



Satellite Detection of Surface Water Extent: A Review of Methodology

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Abstract: Water is an imperative part of the Earth and an essential resource in human life and production. Under the effects of climate change and human activities, the spatial and temporal distribution of water bodies has been changing, and the shortage of water resources is becoming increasingly serious worldwide. Therefore, the monitoring of water bodies is indispensable. Remote sensing has the advantages of real time, wide coverage, and rich information and has become a brand-new technical means to quickly obtain water information. This study summarizes the current common methods of water extraction based on optical and radar images, including the threshold method, support vector machine, decision tree, object-oriented extraction, and deep learning, as well as the advantages and disadvantages of each method. These methods were applied to the Huai River Basin in China and Nam Co on the Qinghai-Tibet Plateau. The extraction results show that all the aforementioned approaches can obtain reliable results. Among them, the threshold segmentation method based on normalized difference water index is more robust than others. In the water extraction process, there are still many problems that restrict the accuracy of the results. In the future, researchers will continue to search for more automatic, extensive, and high-precision water extraction methods.

Keywords: water extraction; remote sensing; water body index; classification; machine learning

1. Introduction

Various inland waters, such as rivers, lakes, ponds, reservoirs, and wetlands, are widely distributed on the Earth's surface. Water provides invaluable supplies and resources to support human life, living, and production, such as drinking water, food, transportation, and recreation [1]. In addition, water information is widely used for many purposes [2–5], including water resource surveys, environmental protection, land classification, and flood monitoring. As a result of climate change and human activities, spatial and temporal distributions of water extents are changing [6,7], and water shortages and water pollution are becoming progressively more severe [8]. It is imperative to monitor water bodies for addressing their distribution and subsequent driving factors. Recent scholarly research has focused on determining how to obtain surface water information in an efficient, accurate, and timely manner [9,10].

Traditional methods for acquiring water bodies and hydrological information mainly include manual field surveys and data acquisition based on hydrological monitoring



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Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). stations [11]. Despite the high accuracy, the process is time-consuming and laborious, and it may be difficult in remote areas. In addition, it is not suitable for the acquisition and monitoring of real-time water quality information on a large scale and over a long period. Remote sensing has several advantages, including broad coverage, periodic replay, real-time solid performance, and rich information. Since the emergence of high-space, hightime, and high-spectral resolution remote sensing data and the extensive study of remote sensing quantitative retrieval, extracting water body information has become the focus of current research in water conservation remote sensing technology [12]. Using satellite imagery, researchers and institutions have created a large-scale water distribution dataset (Table 1), which is no longer confined to a single lake or river [13]. Waterbody information is extracted primarily from optical remote sensing and microwave radar remote sensing data sources. According to the imaging characteristics of water bodies, various water body extraction algorithms have been developed, including threshold and machine learning methods. Among these methods, there are classical water body index and segmentation methods, including various water body indexes [14] improved in different regions [15,16]; In recent years, a large number of methods based on support vector machine [17], decision tree [18], and deep learning have also been widely used in water extraction [19].

Table 1. Several typical water remote sensing products.

Name	Time Span	Research Area	Spatial Resolution	References
Global Land 30-water	2000, 2010	Globe	30 m	[20]
Global Surface Water Data	1984-2015	Globe	30 m	[21]
ASTER Global Water Body Dataset	2000-2013	Globe	30 m	[22]
Global surface water dynamics	1999–2018	Globe	30 m	[23]
500 m 8-day Water Classification Maps	2000-2015	Globe	500 m	[24]
Global Lake/Reservoir Surface Inland Water Extent Mask Time Series	1992–2018	Globe	500 m	[25]
Global Lakes Forel-Ule Index Dataset	2000-2018	Globe	500 m	[26]
High Mountain Asia Glacial Lake Inventory database	2008-2017	Asia	30 m	[27]
Inland Surface Water Dataset in China	2000-2016	China	500 m	[28]
Open-surface Water Body Area in the contiguous United States	1984–2016	USA	30 m	[29]

When water bodies are distinguished from other ground features using spectral characteristics, other methods can combine multiple characteristics to classify and identify them. Water body information extraction accuracy varies between algorithms [30,31]. For a given algorithm based on different data, the water body extraction accuracy will vary; therefore, using a combination of different algorithms and datasets will produce results with different accuracies [32]. In order to optimize suitable water extraction methods, many studies have summarized the progress of water extraction. For example, Huang, et al. [33] introduced the water extraction method based on optical remote sensing and summarized the relevant research progress on water monitoring. Yan and Jinwei [32] described the development of sensors, methods, data processing platform, and water research content in recent years. Gholizadeh, et al. [34] introduced the qualitative parameters used for water quality monitoring and evaluated the commonly used methods and sensors for inversion of water quality parameters. Wang and Yesou [35] reviewed research developments using state-of-the-art remote sensing technologies for monitoring dynamics of floodpath lakes and wetlands. Many studies need water boundary as the research basis. Although these reviews summarized the advantages and disadvantages of various methods, they did not carry out specific tests. Likewise, the applicability and accuracy of traditional methods and machine learning in different water extraction are still unknown.

Recognizing the poor understanding of the applicability of various water body methods, this study aims to summarize the current methods with respect to the water body extraction and conduct water body extraction tests in the Huai River Basin and Nam Co on the Qinghai-Tibet Plateau to evaluate their applicability. The specific purposes are: (1) to summarize the commonly used sensors in water extraction, including optics and radar; (2) to introduce the principle of common water extraction methods, including threshold method and classification method, and to identify the progress of new methods in recent years; (3) to examine the performance of several state-of-the-art algorithms regarding water extract, such as water spectral index, support vector machine, cart decision tree, objectoriented classification, and deep learning, on extracting water bodies in the Huai River Basin and Nam Co. This review was anticipated to serve as a reference and support for researchers in related research fields and lay a theoretical foundation for future scientific studies.

To form a primary literature database with respect to water extraction with satellite, we searched the publications from the Web of Science database since 2010 (e.g., TI = (Satellite OR Remote sensing) AND (Water extraction OR Water Extent OR water boundary OR water body mapping)) and excluded documents with less than 10 citations. By quickly reading the literature abstracts, we removed the literature with little correlation. The information of each publication regarding remote sensing dataset, study area, method and accuracy of water extraction used in that study was extracted.

2. Data Sources

Remote sensing data sources for water extraction and monitoring include optical and radar data (Table 2). Generally, the Earth observation satellites provide data that can be used for water extraction. In recent years, data obtained from remote sensing of water bodies have evolved towards high spatial resolution, high temporal resolution, and high spectral resolution [32].

Optical imagery is part of passive remote sensing, which obtains the spectrum of ground objects by receiving the reflected sunlight from ground objects, mainly in the visible and infrared bands. It is currently the primary data source for extracting water body information. In comparison to other ground objects, water exhibits a low reflectivity in the visible and near-infrared ranges [36], as well as an extremely low reflectivity in the nearinfrared and shortwave infrared spectra. These spectral characteristics are the main basis for identifying water bodies. Remote sensing data can be divided into low-resolution (more than 200 m) EOS MODIS, NOAA AVHRR, etc. For example, Landsat Multispectral Scanner (MSS)/Thematic Mapper (TM)/Enhanced Thematic Mapper Plus (ETM+)/Operational Land Imager (OLI), Sentinel-2 MSI, etc. have a medium-spatial resolution (10-200 m). IKONOS and Quickbird have a high-spatial resolution (~1 m). Landsat, Sentinel 2, and other high-resolution images provide more accurate results; therefore, they are commonly used to identify water bodies in single lakes or small watersheds. However, most high-spatial resolution data have a low-temporal resolution. When long-term continuous monitoring of water bodies is required, or the research scale is large, low-resolution data should be selected more frequently. MODIS data can provide daily images and cover large areas, and they are mainly used for global research purposes.

Satellite	Sensor	Spatial Resolution	Time Resolution	Application	
Optical Data					
Terra/Aqua	MODIS	250 m	2 times/day	Remote sensing mapping of large-scale water bodies [24,28]	
Landsat 4,5	TM	30 m	16 d	Land use and land cover change, water body	
Landsat 7	ETM+	30 m	16 d	manitaring water color remate consing [27, 20]	
Landsat 8/9	OLI	15, 30 m	8 d	monitoring, water color remote sensing [37–39]	
Sentinel-2	MSI	10, 20, 60 m	5 d	High-precision water system map, water body	
Sentinel-3	OLCI	300 m	2 d	monitoring [40,41]	
GF-1	WFV	16 m	2 d	Water quality monitoring, water body	
GF-2	MSS	3.2 m	5 d	extraction [42,43]	
HJ-1A/B	CCD	30 m	2 d	Disaster monitoring and forecasting [44]	
IRS-P6	LISS-3	23.5 m	24 d	Land use and land cover change [45]	
Radar Data					
GF-3	SAR	1–500 m	1.5–3 d	Water extraction [46]	
Sentinel-1	SAR	5 m	12 d	Flood monitoring [47,48]	
Envisat	ASAR	30 m	35 d	Lake ice and sea ice detection [49,50]	

Table 2. The typical data sources for water body extraction.

Radar remote sensing belongs to active remote sensing. It actively emits microwave radiation and receives electromagnetic waves reflected or scattered by the Earth's surface. Synthetic aperture radar (SAR), which is a component of the radar remote sensing system, can provide high-resolution radar images, increasing the possibilities for water extraction research. Based on the fact that water backscatters less in the microwave range, radar can be used to detect and extract water information [51]. SAR remote sensing grew in technical sophistication with the emergence of high-resolution wide-range SAR, synchronous orbit SAR, and video SAR. Radar has the characteristics of ignoring the weather and having certain penetrating power [52].

Various sensors provide different advantages when acquiring ground information, and, when extracting water bodies, two or more sources may be selected. Optical images have high spatial resolution and rich spectral information, but they are greatly affected by clouds and shadows during water recognition; SAR images can provide information on shallow water and shadow areas, but coherent speckle noise cannot be avoided. Combining textural features can reduce the impact of noise, but the calculation takes considerable time and requires continuous experimentation to obtain the optimal feature combination [53,54]. In addition, digital elevation models (DEMs) and digital surface models (DSMs) are often used to aid in water body estimation by calculating terrain factors [55] or modeling terrain [48,56] to eliminate missed water bodies and reduce shadow interference. Two methods are available for extracting water body information from multisource data: optical remote sensing for rough water extraction and, on the basis of rough extraction, radar images or combined DEM data for fine water extraction [57]. Another method is to directly perform image fusion processing of these two kinds of data, combining the characteristics of the original image and the information of the ground features to produce a higher-performance remote sensing image [58,59]. A large amount of data and rich spectral information allow for a flexible and effective water extraction method and a long-term water monitoring effort.

3. Water Extraction Method

A majority of the automatic extraction methods of remote sensing water body information can be divided into two categories: threshold segmentation and image classification. The threshold segmentation is mainly based on the spectral characteristics of water [36]. It uses spectral knowledge to construct various classification models and water body indices to extract water bodies. The image classification synthesizes the spectrum, texture, and spatial characteristics of the image and makes full use of the spectrum, shape, structure, and texture of the ground features to extract water body information [11].

In low- and medium-resolution images, small water bodies often appear in the form of mixed pixels, which cannot be accurately divided by the threshold method. With the development of high-spatial resolution satellites, images have more abundant spatial and texture information. Wavelet texture [60] and grey-level co-occurrence matrices (GLCMs) [61] are often used to extract the texture features of images. Researchers have constructed image classification and extraction methods by combining features such as spectrum, space, and texture. Various features can help extract more refined water information [62], but overly complex classification criteria may reduce efficiency and accuracy. Current image classification methods. With the development of computer technology and the arrival of the era of big data, deep learning has been widely used in water extraction [63,64].

3.1. Threshold Segmentation

Compared with other ground objects, water bodies show lower reflectivity almost in the range of visible light to near-infrared, especially in the range of near-infrared and shortwave infrared. By choosing a threshold value derived by the single or multiple spectral bands, the water body could be extracted. The choice of the threshold value directly affects the accuracy of the results (Figure 1).



Figure 1. The diagram to illustrate the water extraction using the normalized differenced water index (NDWI) and threshold.

3.1.1. Single Band Threshold

The single-band method in optical imagery was mainly used in early water remote sensing research [65]. A specific waveband was selected, an appropriate threshold was set to extract water information, and the near-infrared or mid-infrared wavebands with low water reflectivity were used. Although the single-band threshold method is simple and easy to implement, the accuracy is not high, and this method also easily causes misprovisioning and omission of water body information; it is difficult to eliminate the influence of mountain shadows, and the water body boundary is blurred [66]. With the co-existence of multiple types of features in remote sensing images, it is difficult to accurately extract all water bodies based on the information of only one band. With the development of multiband methods, the application of single-band methods in water body extraction is no longer common [67].

Threshold segmentation is a method of extracting water bodies from radar images, primarily based on the low backscattering characteristics of water bodies in the microwave range [68], which appears as a dark area in the image, thus distinguishing the water bodies

from other ground objects [69]. Its advantages are simple principle, small calculation amount, and suitability for water extraction from SAR images with low noise and small maps. The most commonly used grey-level threshold segmentation methods include the maximum between-class variance method [70], entropy threshold method, and bimodal histogram method. However, processing large-area images take a long time, is poor in accuracy and robustness, and is affected by coherent speckle noise and uneven grey information throughout the image. It is difficult to obtain accurate threshold points, and it is impossible to distinguish ground objects with similar water-scattering characteristics. Some researchers have improved the maximum between-class variance method to ensure the maximum between-class variance while ensuring that various internal pixels have better cohesion and obtaining higher-precision water extraction results [71]. Combining the threshold segmentation method with other methods, such as Markov random fields, can achieve high-precision and automated water information extraction [46].

3.1.2. Multiband Threshold Method

The multiband method mainly uses the advantages of multibands to comprehensively extract water information, including the interspectral relationship method and the water index method. This method extracts water bodies by analyzing the original waveband of the remote sensing image or the spectral characteristic curve of the characteristic waveband derived from the original waveband and constructing logical judgment rules [72]. The spectral characteristics of the water body in the AVHRR data indicate that CH1 is much greater than CH2, CH2 is less than the average value of the image, and CH3 is greater than the average value of the entire image [73].

The water body's reflection gradually decreases from the visible to mid-infrared wavelength range, and the absorption is highest in the near-infrared and mid-infrared wavelength ranges, with almost no reflection, which is obviously different from other objects on the ground [74]. The water index is calculated by using the ratio of the strongest and weakest wavebands of the water body to achieve the purpose of increasing the difference between the water body and other ground features and then selecting a threshold to extract the water. The ratio index is usually normalized to make its value range between -1 and 1. Researchers have proposed a number of water indices (Table 3). The earliest normalized difference water index (NDWI) [14] uses the ratio of the green light band to the near-infrared band to suppress vegetation information to the greatest extent to highlight water body information. However, it ignores the influence of shadows, land, and buildings. Later, the modified normalized difference water index (MNDWI) [15] was proposed, which replaced the near-infrared in the NDWI with the mid-infrared band, which can be used to accurately extract water information within a town and effectively reduce the impact of shadows. Later, researchers proposed many improved water indices, which can enhance the applicability of specific areas and effectively suppress the influence of shadows. NDWI₃ [75] has achieved good results in urban water body extraction; the enhanced water index (EWI) [76] is suitable for water body extraction in semiarid areas; and the new water index (NWI) [77] can be determined by simple thresholds. By quickly and accurately extracting water body information, the Gaussian normalized difference water index (GNDWI) [16] realizes the automatic extraction of complex and diverse river water body information. The temperature vegetation water index (TVWI) [78] has a certain universality, and water bodies are the threshold for nonwater bodies and can be set stably to 0. The automated water extraction index (AWEI) [79] can improve classification accuracy in areas that include shadow and dark surfaces that other classification methods often fail to classify correctly. The above water body indices are all used for optical data. The Sentinel-1 dual-polarized water index (SDWI) [80] is used for water body extraction from Sentinel-1 radar data, eliminating the presence of soil and vegetation, but it is susceptible to shadows.

In fact, the types of features in a region are often diverse, and using only one water index may not meet the accuracy requirements. The selection of the threshold is also a complicated process. Therefore, some scholars have comprehensively used multiple indices, and their results could obtain higher accuracy than using a single water body index. Rao and Wang [81] utilized the optimal partition and optimal index joint decision tree composed of three indices—MNDWI, AWEI, and NDTBI—and the results obtained by the joint decision tree was more accurate than any of them. Wen et al. [82] established collaborative decision-making with water indices (CDWI) with five water body indices and achieved good results in both water and land environmental tests worldwide.

Table 3. Several common water spectral indexes.

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Water Index	Formula	Describe
NDWI [14]	NDWI = (G - NIR)/(G + NIR)	Information that suppresses vegetation; can be affected by shadows, land, and buildings
NDWI ₃ [75]	$NDWI_3 = (NIR - MIR) / (NIR + MIR)$	Town
MNDWI [15]	MNDWI = (G - MIR)/(G + MIR)	Cities and towns, effectively suppressing shadows
EWI [76]	EWI = (G - NIR - SWIR)/(G + NIR + SWIR)	Semi-arid areas
NWI [77]	NWI = [B - (NIR + MIR + FIR)] / [B + NIR + MIR + FIR]	Simple threshold setting
GNDWI [16]	$\text{GNDWI}_{i,j} = \left(\text{NDWI}_{i,j} - \overline{\text{NDWI}}\right) / \sigma$	Suitable for complex river water bodies
TVWI [78]	$\text{TVWI} = \frac{\text{Ts} - \text{Ts}_{min}}{\text{Ts}_{max} - \text{Ts}_{min}}, \text{Ts}_{max} = a \times \text{NDVI} + b, \text{Ts}_{min} = c \times \text{NDVI} + d$	Universal, the threshold can be set stably to 0
AWEI [80]	$\begin{aligned} AWEI_{nsh} &= 4(G - SWIR1) / (0.25NIR + 2.75SWIR2) \\ AWEI_{sh} &= B + 2.5G - 1.5(NIR + SWIR1) - 0.25SWIR2 \end{aligned}$	Suitable for areas with more shadows

R, G, B, NIR, SWIR, MIR, and FIR are pixel values of red, green, blue, near infrared, short wave infrared, mid infrared, and far infrared bands, respectively; $GNDWI_{i,j}$ is the Gauss normalized water body index at point (I, J); $NDWI_{i,j}$ is the normalized difference water body index at point (I, J); \overline{NDWI} is the mean value of NDWI of all pixels in the image; σ It is the standard deviation of NDWI of all pixels; FG is the constructed pseudo green band; Ts_{max} and Ts_{min} are obtained by fitting vegetation index NDVI and land surface temperature according to dry edge and wet edge; a, b, c, and d are the coefficients of the dry edge and wet edge linear fitting equation, respectively. VV is the pixel value of SAR image with VV polarization mode, and VH is the pixel value of SAR image with VH polarization mode.).

3.2. Machine Learning Methods

3.2.1. Support Vector Machine

Support vector machine (SVM) [83] is a machine learning method based on statistical learning theory. They use structural risk minimization (SRM) criteria to find the optimal classification hyperplane in the high-dimensional feature space to distinguish the water body from other ground objects, so as to identify the water body.

The basic mathematical form of the support vector machine is:

$$\min_{\omega,b} \Phi(\omega, b) = \frac{1}{2} (\omega \times \omega).$$
(1)

The constraint is: $y_i[(\omega \times x_i) + b] \ge 1, i = 1, \dots, n$. Introducing the Lagrange multiplier α_i , the solved equation of the above formula is:

$$\min_{\omega,a,b} L(\omega,b,\alpha) = \frac{1}{2}(\omega \times \omega) - \sum_{i=1}^{k} \alpha_i \{ y_i [(\omega \times x_i) + b] - 1 \}.$$
(2)

The optimal solution is $\omega = \sum_{i=1}^{k} \alpha_i^* y_i x_i$. Any $\alpha_i \neq 0$ is taken to find *b*. In the result, most α_i are 0, and the samples whose α_i is not 0 are called support vectors.

For a high-dimensional space, if one wants to transform the original feature space to a high-dimensional feature space, one must replace the dot product in the optimal classification surface with the inner product K(x, x').

Using SVM to extract water information in high-resolution data can obtain highprecision extraction results [17], which is better than the traditional water index and easier to distinguish from hilly shadows [84]. The performance of the SVM method mainly depends on the selection of the kernel function type and the setting of the kernel function parameters. It has the advantages of small sample learning, anti-noise performance, high learning efficiency, and good generalization, but too many samples will increase missed points and errors. The commonly used kernel functions of support vector machines include the radial kernel function, sigmoid kernel function, linear kernel function, and polynomial kernel function (Table 4). The accuracy of the radial basis kernel function is relatively high [85], but its hardware requirements also vary. Improvements are made at the expense of extensive training.

Table 4. Common kernel functions.

Kernel Functions	Formula
Linear Kernel Function	$\mathbf{K}(\mathbf{x}_{i},\mathbf{x}) = (\mathbf{x}_{i} \times \mathbf{x})$
Polynomial Kernel Function	$\mathbf{K}(\mathbf{x}_{i},\mathbf{x}) = \left(\gamma(\mathbf{x}_{i}\times\mathbf{x}) + \mathbf{c}\right)^{n}$
Radial Basis Function	$\mathbf{K}(\mathbf{x}_{i},\mathbf{x}) = \exp\left[-\gamma \ \mathbf{x} - \mathbf{x}_{i}\ ^{2}\right]$
Sigmoid Kernel Functions	$K(x_i, x) = tanh(\gamma(x_i \times x) + c)$

3.2.2. Decision Tree

The decision tree is based on the hierarchical classification idea as its guiding principle, and it uses a tree structure to divide the data into subsets that have more homogeneous characteristics in accordance with a certain segmentation principle. The decision tree method for remote sensing image classification first uses training samples to generate a discriminant function, second builds tree branches according to different values, repeats the establishment of lower nodes and branches in each branch subset, and finally forms a classification tree. The most famous algorithm is ID3, followed by algorithms such as C4.5, CART, SLIQ, and SPRINT. The decision tree method uses knowledge other than spectral characteristics, including digital elevation models, water indices, texture, and spatial characteristics [86]; the recognition results are more accurate, but the abstraction of the decision-making process or the determination of the decision rules are more complicated [18].

3.2.3. Object-Oriented Classification

The object-oriented image analysis method is developed based on Hay and Niemann [87] concept of image objects [88]. Based on the results of image segmentation, this method fuses pixels with similar spectral characteristics and spatially adjacent pixels into one object, ensuring maximum local homogeneity in the same area, and classifying the object as the basic processing unit. Among them, image segmentation is the key to object-oriented classification, and the segmentation scale (scale) is the key to determining the segmentation effect. The most commonly used segmentation method is the multiscale segmentation algorithm. To determine the optimal segmentation scale, other judgments are needed. The classification-vector distance index method (classification-vector distance index method) judges whether the segmentation scale is accurate according to the distance between the boundary of the ground feature and the actual boundary. Compared with the more mature human trial and error method ("trial and error" method), accurate results have been obtained in the classification of water bodies and paddy fields. Traditionally, pixel-level analysis uses one pixel as the basic unit and cannot take advantage of pixel neighborhood information or its mutual relationship. Images are frequently isolated, with "same objects with different spectra" or "foreign matter with the same spectrum" phenomena, and the accuracy of water body extraction is low, making it difficult to meet the requirements of high-resolution images. In their paper, Gao et al. [89] introduced local variance variables and Moran's I indices and combined them with the principle of the minimal risk Bayes decision to identify the optimal spatial segmentation scale intuitively, accurately, and uniquely.

3.2.4. Deep Learning

Benefiting from the development of computer technology and the advent of the era of big data, deep learning [90] has also ushered in a development climax. Deep learning mainly uses artificial neural networks for feature extraction and self-learning of remote sensing image water samples to automatically distinguish water bodies [91]. At this stage, deep learning was widely applied in remote sensing image classification and recognition, mainly including restricted Boltzmann machines (RBMs), convolutional neural networks (CNNs) and autoencoders (AEs). The multilayer RBM and backward propagation algorithm (BP) form deep belief networks (DBNs). Liu et al. [92] uses the characteristics of unsupervised learning to better extract image features, but its network parameter selection requires manual input. It is difficult to determine appropriate experimental parameters due to the intervention of experimental knowledge. The CNN is often used for remote sensing classification and has obvious advantages in processing image hyperspectral data. Stacked autoencoder (SAE) produces fewer reconstruction errors in dimensionality reduction and feature extraction. To achieve high-precision classification results, it must be combined with other classifiers [63].

A convolutional neural network and a DeepLabv3 semantic segmentation neural network are used to extract water information from high-resolution satellite remote sensing data. The results are better than those of the water index method, object-oriented method, and support vector machine method, and they can effectively remove the influence of shadows and buildings [64]. By introducing the dense block of the DenseNet neural network to construct a water body extraction deep learning full convolution neural network, it can enhance the sensitivity to small water bodies, improving the water extraction accuracy of remote sensing images, but remains vulnerable to the influence of building shadows [93]. By combining deep learning and multiple checkerboard segmentation methods for highresolution remote sensing image river extraction, and fully considering the spatial geometric relationship between pixels with high recognition accuracy, it is possible to extract rivers with a width of up to two pixels [94]. He, Huang, and Li [19] proposed an improved U-Net network model for extracting water body information from GF-2 remote sensing images. In terms of small water bodies, shadow differentiation, and boundary segmentation, it is more advantageous in the environment of the study area. The extraction effect of regions with large differences needs to be further improved.

4. Applications of Common Methods on Landsat-8 Imagery

4.1. Material and Methods

We selected the Huai River Basin ($32^{\circ}08' \sim 32^{\circ}51'$ N, $116^{\circ}10' \sim 117^{\circ}03'$ E) and Lake Nam Co $(30^{\circ}30' \sim 30^{\circ}35' \text{ N}, 90^{\circ}16' \sim 91^{\circ}03' \text{ E})$. The Huai River Basin is part of Huai'an city in the north-central part of Jiangsu Province. Nam Co is the third-largest saltwater lake on the Qinghai-Tibet Plateau. It is located in the southeastern part of the northern Tibetan Plateau. We choose these two areas to examine the performance of the typical algorithms to extract water extent, because: (1) In the middle and lower reaches of the Huai River, the population densely populated and easily affected by human activities; Nam Co is not affected by human activities. The lake is dominated by mountains, and its ecological environment is basically natural. (2) There are interlaced breeding ponds, rivers, and lakes in the Huai River Basin; Nam Co is a closed inflow lake. (3) The Huai River Basin has abundant summer rainfall and large inter-annual variability; the area of Nam Co has changed from 1920 km² to 1980 km² in the past 30 years, and the lake area has not changed drastically. In general, these two regions represent plain area and plateau large area. Figures 2a and 3a show that water bodies in the Huai River Basin are in different sizes and have complex boundaries, where the river network is dense and complicated, largely increasing the difficulty to accurate extract water extents. On the contrary, Lake Nam Co is a complete lake with clear land and water boundary. Researchers pay more attention to the interference of mountain shadows in the classification results.



Figure 2. Water extraction results of several methods in the HuaiHe River Basin. (**a**) original image; (**b**) NDWI; (**c**) SVM; (**d**) CART; (**e**) Object-Oriented; (**f**) Deep Learning.



Figure 3. Water extraction results of several methods in Nam Co (**a**) original image; (**b**) NDWI; (**c**) SVM;(**d**) CART; (**e**) Object-Oriented; (**f**) Deep Learning.

We mainly used the Landsat Collection 2 Level-2 Science Products by the USGS, which has been atmospherically corrected. The NDWI, support vector machine, CART decision tree, and object-oriented methods are used to extract lake water. The threshold of the NDWI is determined using the OTSU algorithm [70]. SVM, CART, and object-oriented methods use the same training samples for training, and the categories include water and nonwater. We use the libsvm function and smileCart function on the Google Earth Engine (Google Inc., Santa Clara, CA, USA) [95] platform to train samples and SNIC algorithm for image segmentation. In addition, the global surface water dynamic dataset [23] will be compared with other methods as the classification results of deep learning below. We used confusion matrices to evaluate the precision of the extraction results, and the ANOVA test was used to examine whether the difference among groups was significant. p < 0.05 is significant throughout the manuscript.

4.2. Performance of Algorithms on Extracting Water Extents

These methods showed noticeable differences in identifying the water body (Figures 2 and 3). The water distribution obtained by the four methods, SVM, CART, object-oriented, and deep learning, is superimposed in the figure with the NDWI extraction results, as shown in Figures 4 and 5. It can be found that the water extraction results of several methods are approximately the same; that is, the pixels of type X water and N water account for the majority. However, there are also local differences in the extraction results in the figure, which are manifested by inconsistent boundary contours and disconnected small rivers. Therefore, these local differences are compared with the original Landsat image, and further analysis is done.



Figure 4. Superimposed comparison of different methods and NDWI water extraction results in some basins of Huai River. (a) SVM; (b) CART; (c) Object-Oriented; (d) Deep Learning (the water distribution obtained by the four methods of SVM, CART, object-oriented, and deep learning are superimposed with the NDWI extraction results. X represents the extraction result of the method used in this figure and N represents the extraction result of NDWI. The four pixel types will be generated: X water N water, X water N non-water, X non-water N water, and X non-water N non-water.).



Figure 5. Superimposed comparison of different methods and NDWI water extraction results in Nam Co (a) SVM; (b) CART; (c) Object-Oriented; (d) Deep Learning.

Part of the Huai River Basin is located in a plain area with complex lake boundaries. In addition to large rivers and lakes, there are many small rivers, narrow artificial canals, and scattered ponds. As shown in the red box (Figure 4), the water and land boundaries extracted by several methods are inconsistent, and the deep learning method does not identify the breeding ponds around the lake. The object-oriented approach is limited by the segmentation scale and cannot identify very small water bodies.

Lake Nam Co is located on the Qinghai-Tibet Plateau, and mountain shadows, ice, and snow are the main interference factors in water extraction. These five methods can extract the outline of the lake with clear water and land boundaries, but not all methods can accurately identify small and intermittent rivers (Figure 5). The SVM, CART, object-oriented, and deep learning in the red box can all identify more rivers than the NDWI, but the object-oriented method is most disturbed by the shadow of the mountain.

Accuracy evaluation of the extraction results of all water bodies in the Nam Co and Huai River basins was carried out, and the results obtained by calculating the overall accuracy and Kappa coefficient are shown in Tables 5 and 6. The overall accuracy of the five methods in Nam Co is above 0.94, and the Kappa coefficient is above 0.95 except for the object-oriented method. In the Huai River basin, the overall accuracy of all methods is above 0.90, and the Kappa coefficient does not reach 0.94 only in deep learning. In addition, the NDWI, CART, and SVM can obtain similar results in both regions (p > 0.05), and SVM is slightly better than the other two methods (p < 0.05).

Table 5. Evaluation of the accuracy of Nam Co water extraction results.

Nam Co	NDWI	CART	SVM	Object-Oriented	Deep Learning
Overall Accuracy	0.9951	0.9937	0.9963	0.9464	0.9878
Карра	0.9898	0.9869	0.9924	0.8905	0.9746

Huai River Basin	NDWI	CART	SVM	Object-Oriented	Deep Learning
Overall Accuracy	0.9735	0.9788	0.9788	0.9788	0.9023
Kappa	0.9466	0.9576	0.9576	0.9576	0.8065

Table 6. Evaluation of the accuracy of Huaihe River Basin water extraction results.

The NDWI is a fast water extraction method with wide applicability, and good results can be obtained in any area [96]. Furthermore, the NDWI can also be used as a feature in other water extraction methods to help improve the accuracy of the results [97]. The extraction results of SVM and CART are similar to the NDWI, but they are more advantageous when identifying small water bodies. Object orientation requires choosing a suitable segmentation scale to obtain smooth water and land boundaries. When extracting small water bodies, pixel-based methods are a better choice. Deep learning has high accuracy and vital applicability, but it requires a large number of samples for training, and various situations must be considered when selecting samples.

5. Conclusions

At present, there are many methods for extracting water information from remote sensing data, such as the threshold method and classification method based on optical remote sensing images, the threshold method and filtering method based on radar remote sensing images, the texture extraction method, and the combined DEM extraction method. In addition, there are complementary advantages of optical remote sensing and radar remote sensing that can be used to extract water body information. Researchers continue to improve and innovate on existing methods, looking for more automatic, extensive, and high-precision water extraction methods. There are some problems that need further study.

- 1. Medium- and low-resolution images have a short revisit period and strong real-time performance, but the approximate resolution limits the accuracy of water body extraction. High-resolution images can obtain fine water body extraction results, but the time resolution is low, and the data are difficult to obtain. This problem of temporal and spatial resolution mismatch limits the accuracy of water body information extraction and real-time monitoring. At present, there are an increasing number of remote sensing data to choose from, and the fusion of multisource remote sensing data brings more possibilities for water body extraction;
- 2. Water bodies do not always appear in the form of pure pixels in images. River networks, small rivers, and water and land boundaries mostly appear as mixed pixels. These water bodies are more difficult to identify [98]. Although higher-spatial resolution images can reduce these problems, they are still inevitable. When extracting the water body from a mixed pixel, not only are the abundances of the end members of the water body required, but also the position distribution of the water body must be known. Some scholars have made efforts in this regard [99], obtaining high-precision water maps through mixed pixel decomposition and super-resolution mapping;
- 3. There are various methods of water extraction, but they lack universality. One reason is that there are widespread differences in the parameters of many remote sensing sensors at present, and different classification rules are often set for remote sensing images from different sensors. This makes the water extraction method not very versatile and poor in generalization. Another reason is that the spectral characteristics of water in the natural environment are affected by sediment, chlorophyll, etc., and many methods cannot take into account plains, mountainous areas, and urban areas. In addition, compared with ocean waters with simple optical properties, inland waters have more complex optical properties, which vary greatly with regions and seasons, and lack satellite remote sensors specifically for inland waters [100];
- 4. There is no uniform evaluation standard for the results of water extraction, which is not conducive to a comparison between various methods. One of the current accuracy evaluation methods is based on the results of field investigation or manual

interpretation, and the other is based on the extraction results of other images, using a confusion matrix, Kappa coefficient [101], and other parameters to evaluate the extraction results. Establishing a unified evaluation standard and standardizing the data quality evaluation system will make the water extraction method more mature and will accelerate its popularization and application;

5. The large volume of remote sensing data and complicated processing has resulted in a concentration of research in a small area or local area. With the rapid changes in network and computer technology, cloud storage and cloud computing technologies have developed rapidly. The emergence of the NASA Earth Exchange (NEX), Amazon Web Services (AWS), and Google Earth Engine (GEE) have changed the traditional remote sensing processing method. Remote sensing images and high-performance computing power form a large-scale, long-term sequence. Remote sensing data analysis provides a new approach [102]. Currently, a large number of researchers are conducting scientific research utilizing GEE's cloud platform [103,104].

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