved SAM
Fig 4 MNF eigenvalue curve

Fig 5 Schematic diagram of watershed image segmentation
(A) Image showing the internal markers (Minima) and Watershed Line (B) Results of watershed image segmentation
Fig 6 The results of the improved SAM using the watershed segmentation algorithm

(A) SAM (B) Final classification results

Fig 7 Map of the study area
Fig 8 Field spectral reflectance curves for mangroves along the Guangxi coast, and the SPOT5 multispectral band range

Fig 9 Guangxi mangrove classification map