River Extraction from High Spatial Resolution Remote Sensing Image Using Machine Learning Approaches

Hanwen Cui
School of Computer Science, Zhuhai College of Science and Technology, Zhuhai 519041, China.
cuicui_0504@163.com

Abstract*—The river is a critical freshwater resource for human civilization and plays a pivotal role in sustaining diverse plant and animal species within the ecosystem. Recognizing the paramount importance of rivers, it is imperative to preserve their healthy ecosystems to ensure sustainable utilization. Using machine learning models, this study uses high-resolution remote sensing data from China's Gaofen-2 satellite (GF-2) to promptly and accurately extract real-time river distribution data. The city of Zhuhai, situated downstream of the Pearl River Basin and characterized by an extensive network of rivers, was selected as the study area. This paper employed the Random Forest (RF) and Support Vector Machine (SVM) models for river extraction. The findings revealed superior performance of the RF model over the SVM model, with an overall classification accuracy (OA) of 97.88% and a Kappa coefficient of 0.9577, relative to SVM's 87.55% and 0.7511, respectively. This study demonstrated a substantial enhancement in classification accuracy compared to prior research utilizing SVM with lower-resolution multispectral remote sensing images. Applying machine learning models based on high spatial resolution images holds promise for providing precise information essential for efficient management and preservation of river resources, thereby serving as a powerful instrument to ensure their scientific exploitation and sustainable development.

Keywords—Gaofen-2 satellite image; machine learning; river extraction

I. INTRODUCTION

Rivers play a crucial role as carriers of water resources and are vital for human survival and development. However, in some circumstances, such as high mountain meltwater or excessive precipitation, rivers can experience a surge in water volume, leading to flash floods, which pose significant threats to life and property. Therefore, the quick and accurate extraction of river data has become a top priority.

The traditional techniques for river extraction involve manual sampling and field surveys, which are inefficient and struggle to provide global, real-time, and accurate information. The 2017 release of the "New Generation of Artificial Intelligence Development Plan" by the State Council explicitly called for enhanced research on the application of AI technology in water resource management and ecological environmental protection. Machine learning, capable of extracting rich spectral and spatial features from remote sensing data without the need for complex spectral characterization of images, has the potential to enhance classification accuracy and automation significantly. Therefore, integrating machine learning methods with high spatial resolution remote sensing images could further improve the accuracy of river extraction processes.

Presently, high spatial resolution remote sensing data sources commonly used for river extraction include GF-2 [1], ZY-3 [2], Jilin-1 [3], among others. Nevertheless, there are limited instances of utilizing GF-2 data in conjunction with machine learning techniques for studying rivers in Zhuhai City.

In this paper, China's high-resolution remote sensing image, GF-2 image, was utilized as the primary data source. Two machine learning methods, RF and SVM, were employed to conduct an extraction study of rivers in the study area of Zhuhai City. The performance of the two classifiers in extracting rivers from high spatial resolution images was thoroughly analyzed and compared. Zhuhai City is situated in the coastal zone of the lower reaches of the Xijiang River, the primary stream of the Pearl River Basin, characterized by abundant precipitation, numerous rivers, and a network of delta rivers. The region has witnessed large-scale floods for years due to heavy rainfall upstream affecting the Pearl River Basin. The resulting river flooding poses a significant hazard to Zhuhai. Accurate, real-time access to the distribution of rapidly changing rivers during the flood season can serve as a scientific basis for developing flood defense plans, encrypted monitoring and forecasting, early warning, and effectively mitigating the impact of floods on people's production and life.

II. OVERVIEW OF THE STUDY AREA

The study area of this paper is Zhuhai City, which is situated in the southern part of Guangdong Province on the west bank of the Pearl River estuary, with latitude and longitude ranging from 21°48′-22°27′ N, 113°03′-114°19′ E. Zhuhai City covers a land area of 1,732 square kilometers. Being in the path of the southern subtropical monsoon winds, the city experiences a high frequency of thunderstorms and abundant rainfall. The average yearly rainfall ranges from 1700-2300mm, with a significant portion (85%) occurring from April to September. This period is often characterized by disastrous weather, including tropical cyclones and heavy rain. The multi-year average runoff in the city is measured at 1,429.68 cubic meters, with total water resources estimated to be 1,757 million cubic meters.

III. MATERIAL AND METHODS

A. Data

The data source selected in this article, the GF-2 data, was launched successfully on August 19, 2014. It is China's independently developed civilian optical remote sensing satellite, with a spatial resolution superior to 1 meter. This satellite also holds the distinction of being China's highest-resolution civilian land observation satellite. It includes a 1-meter panchromatic and 4-meter multispectral high-resolution camera, achieving sub-meter spatial resolution and high positioning accuracy up to 0.8 meters at the sub-satellite point [4].

This study selected data from April to September, with the highest precipitation in the study area. After considering factors such as cloud coverage and data quality, 17 scenes of GF-2 remote sensing data were chosen to cover the entire study area. The time phases focused on July 23, 2016, April 30, 2017, and August 26, 2017. Any remaining uncovered areas were filled in using data from 2015 and 2018.

B. Methods

1) 3.2.1 Data processing

ENVI software was used to process GF-2 images. Radiometric calibration, atmospheric correction, and orthographic correction were performed on MSS images. Additionally, radiometric calibration and orthographic correction were performed on PAN images. Then, MSS and PAN images were fused. This process effectively enhanced the resulting image's spatial resolution while preserving the multispectral image's spectral information. Subsequently, image cropping was carried out based on the boundary range of the study area, and the resulting cropped images were mosaiced to obtain a comprehensive remote-sensing image of the entire study area. This was undertaken in anticipation of utilizing various methodologies for river extraction.

This study employed RF and SVM to extract two distinct features - rivers and non-rivers - from GF-2 satellite imagery. The machine learning samples were generated using the ArcGIS Pro software. To enhance the accuracy of river extraction, a specific band combination scheme comprising Band3, Band4, and Band2 was utilized, and river and non-river samples were delineated through visual interpretation methods. It is important to note that the number of non-river samples exceeded that of river samples, resulting in an unbalanced sample dataset, which can adversely impact model accuracy. Consequently, a random extraction of non-river samples was carried out, reducing the sample size to align with the river sample size. Furthermore, the sample order was deliberately disrupted to ensure an even distribution of both feature types in the training and test sets, followed by normalization. All four bands of GF-2 were leveraged as samples to facilitate comprehensive learning of river and non-river characteristics.

2) 3.2.2 Machine learning approaches

Breiman first proposed the RF as a machine learning method that utilizes an integrated algorithm [5]. It is a classification method that leverages multiple decision trees for the training and prediction of samples. The classification result of each decision tree represents its voting outcome, and these results are amalgamated into a classification scheme to enhance the predictive capacity of the model [6]. This study implemented the two river extraction algorithms based on the TensorFlow framework and Python language. The RF was implemented using the Scikit-learn library, with *n_estimators* set to 100 and *max_features* set to *sqrt*. The classifier demonstrates successful utility in selecting and ranking variables based on their ability to distinguish target categories. This capability is particularly valuable for remote sensing applications, as the high dimensionality of remote sensing data often makes the selection of relevant variables time-consuming and error-prone.

In machine learning, SVM is an extensively utilized kernel-based learning algorithm that Vapnik and his research team initially presented. SVM aims to address a convex quadratic optimization problem to derive a globally optimal solution, thus mitigating the local extremum issue encountered in other machine learning methodologies [7]. This supervised learning algorithm serves as a model for binary classification, effectively segregating input sample data by identifying the optimal margin hyperplane. Nevertheless, the application of SVM in multiclass classification scenarios poses challenges, and the model's efficacy is intricately linked to the selection of parameters and kernel functions. In this paper, our implementation of the SVM algorithm uses the Scikit-learn library, with optimal parameters being determined by the grid search approach. Specifically, the parameter C is set to 0.03125, the kernel function utilized is *rbf*, and the gamma value is 0.125.

IV. RESULTS

For the classification results, this study employs the confusion matrix for validation and additionally employs the following metrics to assess the accuracy of the classification results: Overall accuracy (OA), Kappa coefficient, User's accuracy (UA), and Producer's accuracy (PA).

For binary classification problems, samples can be divided into four categories according to the combination of their true categories and the model-predicted categories: true positive (TP), false positive (FP), true negative (TN), and false negative (FN). TP+FP+TN+FN = Total number of samples.

$$OA=(TP+TN)/(TP+FN+FP+TN). \quad (1)$$

$$Kappa=(Po-Pe)/(1-Pe). \quad (2)$$

Where Po = OA,

$$Pe=((TN+FN)\times(TN+FP)+(FP+TP)\times(FN+TP))/(TN+TP+FN+FP)^2$$

$$\text{Category 1 } PA=TP/(TP+FN). \quad (3)$$

$$\text{Category 2 } PA=TN/(TN+FP). \quad (4)$$

$$\text{Category 1 } UA=TP/(TP+FP). \quad (5)$$

$$\text{Category 2 } UA=TN/(TN+FN). \quad (6)$$

The confusion matrix, OA, Kappa coefficient, UA, and PA of RF and SVM are shown in Tables 1 to 2 and Figure 1. The OA of the RF is 97.88%, which is 10.33% higher than that of the SVM. The Kappa coefficient, which ranges from -1 to 1, indicates image classification accuracy. A larger value signifies better classification performance. Notably, both models examined in this study yielded Kappa coefficients exceeding 0.75, demonstrating excellent classification quality that aligns entirely with the ground object category within the actual images. UA denotes the ratio of the accurately classified pixels to the total number of pixels in an image belonging to a specific category, representing the misclassification error. Except for the UA for the river in the SVM, which stands at 81.27%, all others exceed 96%, indicating a commendable classification effect. The UA for

Table 1. Confusion Matrix of RF

	River	Non-River	PA(%)
River	419718	11796	97.27
Non-River	6462	424374	98.50
UA(%)	98.48	97.30	

Table 2. Confusion Matrix of SVM

	River	Non-River	PA(%)
River	420461	10475	97.57
Non-River	96872	334549	77.55
UA(%)	81.27	96.96	

the river in the RF is particularly noteworthy, reaching an impressive 98.48%. On the other hand, PA refers to the ratio of accurately classified pixels to the total number of actual references for a particular category, primarily used to measure the omission error [9]. The non-river PA of the SVM was the lowest at 77.55%, while all others surpassed 97%. Notably, the highest non-river PA for the RF reached 98.50%, indicating a strong classification performance.

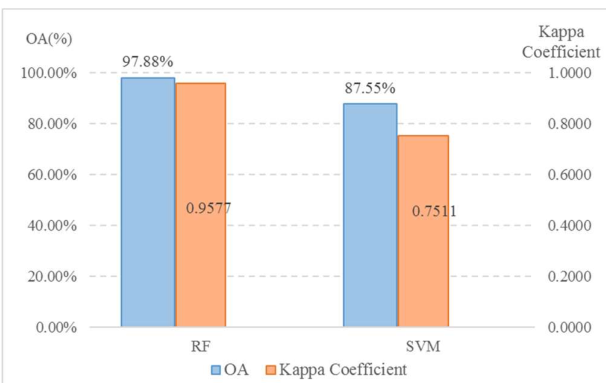
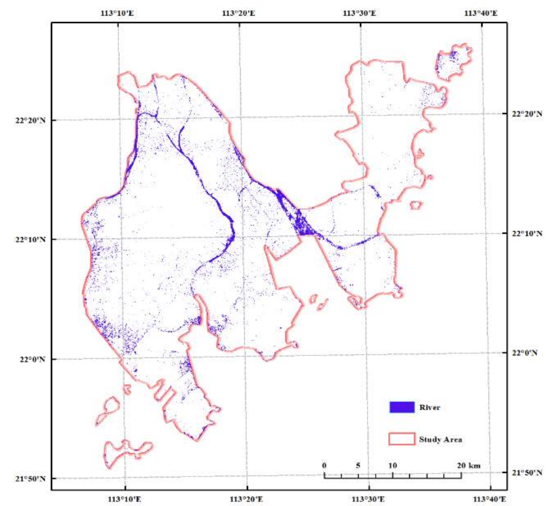


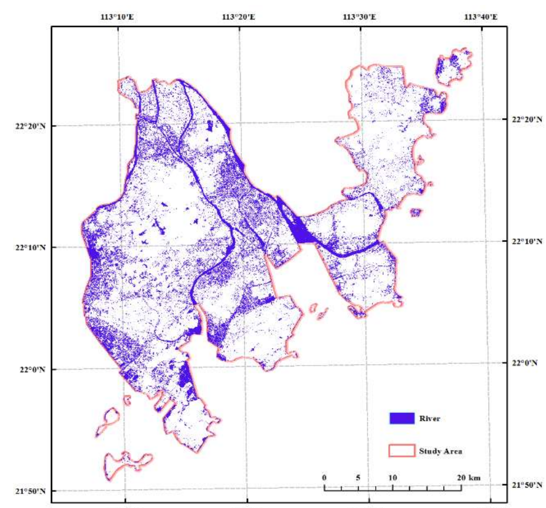
Fig. 1 The OA and kappa coefficient of RF and SVM

The distribution of rivers in the study area predicted by the two models is shown in Figure 2. The main rivers have been extracted. However, compared with the prediction results of the RF, there are many cases in which lakes and aquaculture farms are incorrectly extracted as rivers in the prediction map of the SVM.

The SVM results presented in this paper were compared to similar studies in the literature that utilized multispectral remote sensing data for river classification. The classification accuracy demonstrated in this paper has shown significant improvement. For instance, Han Zhen et al. [10] utilized Sentinel-2 data and SVM for river classification, achieving a classification accuracy (PA) 66.49. In contrast, this paper's employment of SVM resulted in a notable increase in classification accuracy, reaching 97.57, which is particularly noteworthy considering the higher 1m resolution of the GF-2 image used in this study compared to the 10m resolution of Sentinel-2.



(A) RF



(B) SVM

Fig. 2 The GF-2 river prediction result of RF and SVM

V. CONCLUSIONS

The study demonstrates that high spatial resolution images and machine learning models, particularly RF, offer an efficient and real-time method for accurately extracting river data. The study compared the extraction results of RF and SVM using GF-2 remote sensing images and found that SVM's extraction effectiveness was unsatisfactory. Despite using the grid search method to optimize parameters when training the SVM, the results were deemed inadequate based on evaluation indicators such as the confusion matrix, OA, Kappa coefficient, UA, and PA. Moreover, in the SVM prediction results of the study area, lakes and aquaculture farms were incorrectly identified as rivers. On the contrary, RF exhibits high classification accuracy and reliable prediction results and offers a relatively simple approach with minimal input variables. Furthermore, future studies will explore implementing deep learning methods to enhance the precision of extracting rivers from high spatial resolution remote sensing images.

V. ACKNOWLEDGEMENTS

The author is grateful for the support of the Department of Education of Guangdong Province's "Innovation and Strengthening Project" Scientific Research Project (Scientific Research Platform and Project of Guangdong College and Universities, 2021KTSCX176).

REFERENCES

[1] H. Jianjun, X. Jindong, C. Qianpeng, “Black and odorous water detection of remote sensing images based on improved deep learning,”. Canadian Journal of Remote Sensing, 2023, 49(1): 1-14.

[2] X. Yuan, Q. Chao, W. Baosheng, “Automatic extraction of mountain river surface and width based on multisource high-resolution satellite images,”. Remote Sensing, 2022; 14(10): 2370-2390.

[3] H. Zhi, H. Dan, M. Xiangqin, “Wetland classification based on a new efficient generative adversarial network and Jilin-1 satellite image”. Remote Sensing, 2019; 11(20): 2455-2470.

[4] L. Siqi, H. Guanqi, W. Yulu, “Monitoring and assessing land use/cover change and ecosystem service value using multi-resolution remote sensing data at urban ecological zone”. Sustainability, 2022; 14(18): 11187-11204.

[5] L. Breiman, “Random forests”. Machine Learning, 2001, 45: 5-32.

[6] T. McCandless, P. Angel Jiménez, “Examining the potential of a random forest derived cloud mask from GOES-R satellites to improve solar irradiance forecasting”. Energies, 2020; 13(7): 1671-1685.

[7] C. Cortes, V. Vapnik, “Support-vector networks”. Machine Learning 1995, 20: 273–297.

[8] Z. Zhihua, “Machine learning”. Beijing: Tsinghua University Press, 2016.

[9] W. Di, “Research on deep convolution neural network in wetland type information extraction”,. Harbin: Harbin Normal University, 2019.

[10] H. Zhen, G. Yunhao, J. Xiangyang, “Multisource remote sensing classification for coastal wetland using feature intersecting learning,”. IEEE Geoscience and Remote Sensing Letters, 2022, 19: 1-5