

STUDY ON THE WATER BODY EXTRACTION USING GF-1 DATA BASED ON ADABOOST INTEGRATED LEARNING ALGORITHM

Jiayue Sun^{1,2}, Guizhou Wang², Guojin He², Dongchuan Pu^{1,2}, Wei Jiang², Tingting Li¹, Xuefeng Niu^{1*}

¹ College of Geo-exploration Science and Technology, Jilin University, Changchun, 130026, China-(sjy17,pudc17)@mails.jlu.edu.cn, niuxf@jlu.edu.cn, ttli18@mails.jlu.edu.cn

² Aerospace Information Research Institute, Chinese Academy of Science, Beijing, 100094, China-(wanggz01,hegi)@radi.ac.cn, jiangweifz@163.com

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ABSTRACT:

Surface water system is an important part of global ecosystem, and the changes in surface water may lead to disasters, such as drought, waterlog, and water-borne diseases. The rapid development of remote sensing technology has supplied better strategies for water bodies extraction and further monitoring. In this study, AdaBoost and Random Forest (RF), two typical algorithms in integrated learning, were applied to extract water bodies in Chaozhou area (mainly located in Guangzhou Province, China) based on GF-1 data, and the Decision Tree (DT) was used for comparative tests to comprehensively evaluate the performance of classification algorithms listed above for surface water body extraction. The results showed that: (1) Compared with visual interpretation, AdaBoost performed better than RF in the extraction of several typical water bodies, such as rivers, lakes and ponds. Moreover, the water extraction results of the strong classifiers using AdaBoost or RF were better than the weak basic classifiers. (2) For the quantitative accuracy statistics, the overall accuracy (96.5%) and kappa coefficient (93%) using AdaBoost exceeded those using RF (5.3% and 10.6%), respectively. The classification time of AdaBoost increased by 403 seconds and 918 seconds relative to RF and DT methods. However, in terms of visual interpretation, quantitative statistical accuracy and classification time, AdaBoost algorithm was more suitable for the water body extraction. (3) For the sample proportion comparison experiment of AdaBoost, four sampling proportions (0.1%, 0.2%, 1% and 2%) were chosen and 0.1% sampling proportion reached the optimum classification accuracy (93.9%) and kappa coefficient (87.8%).

1. INTRODUCTION

Surface water system is an important part of global ecosystem, which is composed of natural water and artificial water. The changes in surface water may lead to some disasters, such as drought, waterlogging, or even outbreaks of water-borne diseases (Yao et al., 2015; Wei et al., 2018). Therefore, surveying and monitoring of water bodies is of great significance. The satellite remote sensing technologies have the merits: macrography, accuracy, high spatiotemporal resolution, and real-time characteristic, which is conducive to the consequent earth observation system playing an increasingly important role in many fields, such as resource survey, environmental monitoring, disaster prevention and reduction (Xu, 2005).

Researchers have proposed several algorithms to extract water from remotely sensed images, which include four main categories:

(a) Single band or multi-band threshold method. Threshold extraction is based on the principle that the reflectance rate of water body is relatively low in a specific band, which makes water extraction suitable from single or multiple bands through threshold or spectral relationship (Bryant et al., 2002; Sun et al., 2012; Jain et al., 2005).

(b) Spectral index method. Spectral index method is used to analyse the spectral differences between water and background objects. The strongest and weakest reflective bands of water are chosen to construct a band calculation model, such as NDWI (Xu, 2005; Xu, 2008;), AWEI (Gudina et al., 2014; Adrian et al., 2016) and SWI (Malahlela, 2016).

(c) Object-Oriented Classification method. This method makes more use of the spatial texture and structure information of high-resolution images to classify ground objects, because the

spectral information of high-resolution data is not so abundant as domestic GF-1 satellite data.

(d) Supervised or unsupervised classification methods. This classification method can use the sample training classifier to achieve fast and high precision extraction of ground objects based on statistics and machine learning. It mainly includes support vector machine (SVM), decision tree (DT), random forest (RF), Adaboost, multi-layer perceptron neural network (MLP), full-link convolutional neural network (FCN), fuzzy clustering (FC), maximum likelihood method (ML) and improved constrained energy minimization (CEM) classification algorithm. Among them, Random Forest (RF) and AdaBoost belong to the integrated learning method, which have both similarities and differences. Many authors have demonstrated significant performance improvements through integrated learning method (Breiman, 1996; Kohavi, Kunz, 1997; Bauer, Kohavi, 1999; Maclin, Opitz, 1997). This paper discussed the differences of RF, AdaBoost and DT in water extraction using GF-1 satellite images.

It's widely accepted that the accuracy of machine learning depends on sampling design. At present, most of the samples are collected manually. And it takes more time and energy to collect samples in large areas, so it is necessary to summarize the sampling methods. The selection strategy of samples in machine learning classification algorithm is quite important, because the sample generation is a time-consuming, laborious and subjective task (Ghimire, 2012) such as sample size (Shahriar, 2018), sample ratio and sample quality. Therefore, it is necessary to discuss the sample selection to evaluate the quality of a classification algorithm. And the selection of sample size is the primary consideration of the sample selection strategy. On the basis of discussing the performance of RF, AdaBoost and DT classification algorithms, this paper further

explores the impact of sample selection ratio on classification results.

2. RESEARCH AREA AND DATA

2.1 Data introduction

The GF-1 satellite data used for this research was licensed from China Center for Resources Satellite Data and Application. GF-1 satellite was successfully launched into orbit on April 26, 2013 by CZ-2D at Jiuquan Satellite Launch Centre, carrying two 2m resolution panchromatic/8m resolution multispectral cameras. The satellite technology has great strategic significance for promoting the improvement of satellite engineering level and improving the self-sufficiency rate of high-resolution data in China. The detailed satellite parameters were shown in Table 1.

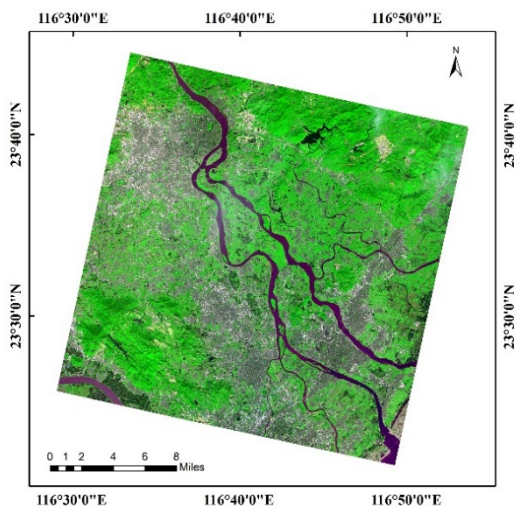


Figure 1. Research area — Beijing, China

Parameter	Index
Orbital type	Repeat sun-synchronous orbit
Orbital height	645km
Orbital inclination	98.0506°
Regression cycle	41 days

Table 1. Satellite orbit parameters

2.2 Research area

Chaozhou is located in the north of Hanjiang Delta, Guangdong Province, China. The terrain of Chaozhou decreases from the north to south. The Hanjiang River and Huanggang River are the main stream with rich water resources, and there are a large number of artificial aquaculture areas in the study area. Most of cities are concentrated and widely distributed around the main rivers. In this paper, a cloud-free GF-1 satellite remotely sensed image (December 2016) which covers Chaozhou area is downloaded from the China Center for Resources Satellite Data and Application (Figure 1).

3. METHODS

Integrated learning is one of the research hotspots in machine learning by drawing on the advantages of others, such as generalization ability. Essentially, integrated learning utilizes the merits of multiple single classifiers to improve the overall

classification accuracy. By synthesizing relatively simple and easy-to-implement learning methods, it establishes several different basic learners on the premise of guaranteeing their respective accuracy. And then composes an integrated classifier according to the combined rules to improve the learning accuracy and maximize the generalization ability of the system which makes that the generalization performance is often significantly better using multiple learners compared with a single learner. According to the types of individual learners (also called weak learners) included in integration, integrated learning is composed of homogeneous and heterogeneous integration. Homogeneous integration only contains the same type of individual learners. The heterogeneous integration includes multitype individual learners, such as both decision trees and neural networks. Among the homogeneous integrated learning, Random Forest (RF) (Rodriguez-Galiano et al., 2012a; Rodriguez-Galiano et al., 2012b; Pall et al., 2006) and AdaBoost (Chan et al., 2001; Thomas et al., 2000; Chan et al., 2008; Bardan et al., 2012) are widely used to extract ground objects. However, two main problems still need to be considered. One is how to get different basic weak classifiers, and the other is what strategies are used better to combine the weak classifiers to form a strong classifier. The integration principle is shown in Figure 2.

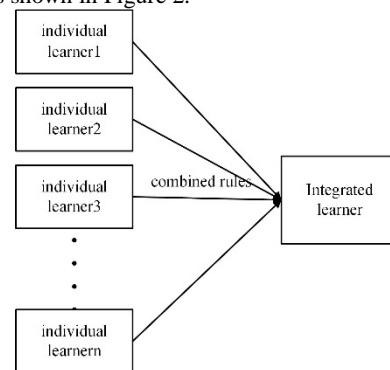


Figure 2. Schematic diagram of integrated classifier

3.1 Random Forest

Random Forest has the characteristics that no dependence exists among weak classifiers, which belongs to bagging (Thomas, 2000) school in integrated learning. The Random Forest classifier has two aspects of randomness: acquiring sub-sample sets randomly, and selecting features randomly to build trees. The former is one type of sampling with replacement method essentially, which choose samples with fixed number from the existing training set.

Assuming that the existing sample size is N , the sample x_1 is randomly extracted from N samples, labelled and replaced, then x_2 is extracted as the same strategy. After repeating selection N times, a new sub-sample of size N is obtained. The duplication might exist in new sub-sample. Each sample has a $1/N$ probability to be selected at each random sampling. Moreover, Random Forest can be validated without additional samples: the probability of each sample not being chosen is $(1-1/N)$ in every extraction, while a total of N times is extracted. Each sample not getting into the new sub-sample has the probability $(1-1/N)^N$, which consists of validation sets. When N tends to infinity, the result is approximately 36.8% and this validation method is called out of bag estimate in the Random Forest algorithm. Random Forest uses decision trees (CART) as weak classifiers. It selects sample features of nodes randomly, and then selects the optimal feature to divide right and left subtrees in the decision tree, which can further enhance the generalization ability of the model. Totally, Random forest divides the training

set into N new training sets, then builds independent models on each training set, and finally integrates them with the maximum voting rule. The last category of variables is determined based on the largest number of votes, and the detailed schematic diagram is shown in Figure 3.

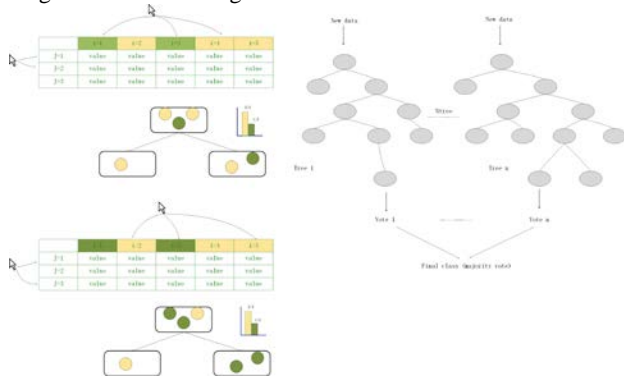


Figure 3. Schematic diagram of Random Forest

3.2 AdaBoost

AdaBoost is characterized by the dependence among weak classifiers, which belongs to the boosting (V.F. Rodriguez-Galiano et al., 2012) school in integrated learning. There are two significant differences between AdaBoost and RF. One is that the weight of wrong classified samples increases in Adaboost according to that of correct classified samples in the previous round. The other is that AdaBoost uses the combined strategy of weighted majority voting to form a strong classifier, and the weight of weak classifier with small classification error rate increases, while that with large classification error rate decreases. The Adaboost takes the weak classifier as the decision tree, and the schematic diagram is shown in Figure 4.

1. Input: The training data set:

$T = \{(x_1, y_1), (x_2, y_2) \dots (x_N, y_N)\}$, $x_i \in X \in R^n$, $y_i \in Y = -1, 1$; Weak classification algorithm.

2. Initial training sample weight distribution:

$D_1 = (w_{1,1}, w_{1,2} \dots w_{1,i})$, $w_{1,i} = 1/N$, $i = 1, 2, \dots, N$

3. For $m = 1, 2, \dots, M$

(a) The training data set with weight distribution D_m is used for learning. And the weak classifier is obtained based on the following principle:

$$G_m(x): X \rightarrow \{-1, +1\} \quad (3-1)$$

(b) Calculate the classification error rate of $G_m(x)$ on the training data set:

$$e_m = P(G_m(x_i) \neq y_i) = \sum_{i=1}^N w_{mi} I(G_m(x_i) \neq y_i) \quad (3-2)$$

w_{mi} represents the weight of the i th instance in round m .

(c) Calculate the weight of $G_m(x)$ in the strong classifier:

$$\alpha_m = \frac{1}{2} \log \frac{1 - e_m}{e_m} \quad (3-3)$$

The logarithm here is the natural logarithm.

(d) Update the weight distribution of the training data set:

$$D_{m+1} = (w_{m+1,1}, \dots, w_{m+1,i}, \dots, w_{m+1,N}) \quad (3-4)$$

$$w_{m+1,i} = \frac{w_{mi}}{Z_m} \exp(-\alpha_m y_i G_m(x_i)), i = 1, 2, \dots, N \quad (3-5)$$

Here Z_m is the normalization factor.

$$Z_m = \sum_{i=1}^N w_{mi} \exp(-\alpha_m y_i G_m(x_i)) \quad (3-6)$$

It makes D_{m+1} a probability distribution.

4. Construct a linear combination of basic classifiers:

$$f(x) = \sum_{m=1}^M \alpha_m G_m(x) \quad (3-7)$$

Get the final classifier:

$$G(x) = \text{sign}(f(x)) = \text{sign}\left(\sum_{m=1}^M \alpha_m G_m(x)\right) \quad (3-8)$$

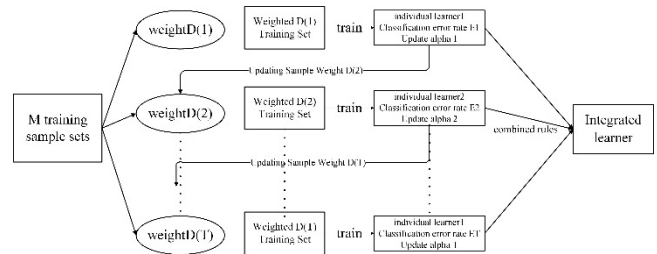


Figure 4. Schematic diagram of AdaBoost

4. TEST AND RESULTS

4.1 Data Pre-processing

The downloaded image of GF-1 is a Level-1A product, which requires image registration, adjustment, geometric correction and image fusion (Jiang et al., 2017). Image registration corrects panchromatic and multispectral malposition. The positioning accuracy of GF-1 images is still low after using the self-contained RPC (Rational Polynomial Coefficients) for correction. To achieve high-precision ortho-calibration, it is necessary to optimize the self-contained RPC coefficient of images by using high-precision control point in the reference image. Besides, the overlap between GF-1 images is relatively large, which needs to adjust the connection points of image to ensure the high edge joining accuracy between images (Long et al., 2015; Long et al., 2016). The aim of ortho-calibration is to eliminate the geometric distortion of satellite images caused by many factors in the process of imaging, such as the influence of topographic fluctuations and sensor error. Figure 5 shows the image pre-processing process of GF-1 images.

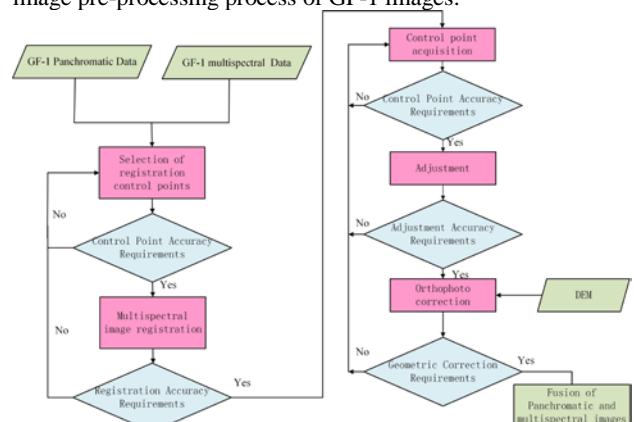


Figure 5. GF-1 image preprocessing process

4.2 Classifier Contrast Test

This paper focuses on the applicability of Random Forest and AdaBoost algorithm, which use CART decision tree as weak classifier to extract water body from high resolution images. An independent CART decision tree is set up to verify the ability of different integrated learning methods in extracting extract water body with GF-1 images. All the experiments were carried out on the same workstation to ensure the comparability of the classification time using the three classifiers. And visual inspection was carried out on the rivers, lakes, small water bodies and ponds to compare the universality of these three algorithms. As shown in Figure 6: a2-a4 represented the river extraction results, which showed that decision trees and random forest evidently omitted large areas of water, while AdaBoost could maintain water integrity better. The uneven water quality mainly leads to the deposition of sediment at the bottom of the river, which makes that the decision tree and random forest hardly extract the whole river well, but AdaBoost can avoid this deficiency effectively. b2-b4 illustrated the lake extraction effect. b2 and b3 could clearly show that decision tree and random forest have a relatively small part of the lake water body missing, while b4 displayed that AdaBoost algorithm have the ability to extract the lake and maintain the integrity of the lake well. c2-c4 illustrated the small water bodies extraction results. The small water bodies in c2 and c3 was usually incomplete due to the fragmentation. Actually, these small water patches are easily interfered by mixed pixels in the 2m resolution image. Similar with other types of water bodies, the results in c4 represented that AdaBoost have the potential to avoid this problem well. The images d and e were the demonstration of the open pond. Open pond is a kind of water with regular shape and relatively easy to be distinguished by naked eyes. However, ponds are usually built for cultivation and aquaculture, which might cause uneven water quality. And the small water area leads to that a large number of mixed pixels

disturb the extraction of ponds easily. From figures d2-d4 and e2-e4, the extraction images represented that the decision tree and random forest hardly overcame these problems, but the AdaBoost algorithm demonstrated that it can retain the integrity of the pond as soon as possible. Totally, compared with the decision tree and random forest methods, the AdaBoost algorithm is much more suitable for the of the water bodies extraction.

In this experiment, the overall accuracy, Kappa coefficient and classification time were selected to comprehensively evaluate the experimental results. The quantitative accuracy statistic results were shown in Figure 7. In terms of overall accuracy, the classification accuracy of AdaBoost was the largest (96.5%), over that of decision tree (91.2%), and random forest (93.9%). As for the Kappa coefficient, the classification accuracy of AdaBoost was still much higher (93%) than that of decision tree 82.4% and random forest (87.8%). The classification time set by the experiment is the sum of training time and prediction time, and the results showed that the time taken by AdaBoost increased by 918 seconds and 403 seconds compared by that taken using decision tree and random forest, respectively. This is mainly caused by that decision tree is a single tree, random forest constructs ten trees in parallel at the same time, while AdaBoost constructs the second tree after the previous tree, which is a serial construction.

To summarize, AdaBoost performs better than Random Forest and decision tree from the four evaluation standards: visual interpretation, overall accuracy, Kappa coefficient and classification time. Although AdaBoost classification algorithm took a much longer time during the procedure process, the comprehensive extraction effect of AdaBoost classification algorithm was the best compared with the other methods.

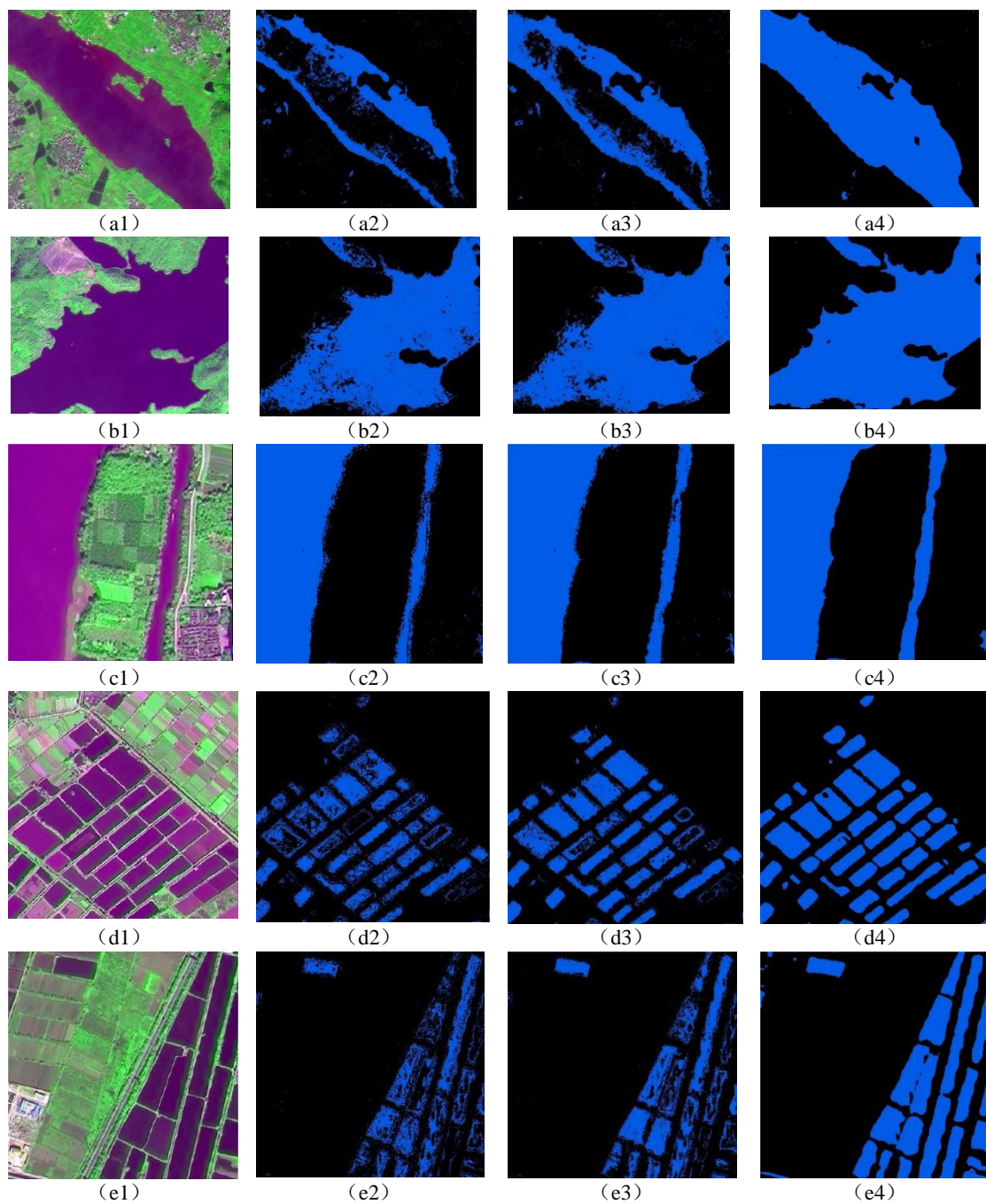


Figure 6. Classification comparison of river (a2-a4), lake (b2-b4), small water body (c2-c4), open pond 1 (d2-d4), open pond 2 (e2-e4). a1-d1 was the original image, a2-d2 was the decision tree classification effect, a3-d3 was the Random Forest classification effect, a4-d4 was the AdaBoost classification effect.

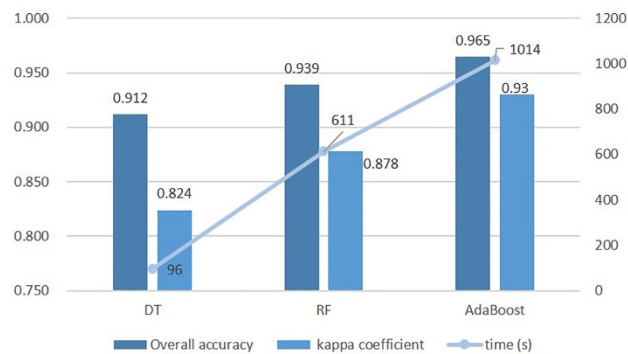


Figure 7. Classifier accuracy statistics

4.3 Sample size comparison test

In this experiment, four different sampling ratios (the proportion of the number of sample pixels to the total number of image pixels) were set up, which were 0.1%, 0.2%, 1% and 2% of the total pixels in the study area. The AdaBoost classification algorithm with good performance in the previous section was used for comparison experiments. Four samples with different proportions were used to classify water bodies in Chaozhou. The experimental results were shown in Figure 8. According to the results of visual interpretation, there was no significant differences in the proportion of samples collected in the four samples, and most of the rivers, lakes, tributaries and ponds could be extracted. From the perspective of quantitative

statistical accuracy (Figure 9), the overall accuracy of 0.1%, 0.2%, 1% and 2% sampling were 93.9%, 92.5%, 91.9% and 92.3% respectively, and the kappa coefficient was 87.8%, 85%, 83.8% and 84.6% respectively, which both detected a decreasing trend in accuracy. Besides, the classification time was 1005 seconds, 1014 seconds, 1033 seconds and 1105 seconds, respectively. The classification time showed an upward trend, indicating that the number of samples was not positively correlated with the classification time. As the number of samples increased, the accuracy did not improve, which also reflected that the improvement of accuracy was not positively correlated with the number of samples.

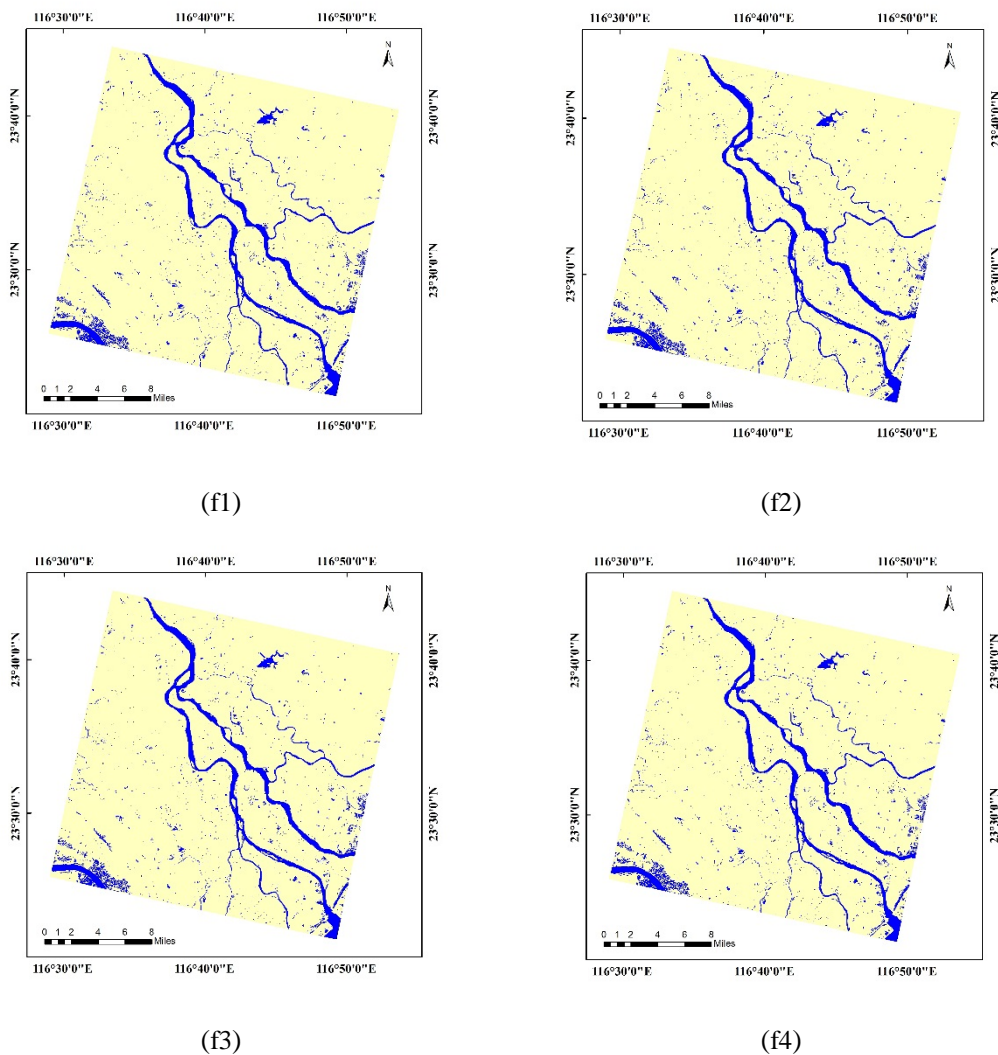


Figure 8. f1-f4 is the experimental results of 0.1%, 0.2%, 1% and 2% AdaBoost classification algorithm, respectively.

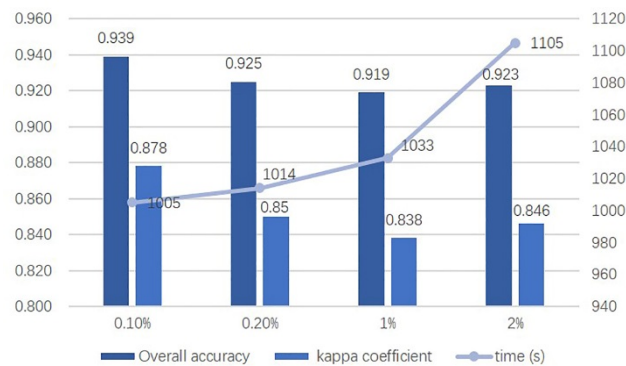


Figure 9. Sampling proportion accuracy statistics

5. DISCUSSIONS

As two representative algorithms in integrated learning, random forest and AdaBoost have showed a strong advantage in water extraction, but there are several significant differences in the construction of weak classifier and combination strategy. Considering the adopted loss function is different, the Boosting algorithm has different types, so AdaBoost is the Boosting algorithm whose loss function is the exponential loss. In the experimental studies comparing the data from various application fields, (Thomas, 2000) confirmed that boosting is more accurate than bagging. That is also the main reason why the performance of Random Forest and AdaBoost in high-resolution image water extraction is relatively different. In visual interpretation, AdaBoost performed better than random forest in extracting typical water bodies such as rivers, open ponds, small water bodies and lakes. However, the performance of two classes of strong classifiers, random forest and AdaBoost, was much better than that of their basic weak classifiers. The feasibility of the integrated learning principle was tested in practice. In terms of the overall accuracy and kappa coefficient of quantitative statistical accuracy, the extraction accuracy of AdaBoost has been correspondingly improved compared with that of Random Forest and decision tree. Although AdaBoost algorithm took a longer time to process compared with random forest and decision tree, this method is still more suitable for water extraction from GF-1 remotely sensed images in terms of visual interpretation, quantitative accuracy and classification time.

In the sample proportion experiment based on AdaBoost algorithm, 0.1%, 0.2%, 1% and 2% of the total number of pixels in the research area were respectively set for sample comparison experiments. The experimental results show that there is no significant difference in the four proportion settings from the comparative analysis of visual interpretation. From the analysis of the overall accuracy and kappa coefficient, the precision decreases with the increase of sample size. From the analysis of classification time, the classification time increases with the increase of sample proportion. Therefore, the classification accuracy is negatively correlated with the sampling ratio, and the classification time is positively correlated with the sampling ratio.

AdaBoost and random forest Algorithms also have shortcomings. Because the spectral characteristics of water and building shadows are similar in GF-1 remotely sensed image, it is impossible to distinguish water and building shadows effectively by using a single spectral feature. Therefore, finding effective features to distinguish the water and shadows of buildings is the focus in the future work.

6. CONCLUSIONS

In this study, a GF-1 remotely sensed image was selected as the experimental data. And three classification algorithms: decision tree, Random forest and AdaBoost were selected for experimental comparison to discuss the performance differences in extracting water bodies (e.g., rivers, ponds, small water bodies, lakes and ponds) and the advantages of integrated learning under different integration methods. Afterwards, visual interpretation and quantitative accuracy were applied to comprehensively compare and quantify the results accuracy. Finally, the AdaBoost classification algorithm was selected to carry out four water body extraction experiments with different sampling ratios, and the classification results were compared by visual interpretation and quantitative accuracy again. The main conclusions were drawn as follows:

(1) Based on visual interpretation, AdaBoost performed better than decision tree and random forest methods in extracting surface water. Moreover, the quantitative accuracy evaluation shows that the overall accuracy and kappa coefficient of AdaBoost were much higher than the other two classification algorithms. It is 5.3% and 10.6% higher than random forest, 2.6% and 5.2% higher than decision tree.

(2) Compared with decision tree and random forest, the performance of AdaBoost reflected that it can extract and retain the integrity of four types of water bodies (i.e. rivers, small water bodies, open ponds and lakes) accurately, but it might take a longer classification time. Classification time increased by 403 seconds and 918 seconds relative to random forests and decision trees

(3) In the comparative experiment of sampling proportion using AdaBoost method, the quantitative accuracy evaluation reflected that among the four sampling ratios: 0.1%, 0.2%, 1% and 2%, the accuracy of 0.1% was the best. And it indicated that the number of samples was not positively correlated with the classification time as well as the improvement of accuracy absolutely.

In this paper, two integrated learning methods for surface water extraction were introduced and their performance differences were compared. The results showed that the performance of AdaBoost method was superior totally. In the future, the automation and generality of the AdaBoost algorithm could be further improved, and it can be used to extract different types of surface cover accurately, such as impervious surface, forest, and vegetation.

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