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Evaluation and Comparison of the Performance of Water Body Extraction Methods from Remote Sensing Data with Emphasis on Traditional Methods, Machine Learning and Deep Learning Approaches

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Abstract

Water forms an important part of human life, and without water, the survival of living beings on Earth is impossible. Water resources include oceans, seas, wells, etc. Research and identification of these important resources are of great value to human health. Water plays a very important role in the political, social, and economic aspects of countries. This research aims to review methods for extracting water from satellite images and introduce the best method. In this research, the modified normalized difference water index (MNDWI) methods , Water Ratio Index (WRI)، Normalized Difference Water Index (NDWI), (SMDPSO+LFE)، (Faster R-CNN) Automated Water Extraction Index (AWEI), Support Vector Machine (SVM), Random Forest (RF), NDWI-PCs، Water Index (WI), Feature Classification with Deep Learning (DLFC), Local Radiative Energy Peak (LREP), Double Band Normalized Difference Water Index (DBNDWI)، Linear Discriminant Analysis (LDA), Artificial Neural Network (ANN)، (DeepLab-v3+)، LinkNet، Multi-scale Feature Extraction Network (MSFEN), Water Extraction Surface Temperature Index (WESTI)، Multilayer Perceptron (MLP)، Corrected Normalized Difference Water Index (CNDWI) ،Decision Tree (DT) and the convolutional neural network (CNN) method have been investigated ,Each method has its own advantages and disadvantages. After examining the methods, the results of the Faster R-CNN method have better performance than other methods. This method has excellent performance on two datasets of Sentinel-2 and Landsat-8 (OLI) satellite images for extracting water areas, the results show that this method has higher accuracy compared to other methods and can identify water more effectively and accurately.

Keywords: Methods, Method Accuracy, Remote Sensing, Satellite Images, Water Area Extraction.

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1. Introduction

Water is an essential resource for life, but access to it is not uniform and depends on geographical location and climate[1]. Water resources include surface water, groundwater, inland waters, rivers, lakes, transitional waters, coastal waters, and groundwater tables[2]. Watershed extraction plays a key role in environmental monitoring[3]. Given the dwindling water resources and natural lands, future city plans should focus on sustainable development, protection of natural resources, and especially effective management of water resources[4]. Satellite images are a powerful tool for mapping water areas and can be used in various studies around the world[5] Recent studies have demonstrated that advanced machine learning algorithms applied to satellite imagery can effectively classify land use and land cover changes and support environmental monitoring and resource management[6]. Currently, a number of researchers are using high-resolution optical satellite remote sensing images and drone orthophotos to extract surface water [7].

Synthetic Aperture Radar (SAR), as a microwave sensor that can sense a target all day or night in any weather conditions, is of great importance in identifying resources such as coastlines, lakes, and rivers[8]. Watershed extraction is a difficult task in remote sensing due to the complexity of identifying surface objects with rich texture of spectral, spatial, radiometric, and temporal features. It has been successful in separating surface waters from their surroundings using spectral indices at the cost of knowledge of appropriate threshold values. It has been investigated by several deep learning (DL) and machine learning (ML) algorithms. In the absence of knowledge about threshold values, water extraction from remote sensing data is a difficult task. In this case, the effectiveness of both ML and DL classification from visual features to semantic categories is seen at the cost of distinguishing between water and non-water features[9]. In 2019, Hong and colleagues claimed that the Automated Sub-Pixel Coastline Extraction (ASPCE) method can accurately separate land and water areas[10]. In 2017, Yang and Du used principal component analysis (PCA) and the modified normalized differential water index (MNDWI) to improve the accuracy of water extraction [11]. Several technologies have been discussed and investigated in the past to obtain water from the ground, air, or sea. These technologies vary depending on the needs of the users. This research consists of 4 parts; the first part is an introduction, and the second part is an overview of water extraction. The third part discusses and reviews the methods and suggests the best method. Finally, the results of the studies are reviewed.

2. A review of water extraction methods from satellite images

Remote sensing is the science and art of obtaining information about any object under investigation using a device or instrument without physical contact. The advantage and superiority of satellite information over other information sources is their repetitive coverage of specific areas at specific time intervals. In remote sensing, information and data are transmitted using electromagnetic radiation (EMR). Remote sensing images are useful in issues such as mapping large areas, monitoring changes, making sound decisions, etc[12]. Surface waters, as vital resources and environmental factors, play a fundamental role in human survival and maintaining ecosystem balance .Therefore,

having accurate information about surface water distribution is absolutely essential. Remote sensing technology is of great importance for extracting and monitoring surface water changes[13]. In conditions of environmental change, water plays a very important role in the political, social, and economic aspects of countries and can be used as one of the main resources to meet the needs of humans and living organisms[14]. Urban water plays an important role in the survival and functioning of urban ecosystems. Accurate and optimal identification of urban water resources using remote sensing data is essential and important for city management and planning[15]. Accurate water resource extraction can help environmental officials better identify and understand surface water resources[16] .Water resources such as rivers and lakes are of great importance for the survival of humans, animals, and vegetation, so collecting and analyzing this information is essential to improve water resource management and environmental protection[17]. Surface water resources such as rivers, lakes, and reservoirs play a vital and irreplaceable role in natural cycles, climate, and global ecosystems[18]. Table 1 provides an overview of water extraction methods, their advantages and disadvantages:

Table 1. Overview of water extraction methods from satellite images.

Platform	**Title**	**Method used**	**Advantages**	**Disadvantages**	**Resources**
Satellite	Study of accurate extraction of blue areas from satellite images using convolutional neural network with blue indices	Normalized Difference Water Index (NDWI)	Suitable for surface waters, analyzing changes over time.	Relatively low accuracy for water extraction and sensitive to sediment, noise, simple and fast.	[17]
Satellite	Comparison of methods for extracting water bodies based on satellite data	SMDPSO+LFE	High accuracy for surface water extraction fundamentally differentiates between surface waters of different strengths.	The process of improving accuracy is relatively slow.	[16]
Satellite	Deep learning for automatic extraction of water areas using satellite images	Faster R-CNN algorithm	High accuracy for water extraction using two datasets Sentinel-2 and Landsat-8 (OLI) achieved accuracies of 98.7% and 96.1% for these two datasets.	There are some limitations that affect its location accuracy.	[19]

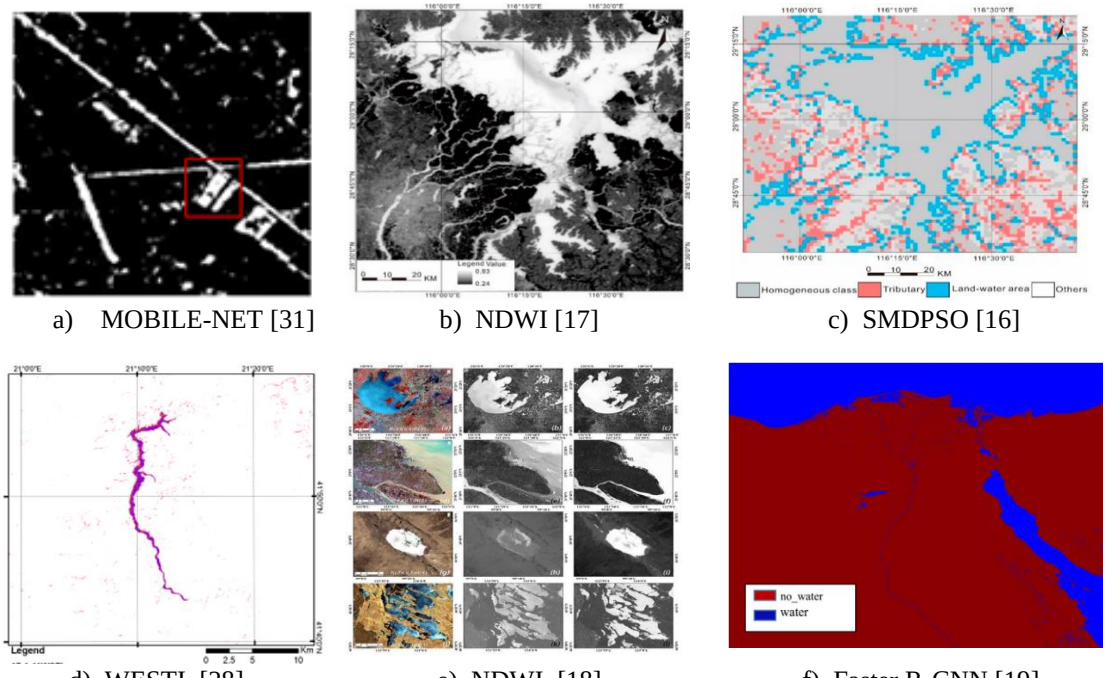
Satellite	New technique for mapping surface water using Landsat 5 images	Automatic Water Extraction Index (AWEI)	The AWEI method has high accuracy, especially in mountainous areas where there is deep shadow from the ground.	Sensitive to shade, the influence of weather conditions, errors in complex and urban areas.	[20]
Satellite	An urban water extraction method combining deep learning and Google Earth engine	RF Random Forest	For automated water extraction research on a large scale and over a long period of time.	It is not stable and reliable enough.	[15]
Satellite	Extracting water features and detecting changes using multi-temporal Landsat images.	NDWI-PCs	It simultaneously detects water level changes at two or three different times, using a fixed threshold on the selected principal component.	This method is unsuitable for detecting surface water changes.	[21]
Satellite	Large-scale extraction and mapping of small surface water resources based on very high spatial resolution satellite imagery	Water Index (WI)	Water body information extraction, high accuracy, easy to implement, and combinable with other methods.	Some water bodies cannot be extracted if they are seasonally dry.	[13]
Satellite	An effective watershed extraction method with a new water index for Sentinel-2 images	Spectral Water Index (SWI)	This method effectively extracts wide river channels and large water resources by eliminating shadow noise in urban areas.	This method cannot effectively extract narrow rivers.	[18]
Satellite	A deep learning method for extracting blue areas from high-resolution remote sensing images using multiple sensors	Deep Learning Feature Classification (DLFC)	DLFC can extract blue areas from multi-source remote sensing images automatically and quickly, and has strong performance in images with noise or cloud cover.	This method cannot effectively extract small water features with a size of less than two pixels.	[22]

Satellite	An automated extraction method for lakes and reservoirs using satellite images	LREP	Accurate extraction of water boundaries from fields, vegetation, and can be applied to different areas with high accuracy.	Sensitivity to shadows and inability to properly identify muddy waters.	[23]
Satellite	Coastal band spectral fusion for extracting water areas using Landsat 8 images	Double Band Normalized Difference Water Index (DBNDWI)	High accuracy and suitable for detecting water level changes over different time periods.	Sensitivity to muddy water and confusion with wet surfaces	[24]
Satellite	Extracting water-related features from reflectance data and principal component analysis of Landsat images	Multivariate Linear Discriminant Analysis (LDA)	Their multivariate approach performs better with a higher degree of accuracy in identifying water bodies where the data is linearly separable, and is still suitable for small-volume data.	This method is not suitable for large amounts of data.	[25]
Satellite	Extracting water level changes of the Miankaleh International Wetland from Landsat-8 satellite images and integrating supervised classifiers	Artificial Neural Network (ANN)	Suitable and highly accurate method for water extraction and suitable for image classification.	It takes a lot of processing time and requires a lot of training.	[14]
Satellite	An automatic coastline extraction method from SAR images using DeepLab-v3+ and its adaptability	DeepLab-v3+	High accuracy in water extraction, accurate determination of land and sea boundaries and effective for coastline extraction.	Long processing time, requires a lot of training and high calculations.	[26]

Satellite	Investigating the performance of ultra-high resolution remote sensing images in coastline segmentation using deep learning-based methods	LinkNet	In water extraction, it showed results that were closer to reality, smaller in size, and more efficient.	This method requires powerful hardware and reduces the noise if the images are noisy.	[27]
Satellite	Multi-scale feature extraction network with machine learning algorithms for extracting water bodies from remote sensing images	Multi-scale Feature Extraction Network (MSFEN)	Surface water body extraction using pixel-level features and machine learning (ML) enables accurate water body extraction.	This method is sensitive to noise, requires a lot of training data, and is time-consuming.	[9]
Satellite	Water extraction technique in mountainous areas from satellite images	Water Extraction Surface Temperature Index (WESTI)	It is used in mountainous and cold regions to remove noise components and has better performance in identifying shallow waters.	This method is not suitable for deep waters and warm areas.	[28]
Satellite	A method for extracting small water areas based on DEM and remote sensing images	Corrected Normalized Difference Water Index (CNDWI)	It is a combination of MNDWI, NDWI, and AWEI indices that covers the weaknesses of each and accurately identifies the boundary between water features.	This method is of low quality in standing water and requires extensive processing.	[29]
Satellite	A review of lake extraction from optical remote sensing satellite data with a special focus on cryospheric lakes	Decision Tree (DT)	For extracting lakes, simple and possible to use combined features.	Less accurate than other methods, requires more analysis.	[30]
Satellite	A lightweight deep neural network method for extracting water bodies from high-resolution multi-sensor remote sensing images	Convolutional Neural Network (CNN)	It has high accuracy for water extraction and is capable of learning from large, complex data and requires less computation.	It requires a lot of data, is time-consuming, and involves complex calculations.	[31]

3. Discussion and review of methods

In this article, several methods of water extraction from satellite images have been reviewed, including the best method for examining water extraction from satellite images. Given the importance and study of water extraction, various methods have been carried out to examine water extraction from satellite images .The methods that have been investigated are: Modified Normalized Water Difference Index (MNDWI) method, Water Ratio Index (WRI) method, Normalized Difference Water Index (NDWI) method، SMDPSO+LFE method ,Faster R-CNN method, Automatic Water Extraction Index (AWEI) method, Support Vector Machine (SVM) method ,Random Forest (RF) method ,NDWI-PCs method, Water Index (WI) method, Deep Learning Feature Classification (DLFC) method, Local Radiative Energy Pattern(LREP), The Double Band Normalized Differential Water Index (DBNDWI), method Linear Discriminant Analysis (LDA) method, Artificial Neural Network (ANN) method, DeepLab-v3+ method ,LinkNet method, Multi-scale Feature Extraction Network (MSFEN) method, Water Extraction Surface Temperature Index(WESTI), Multilayer Perceptron(MLP), Corrected Normalized Difference Water Index(CNDWI) Decision Tree Method (DT), and the convolutional neural network (CNN) method All of these methods were examined, each of which has its own advantages and disadvantages. As can be seen in Figure 1; the Faser R-CNN method performs better and provides the most accurate results compared to other methods.



a) MOBILE-NET [31] b) NDWI [17] c) SMDPSO [16]

d) WESTI [28] e) NDWI [18] f) Faster R-CNN [19]

Fig. 1. Comparison of water extraction methods from satellite images

The Modified Normalized Difference Water Index (MNDWI) method is one of the classical methods and spectral indices. Which has the ability to reduce and eliminate noise and is used in water level monitoring, especially in areas where non-aquatic cover is high,

it is fast and easy to calculate. Normalized Difference Water Index (NDWI) method This method is still one of the classic methods and spectral indices, which have relatively low accuracy for extracting water in urban or shaded areas, sometimes it also identifies wet vegetation instead of water, it is simple and fast[17]. The Double Band Normalized Differential Water Index (DBNDWI) method is also one of the classical methods and spectral indices, which has high accuracy and is suitable for identifying water level changes in different time intervals. Artificial Neural Network (ANN) method This method is one of the machine learning methods, which is suitable and has high accuracy in extracting water, but it requires a long time to train the mole. Support Vector Machine (SVM) method This method is also one of the machine learning methods, It has high accuracy for extracting water from satellite images with noise and good separation between classifications even if they overlap. Random Forest (RF): This method is also one of the machine learning methods, which is not stable and reliable enough for automated water extraction research on a large scale and over time. Deep Learning Feature Classification (DLFC): This method is also one of the deep learning methods, which can extract water areas from multi-source remote sensing images automatically and quickly and has shown strong performance in images with noise or cloud cover. And one of the methods to investigate water extraction is an advanced deep learning method for image segmentation, DeepLab-v3+, this method has high accuracy for extracting water from satellite images and the ability to investigate the identification of water coastlines and extract water areas from other phenomena [26]. The Faster R-CNN method is one of the deep learning methods, which has high accuracy for water extraction using Sentinel-2 and Landsat-8 (OLI) datasets[19]. The goal was to improve the extraction accuracy in complex areas using spectral and textural features. After examining the results, it was shown that the Faster R-CNN method performed better than other methods for extracting water from satellite images. Figure 2 presents a set of methods for the detection and extraction of water resources from satellite imagery. These methods have been generally derived from the reviewed articles and, after being organized, are presented in the form of a structured diagram.

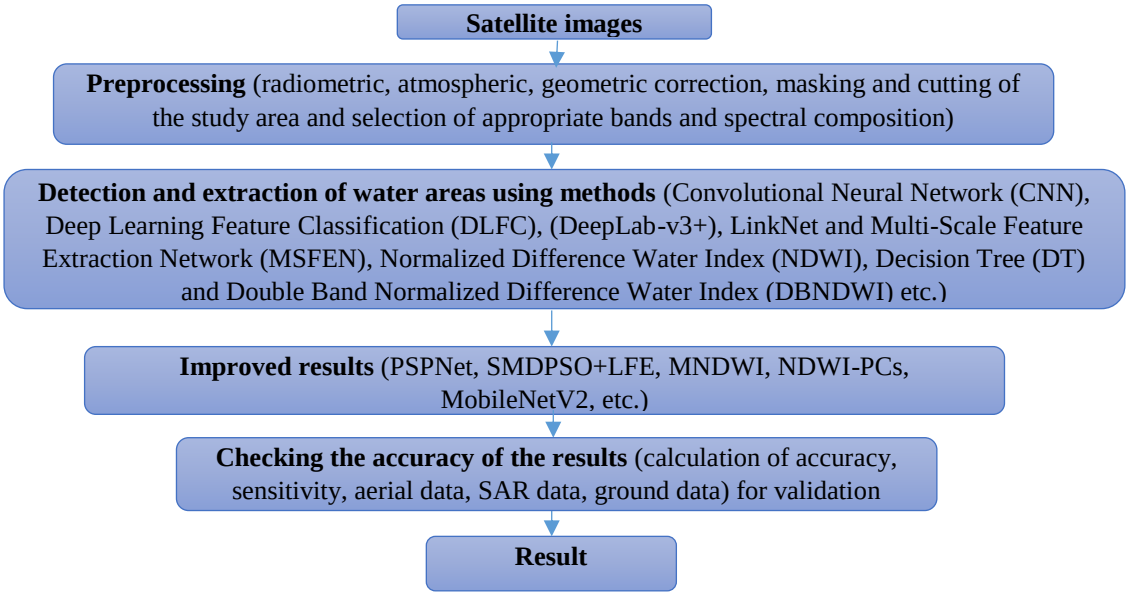


Fig. 2. Water extraction detection methods

4. Conclusion

Water constitutes an important part of human life and living organisms, Its sources include seas, lakes, wells, etc. Proper research and identification of these important sources is of great value to human health. Which we studied. Therefore, in this study, methods for extracting water from satellite images have been investigated; methods for extracting water in different sectors have been investigated .Deep learning includes DeepLab-v3+, MSFEN, U-net and Faster R-CNN methods, which have the ability to accurately identify different water shapes, are suitable for large scales and time changes, and have the ability to work with complex images, but working with these methods requires a lot of training data, requires powerful hardware and more processing time. Classical methods and spectral indices include; NDWI, MNDWI, and AWEI methods are simple and fast, It does not require training data and can be implemented in common software such as ArcGIS, QGIS, and ENVI. But it is sensitive to noise, shadow and has lower accuracy than machine learning. Machine learning methods include SVM, RF, and DT methods, which have high accuracy if properly adjusted, are suitable for various areas, and require less resources than deep learning. But they require training data and expertise to adjust the model. In this study, a large number of articles have been reviewed, after which the methods were compared, and the best method was introduced. Although all these methods have their advantages and disadvantages, one of the methods that has given the best results of the Faster R-CNN method use a more sophisticated architecture that can accurately locate objects and work on two datasets, including blue-field images from Sentinel-2 and Landsat-8 (OLI) satellite images, while the other methods can be applied to one dataset each. The results showed that this method is better for extracting water from satellite images and can identify water more effectively and accurately. In the future, researchers can use this method to extract water from satellite images.

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