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Water Detection Based On Classical Computer Vision Remote Sensing Images

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ABSTRACT

The ability to detect water bodies is a major operation in remote sensing image processing, as it is critical in flood control, water resources, environmental change, farm irrigation planning and ecological conservation. As satellite imaging resolution continues to improve, it has become more difficult to extract water regions with robust and accurate results on complicated backgrounds. In spite of the impressive performance over the past years, the deep learning-based segmentation methods have a limited range of practical use due to their dependence on large-scale labeled datasets, high computational cost, and inability to be interpreted. Conversely, the classical methods of computer vision are still appealing because of their transparency, low level of computation, and little data dependency. This paper suggests a classical image processing-based system of detecting water bodies and generating standard binary masks. The suggested technique combines the Normalized Differences Water Index (NDWI) and blue-channel augmentation to generate a water likelihood map as probabilities of water occurrence. Gaussian smoothing, adaptive thresholding and morphological refinement are used with the aim of maintaining spatial consistency and structural integrity of the water regions that have been detected. The whole system is in the MATLAB and it allows interactive and continuous input of images.

Four RGB scenes from Lake Van, Lake Tana, Hongze Lake, and the Zaling–Eling Lake region were used as a small feasibility set, and the estimated water coverage ranged from 15.85% to 41.26%. Because the exported images do not retain native sensor metadata and no independent pixel-level reference masks were available, these results are treated as a feasibility demonstration rather than a complete accuracy benchmark. The method therefore provides a transparent and training-free baseline, while broader claims of accuracy and generalization require evaluation on georeferenced imagery with independent ground truth.

INTRODUCTION

Remote sensing images have emerged to be amongst some of the most valuable data in earth observation on a large scale, environmental surveillance, and analysis of geographical information. As the satellite platforms, including Landsat, Sentinel, and commercial high-resolution satellites, are developed at an alarming rate, huge amounts of remote sensing data are generated day after day. These data are useful information in knowing surface dynamics, land use pattern and the distribution of natural resources. Water bodies are important types of land cover that ensure the ecological balance, climate regulation, biodiversity, and other human activity maintenance. Precise and dependable capability of identifying water bodies using satellite images is vital in a broad scope of applications such as flood mapping, drought surveillance, reservoir control, agricultural irrigation planning and wetland protection. Nevertheless, extraction of water bodies is a difficult endeavor because the appearance of water is significantly different. Water surfaces may be of various types depending on depth, turbidity, bottom reflection, and environmental condition with deep blue to light blue, greenish, or even brownish. In addition, other factors like atmospheric scattering, sun glint, sensor noise and cloud shadows do not make the segmentation process any easier. The conventional water extraction techniques are mainly dependent on threshold-based regulations or hand-made spectral indices. The most popular of them, the Normalized Difference Water Index (NDWI) suggested by McFeeters (1996), is one of them. It takes advantage of the reflectance difference between the green and near-infrared bands in order to increase the water features. Subsequently, Xu (2006) came up with the modified NDWI (MNDWI) to eliminate constructed regions and enhance the accuracy of the detection. Index-based techniques are cheap to compute and interpret, but cannot work well in complicated situations, like an urban setting or a murky water column. During recent years, the application of deep learning models to the process of water body segmentation has become widespread. CNNs like U-Net and DeepLab have proven to be very successful in the semantic segmentation tasks. However, these models are very intensive in terms of labeled training data and even computational resources. In addition, they are black box in nature and hence, it is challenging to elucidate their choices, a factor that constrains their implementation in certain operational platforms where transparency and explainability is paramount. Classical computer vision methods, on the other hand, are appealing because they are simple, interpretable and low-cost to compute. Such approaches are particularly applicable in situations when the training data is scarce or in such cases as the process should be performed in real time. Nevertheless, crude classical methods, e.g. direct thresholding of pixel values, usually yield noisy and discontinuous outcomes. They are also not spatially coherent and physically realistic. In order to solve these problems, this paper will present a classical frame of the water body detection and standard binary mask generation using image processing. The proposed approach combines several spectral information sources and represents the water presence as a probabilistic map rather than using one feature. A spatial smoothing and structural refinement are then used to guarantee consistency and continuity of the regions identified. The purpose of such a design philosophy is to bring together the efficiency of the classical design with better robustness and stability.

The key findings of the paper are as follows:

- A probabilistic water likelihood modeling framework that integrates NDWI and blue-channel enhancement.
- A structurally constrained post-processing pipeline based on Gaussian smoothing, adaptive thresholding, and morphological operations.
- An interactive MATLAB-based implementation that supports continuous image input and real-time visualization.
- A four-scene feasibility evaluation with explicit limits on the evidence that can be claimed.

LITERATURE REVIEW

Detection of water bodies has been a research issue of close interest in remote sensing and computer vision over the past decades. The first attempts were mainly based on spectral features and threshold-related principles. Normalized Difference Water Index (NDWI), suggested by McFeeters (1996) is one of the most prominent ones. NDWI aims at improving water features as it takes advantage of the reflectance gap between the green and the near infrared bands. Water commonly reflects more at the green band and absorbs heavily at the near-infrared band and thus NDWI is effective in bringing out the open water bodies. But McFeeters (1996) also observed that NDWI can give false positives in urban regions where man-made surfaces have similar spectral characteristics. To solve this problem, Xu (2006) suggested the Modified Normalized Difference Water Index (MNDWI) that substitutes the near-infrared band by the mid-infrared band. Such alteration is highly effective in silencing the built up environment and enhances the accuracy of water detection in the urban surroundings. Subsequent research also improved spectral index based techniques by incorporating multiple indices, including the Automated Water Extraction Index (AWEI) developed by Feyisa et al. (2014), and that is designed to minimize shadow and dark surface interference.

Despite the fact that spectral index-based techniques are cost effective and simple to interpret, they are highly dependent on the presence of specific spectral bands. RGB imagery is the only available imagery in most practical applications, particularly with drones of low cost and commercial satellite platforms. In order to address this drawback, scholars have assessed visible-band-based estimates of water indices.

Du et al. (2016) compared the performance of Landsat-8 imagery in water mapping via visible bands and proved that it is still possible to obtain a satisfactory performance under some conditions. These techniques are however usually vulnerable to atmospheric effects and changes in illumination.

Other spectral indices aside, region-based as well as texture-based approaches have been used in water segmentation. Regions growing methods take advantage of the geographical continuity to extend the water areas based on seed points (Gonzalez & Woods, 2018). Although such techniques may create smooth areas, they need appropriate selection of seed points and criteria of similarity. Texture-based methods examine local patterns with the help of local binary patterns (LBP), or gray-level co-occurrence matrices (GLCM). But even such features of texture are not always adequate to discriminate between water and smooth non-water surfaces.

Improving segmentation results has been an area where morphological image processing has been extensively applied. Soille (2003) presented an elaborate system of the morphological operations dilation, erosion, opening, and closing. Such operations are notably useful in eliminating small noise areas, filling in holes and imposing structural integrity. Morphological post-processing is commonly used in water detection applications to enhance unrefined segmentation results and provide physical plausibility.

One of the most basic forms of segmentation has remained thresholding. Otsu (1979) came up with a global adaptive thresholding algorithm, which maximizes inter-class variance. This method has been widely applied because of its simplicity and strength. Global thresholding can however fail where the lighting is not uniform across the image. To overcome this, adaptive and local thresholding techniques have been suggested but tend to cause more complexity.

During the last few years, deep learning has emerged as the leading paradigm of semantic segmentation. The water body segmentation tasks have been successfully addressed via fully convolutional networks (FCNs), U-Net, SegNet, and DeepLab (Ronneberger et al., 2015; Chen et al., 2018). Such models are capable of learning detail hierarchical characteristics and are very accurate. They however need big annotated datasets and extensive computational resources. In addition, their judgments are hard to decipher, and thus they cannot be used in certain critical tasks like disaster recovery and environmental surveillance.

A number of hybrid methods are trying to merge the classical and learning based methods. As an example, deep models are normally fine-tuned with morphological operations or conditional random fields (CRFs) to enhance local consistency. This implies that classical post-processing methods are still useful in the current pipelines. Although the advancement of learning-based methods has taken place, classical methods have a great practical importance. They are mainly applicable in applications that have low latency, transparency, and data dependency needs. Nevertheless, classical approaches in their direct application are frequently weak. Thus, recent studies have been conducted on the improvement of classical pipelines through the introduction of probabilistic modeling, multi-feature fusion, and structure limits. These methods estimate continuous likelihood maps and refine them progressively in place of taking hard decisions at early stages. This philosophy of design is the basis of the proposed approach to this study. The proposed framework attempts to fill the divide between the simplicity and robustness by incorporating spectral cues, probabilistic modeling, and morphological refinement. It attempts to keep the benefits of classical methods and overcome the traditional drawbacks, including the sensitivity to noise levels and the lack of structural consistency.

METHODOLOGY

Conventional methodologies of water body detections largely use a feature extraction- threshold segmentation-post processing correction paradigm. The primary issue with this method is that, once the misclassification of the item has been made at the initial stages then the steps that follow it cannot adequately rectify the situation.

Simple threshold segmentation may lead to fragmentation, boundary discontinuities and local false detections especially in cases of drastic changes in illumination or where the background is complex or when spectral distribution of water is uneven. Thus, the present paper suggests a water body detection model, which is grounded on a probabilistic model and multi-level spatial constraints, with attention paid to general structural stability.

Design Concept

The approach used in this paper, in contrast to the traditional ones, which directly provide binary outputs, is to first create a continuous representation of probability of water bodies, and finally converts to the final mask by the use of progressive constraints. The point is that natural water bodies are not characterized with an entirely binary distribution of space, but they have loose boundaries, gradient areas, and local uncertainties. Direct hard segmentation is easily subject to oscillations of its boundaries and structural fragmentation. Thus, the water body detection problem is re-posed in the current paper as a continuous probability modeling problem assigning each pixel of the image a probability of being part of water and applying similar constraints to the probability in a consistent manner across space. The result of the convergence of the model to the final binary mask is not the direct result of the model, but the convergence of the probability representation with multi-level constraints.

Spectral feature modeling and the role of NDWI

One of the traditional water enhancement indices, NDWI is based on the fact that water is highly reflective in the green band and less reflective in the red or near-infrared bands and thus the water response is enhanced by normalized difference. Although NDWI works very well on most of the natural scenes, its stability is also influenced by the water color variations, as well as the background interference. The green channel response can be significantly low in water bodies with dense algae or suspended material leading to a change in the distribution of the NDWI values. At the same time, high NDWI responses can occur in other non-water regions (wetlands, dark vegetation, or shadows) as well, which results in false positives. So NDWI in this paper is not the ultimate criterion, but it is one of the essential features sources, but not the only one in the probabilistic water modeling.

Blue Channel Compensation Mechanism

Multiple sets of remote sensing images can be observed which indicate that deep water areas can and frequently have a clear blue attribute. This is due to the fact that water bodies absorb longer wavelengths more than shorter wavelengths are scattered. However, in contrast to that, most non-water features respond less in the blue channel. Thus, the blue channel is proposed as an alternative channel in this paper as a compensating feature of NDWI. The intuitive meaning of this design is that in case NDWI is unsuccessful in some situations the blue channel can be used to supplement discriminative information hence resulting in better robustness.

In this paper, a joint water body probability representation is built by normalizing NDWI and blue channel and weighted fusion: This combination technique is not merely a mere superposition but rather it is founded on the complementary principle: NDWI is highly responsive to a majority of natural water bodies and the blue channel is more steady in deep/dark water bodies. The two can be used together in order to minimize the risk of the failure of any feature.

```
% ================================
% Step 3: Blue channel cue
% 步骤3：蓝色通道线索
% Clear water often appears strong in blue channel
% 清澈水体在蓝色通道通常较强
% ================================
Blue_n = mat2gray(B);
```

Figure 1.Blue Channel code

Spatial Consistency Modeling: Gaussian Smoothing.

Sources of noise in remote sensing images are complicated since they consist of sensor noise, atmospheric interference and local illumination variation. Direct probability map thresholding usually produces a large number of isolated pixels and pieces. Thus, this paper presents the use of Gaussian smoothing in the probabilistic modeling phase to limit the water bodies distribution based on a spatial consistency viewpoint. In effect, Gaussian smoothing is a weighted average of local neighborhoods which makes regions with similar probability values tend to coherently structure. This method is theoretically consistent with the hypothesis of spatial continuity in natural water bodies (i.e., an assumption of real water bodies), i.e. that real water bodies are usually continuous distributions not discrete, isolated point structures.

Adaptive threshold

Once a smoothed probability map has been obtained, this paper uses an adaptive thresholding technique to convert the probability map into a first binary mask. The adaptive threshold is able to automatically adjust the boundaries of the segmentation with reference to the current image and its statistical distribution, which reduces the impact of the manual parameter tuning. It is also necessary to underline the fact that threshold segmentation is not the final decision in the context of this paper, but only the half-way step in the process of structural optimization. Its primary role is to give approximate estimation of the water body region as the basis of the further morphological processing and connectivity analysis.

Geometric significance of morphological structure optimization. In nature, natural bodies of water usually have geometric features which are not topologically discontinuous or closed. Nevertheless, the segmentation first results usually have problems of holes, breaks and isolated noise. To solve them, this paper proposes a chain of morphological operations to streamline the structure. Closure operations relate neighboring areas and seal internal cracks; hole fillings recover the integrity of the interior water body; and opening operations suppress small scale noise. These are not mere empirical corrections, but restrict the results on a geometrical level so that they are less inconsistent with morphological properties of actual water bodies. The connectivity constraint used here is a largest-connected-component rule. After morphological cleaning, connected foreground regions are labeled and the component with the greatest area is retained. This suppresses isolated false detections, but it can also remove valid water bodies when several disconnected lakes occur in one scene; the Zaling–Eling example illustrates this limitation.

MATLAB System Implementation

In a bid to ascertain the possibility and sustainability of the proposed approach in the real world setting, the paper assembles a full water body detector system on the MATLAB environment. Not only this system implements the multi-stage water body detection procedure that was suggested by the present paper, but also allows interactive input of various images, visualization analysis, and quantitative evaluation of the findings, which is a good foundation to further experiments and comparative research.

The overall architecture design of the system is provided.

The whole system is designed in the form of a modular structure, comprising mostly of an image input module, a feature extraction module, a probabilistic modeling module, a spatial smoothing module, a binarization module, a morphological post-processing module, a connectivity analysis module, and a results visualization module. The modules interrelate with each other based on standardized data interfaces in creating an entire processing pipeline. The two benefits of this modular design are: first, the comparative independence of each module and hence facilitates future expansion and enhancement; second, the structure of the system is clear, which can understand and replicate, which helps enhance the research transparency and reproducibility.

Multi image interactive input mechanism.

To suit the requirements of experiments under the multi-scenario, the system employs the interactive file selection process, where users can continuously feed the system with various images of remote sensing to be processed. This design is more realistic to the real-life application situation when compared to conventional batch processing on single images and allows making comparative analyses of the data in various regions and time intervals rapidly. Not only does this mechanism enhance the efficiency of an experiment, but also this gives convenient circumstances when the images are to be subjected to further qualitative analysis at the image-by-image scale. The detection results of various images on the same interface can be compared in a more intuitive manner by users and, thus, more fully assess the generalization capability of the algorithm.

Strategies of feature extraction and normalization.

During the feature extraction phase, the system splits the input image into the RGB channels and then uses the resulting image to compute the NDWI index. To avoid the variation in the dynamic range of various images, both the NDWI and the blue channel of the papers are normalized, thus the distribution of the NDWI and the blue channel is uniformly mapped to the range (0,1).

```
% ================================
% Step 2: NDWI (Normalized Difference Water Index)
% 步骤2: 归一化水体指数 NDWI
% Water usually reflects more in Green than Red
% 水体在绿色通道的反射通常高于红色通道
% ================================
NDWI = (G - R) ./ (G + R + eps);
NDWI_n = mat2gray(NDWI); % Normalize to [0,1] / 归一化到 [0,1]
```

Figure2.NDWI code

Normalization is also very important at its introduction. In the case of a direct fusion of the original features, the variations in numerical values of the various features will result in one feature prevailing over the other features in the general outcome hence undermining the efficacy of such multi-feature fusion. With normalization, all features will contribute weight space equally on the fusion step, which has a good ground to proceed with weighted modeling.

Construction of water body probability maps

The system uses weighted fusion strategy in order to integrate NDWI and blue channel information to single water body probability map. This probability map is basically a continuous value field and indicates the probability of the relative likelihood of each pixel that it is a part of a water body. In comparison to the direct output of binary results, the probability map has a more powerful expression capacity, retaining local uncertainty data and forming a foundation of downstream spatial constraints. The design removes the error accumulation issue of traditional methods that is due to premature decision-making.

Spatial smoothing module

The system generates the probabilistic graph, and then smoothing is done using Gaussian to improve spatial consistency. This step is not merely aimed at smoothing out the graph, but actually at the statistical minimization of the effects of local outliers on the general structure. To find a balance between the smoothing of noise and accuracy of the boundary, a scale of the Gaussian kernel is experimentally optimized. Over smoothing causes blurred edge, and under smoothing does not suppress noise, thus the choice of appropriate parameters has a large effect on the performance of a system.

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```
% ================================
% Step 7: Morphological cleaning
% 步骤7: 形态学清理
% Fill holes, remove noise, smooth edges
% 填洞、去噪、平滑边界
% ================================
bw = imclose(bw, strel('disk', 6)); % Close gaps / 闭运算
bw = imfill(bw, 'holes');           % Fill holes / 填充空洞
bw = imopen(bw, strel('disk', 3));  % Remove noise / 去除小噪声
```

Figure3.morphology code

Adaptive threshold segmentation.

The system uses Otsu adaptive thresholding algorithm to binarize the probability map which has been smoothed. The segmentation threshold is automatically determined in this process, by maximizing the variance between the classes, instead of being subjectively determined by parameter tuning. It is important to note that thresholding is merely utilized to create the starting mask and not the final product as discussed in the context of this paper. Its central operation is to map continuous probability representations onto structured regions to offer a basis of morphological and connectivity analysis performed later.

The threshold is recalculated for every input image from the histogram of the smoothed water-likelihood map. Otsu's rule selects the value that maximizes the between-class variance of the two groups separated by the threshold. No scene-specific threshold is entered manually. Per-image normalization of NDWI and the blue channel is completed before this step, so the decision responds to the radiometric range of each image. This adaptation is global rather than local: a single threshold cannot fully compensate for strong spatial changes in illumination, shadow, or mixed shoreline pixels. The fusion, Gaussian, and morphological parameters were held fixed for the four reported scenes.

Morphological post-processing/connectivity analysis.

To make the mask even more geometrically realistic, the system incorporates a sequence of morphological operations, such as closing, hole filling and opening operations. These operations also limit the segmentation results at the structural level, and therefore it is more consistent with the spatial peculiarities of actual water bodies. Moreover, the system uses the connected component analysis to filter the entire candidate water body regions retaining the largest connected region as the final water body mask. This technique has the ability to remove scattered false detection areas and will increase the stability of the results greatly.

Visualization and Quantitative Evaluation Unit.

The system also provides the original imagery, water body probability maps, final binary mask, and overlaid visualization results to help in the analysis of results. This multi-view presentation gives the user an opportunity to intuitively assess the efficiency of every stage of processing. In addition to this, the system estimates water coverage as a quantitative measure to determine the relative percentage of water areas in various situations. This has been a very important indicator to water resource assessment as well as monitoring of change.

```
% Step 11: Display results
% 步骤11: 结果可视化
% ================================
figure('Color','w','Name',fileName);

subplot(2,2,1);
imshow(I);
title('1. Original / 原始图像');

subplot(2,2,2);
imshow(water_score, []);
title('2. Water Likelihood Map / 水体概率图');

subplot(2,2,3);
imshow(bw_clean);
title('3. Binary Mask / 水体二值掩膜');

subplot(2,2,4);
imshow(overlay);
title(['4. Result (Coverage: ' num2str(coverage,'%.2f') '%) / 检测结果']);
```

Figure4.Visualization system

Experimental results

In order to thoroughly test the suitability of the suggested method in various water body morphologies, water color distributions, and background complexities, this paper picks several representative images of remote sensing of lakes as experimental objects, among them Lake Van, Lake Tana, Lake Hongze, and Zaling Lake-Eling Lake region. These lakes have a great variation in terms of geographical position, climatic conditions, water constituents and types of land surface surrounding them making them very representative. In the experiments, parameters of all images were fixed to prevent the interference of manual adjustment of parameters in the results. Both experiments show results of the original image, water body probability map, final binary mask, and visualization of the results of the overlay, and discuss in a systematic manner the water enhancement effect, the spatial continuity, the rationality of a boundary, and the distribution of false detection spots.

Dataset and source information. The evaluation set contains four RGB image scenes, one for each reported test area. The figures retain visible Google Earth/Google imagery attribution, and the tests were performed on the RGB exports available to the study. The geographic settings and scene-specific challenges are summarized in Table 1.

Table 1. Evaluation scenes and available image metadata.

Scene and geographic setting	Source and sample count	Available resolution metadata	Main test condition
Lake Van, eastern Türkiye	Google Earth/Google RGB imagery export; 1 scene	Native sensor, acquisition date, and ground sampling distance were not retained	Large deep-blue water body, bright terrain, and dark land patches
Lake Tana, northwestern Ethiopia	Google Earth/Google RGB imagery export; 1 scene	Native sensor, acquisition date, and ground sampling distance were not retained	Green/turbid water, wetlands, farmland, and a weak shoreline contrast
Hongze Lake, Jiangsu Province, eastern China	Google Earth/Google RGB imagery export; 1 scene	Native sensor, acquisition date, and ground sampling distance were not retained	Turbid water, farmland, canals, wetlands, and built structures
Zaling–Eling Lake region, Qinghai–Tibet Plateau, China	Google Earth/Google RGB imagery export; 1 scene containing two lakes	Native sensor, acquisition date, and ground sampling distance were not retained	Bright bare soil, high reflectance, mixed shoreline pixels, and disconnected lakes

The four composite result figures embedded in this manuscript are 1267 × 963 pixel screen exports, and their input panels were resized by the MATLAB display window. These display dimensions are not a native spatial resolution and cannot be converted to metres per pixel. This missing provenance is a limitation of the present study. Future tests should preserve the original georeferenced files together with platform, sensor, acquisition date, coordinate reference system, pixel dimensions, and nominal ground sampling distance.

Quantitative evaluation protocol. For a reference mask, let TP, TN, FP, and FN denote pixel counts for true water, true non-water, false water, and missed water. Accuracy is (TP + TN)/(TP + TN + FP + FN), precision is TP/(TP + FP), recall is TP/(TP + FN), F1-score is 2 × precision × recall/(precision + recall), and intersection over union (IoU) is TP/(TP + FP + FN). Values should be calculated for each scene and then reported as the mean and standard deviation across scenes. The current four RGB exports do not have independently delineated reference masks, so these five segmentation metrics cannot be calculated without inventing labels. They are therefore defined here as the required protocol for a subsequent benchmark, rather than being reported as unsupported results.

Discussion of the findings of the Lake Van experiment.

Lake Van is a common inland lake of deep water and the water of the lake usually has a separate deep blue color in remote sensing images and the area of water is vast and the shore is not too muddy. This feature renders it a significant sample to establish the performance of the algorithm in ideal conditions. Regarding the original image, one can see that the main territory of Lake Van is distinctly different in color and brightness with the rest of the land territory. There are however some shadowed areas and dark bare soil near the lake shore; they possess a similar grayscale distribution as the water body and are therefore most likely to be false detected in standard thresholding techniques. As evident in the water probability map, the continuous and consistent high distribution response is well displayed in the main lake region whereas the non-water regions are nearly suppressed. This signifies that the combination of NDWI and the blue channel can deliver a fairly great complementary impact in this case. The water response is further improved in the deep water area particularly by introducing the blue channel which contributes to the probability distribution being more concentrated. The local noise of the probability map is largely reduced following Gaussian smoothing, and the structure of the water area is more coherent in general. This property is significant in the future thresholding segmentation since the results of segmentation are less likely to be fragmented. The resulting binary mask has been found to have a good continuity and integrity in its geometry. There are no jagged edges or breaks that can be seen in the lake shore boundary and it is natural. This proves that morphological post processing is an important part of repairing local structural defects. In terms of false detection distribution, a few misjudgments are predominantly located in the highly populated land patches, however, its spatial scope is small, and its contribution to the total coverage measures is small.

All in all, the technique has the potential to create typical and stable water masks within the Van Lake scene, which confirms its efficiency in optimal circumstances.

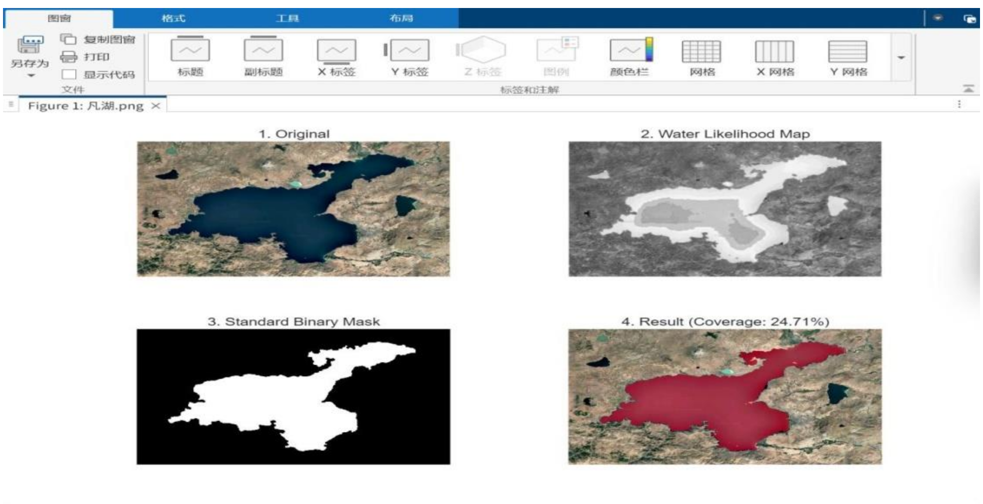

Figure 5. Lake Van processing results.

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Discussion of the data of the Lake Tana experiment.

There is a complex background of Lake Tana as the area is positioned in a high-altitude zone, and the wetlands, farmlands, and sparse vegetation are a major factor affecting the lake. Moreover, the water in this region is very green and this presents a challenge to the traditional NDWI-based approaches. In the original image, one can see that sections of Lake Tana build up to be almost similar in color to the nearby wetlands, and the boundary between the land and water is blurry. This is when a single spectral index may not be able to correctly differentiate. Our proposed method is highly distributed to the main water area in the water probability map whereas the response to the wetland areas is much lower when compared to the actual water areas. This suggests that the blue channel compensation mechanism is an important factor in this case. Following spatial smoothing, the probability distribution of the water area is highly continuous and in effect discourages interference by the local outliers. This gives a better platform on which threshold segmentation can take place. The last binary mask still has good overall structural integrity, neither big breaks nor holes. The geometry of this mask is more natural than the traditional methods making the geometry of the boundary boundaries of the continuity characteristic of the real lake shore.

However, slight false detections still exist in local wetland areas. This indicates that the classical method still has certain limitations when the spectral characteristics of water bodies and wetlands highly overlap. However, overall, the method still exhibits strong robustness under complex background conditions.

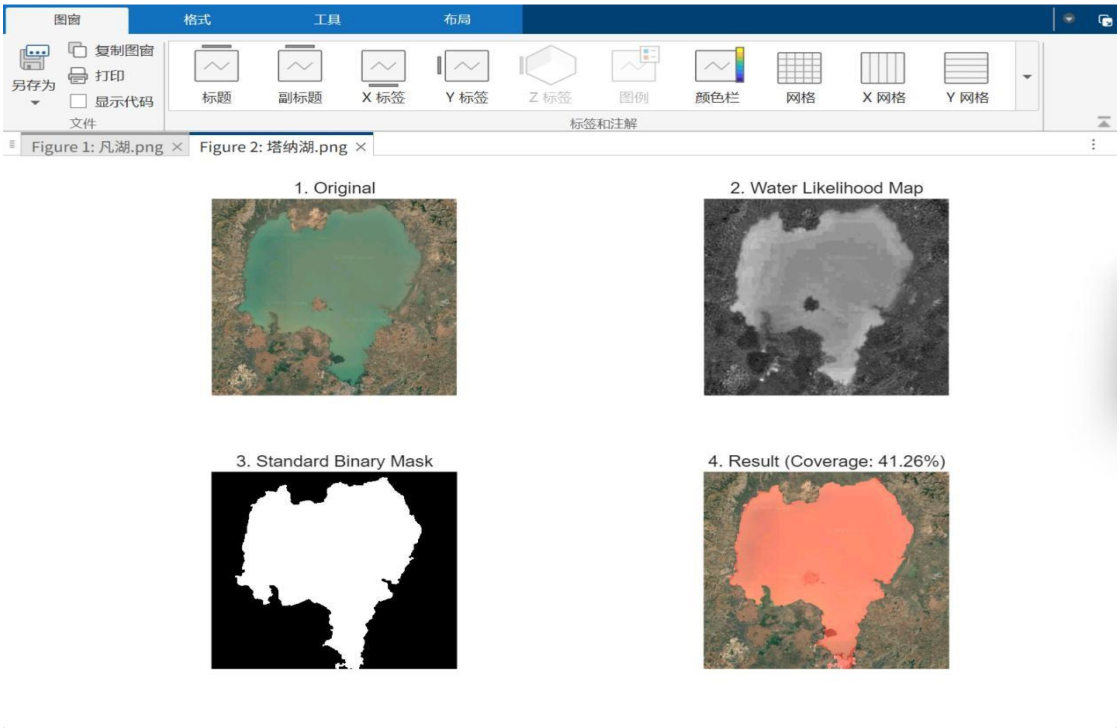

Figure6. Tana Lake processing result

Experimental Results Analysis in Hongze Lake.

The Hongze lake is found in the eastern plains of China with a complex terrain with a large farmland, man-made structures, a series of waterways and wetlands. Such environment imposes more requirements on the algorithms of water body detection: on the one hand, the water color is highly influenced by suspended matter and algae, which have a greenish or yellowish-green shade; on the other hand, there are numerous regions on the surrounding surface that share the spectral characteristics of the water body, including paddy fields, wetlands, as well as shaded areas. The original imagery can be seen to show that the body of Hongze Lake is relatively clean, however, the water-land interface around the lake shore is indistinct, with observable spectral mixing in certain regions. These regions tend to be classified as water or land in the conventional thresholding procedures resulting in unstable borders. In the probability map of water body created by the method used in this paper, the main lake area continues to have a high response value, whereas the surrounding farmland and wet land areas have much lower response values. This suggests that the combined modeling of NDWI and blue channel can to a certain degree differentiate between the mobile water bodies and the water-like regions. It is especially worth noting that in certain waters that have a lot of suspended matter, the NDWI response becomes weak, and the blue channel provides effective compensation, leaving the continuity of the overall probability distribution intact. This effect once again confirms the need of having multi-feature fusion in complicated scenes. Local discontinuities in the probability map are removed effectively after the Gaussian smoothing, which leaves a more coherent structure of the water area. This is essential in case of thresholding then after, otherwise many single tiny areas will be generated. The generated binary mask is significantly consistent with the true lake boundary in its overall form. The coast is intact and continuous without any apparent structural damage. The mask is visually effective in giving a reflection of the space distribution of the actual body of water. False positive of a few is mostly found in the coastal wetlands and paddy fields. These regions are very similar spectrally to the water body and a typical difficulty in the conventional approaches. These false positive regions are however tiny in size and are scattered and the effect they have on the overall result is minimal once maximum connectivity constraints have been imposed.

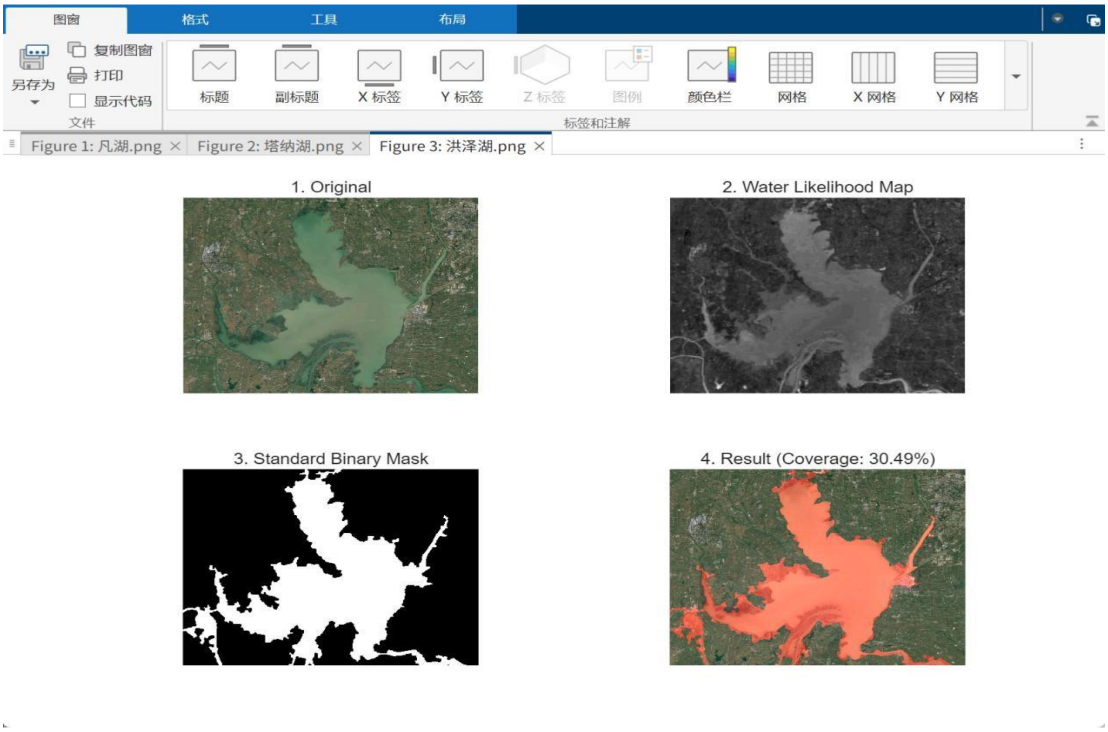

Figure7. HongZe Lake processing result

Discussion of Experimental Results of the Zaling Lake-Eling Lake.

The Zaling Lake-Eling Lake area, which is found on the Qinghai-Tibet Plateau, features the most distinctive natural environment: a high elevation, intense sunshine, radical changes in the surface reflectivity, and a surrounding surface which is mostly comprised of bare soil, gravel, and sparse vegetation. This is a difficult testing situation of water body detection. The original scenery shows that the water here will be aesthetically deep blue or cyan, in contrast to the rest of the exposed land, which is very reflective. Nevertheless, there are bright reflective spots in certain places as a result of strong sunlight which can be easily mistaken as water through the traditional techniques. As in the water probability map, in our proposed method the distribution of high response is highly concentrated around the primary areas of the Zaling Lake and Eling Lake, and is much lower in the other areas of the bare soil. This shows that NDWI is very discriminative in this case and the blue channel further amplifies the response in the deeper waters and the probability distribution becomes more stable. Gaussian smoothing helps to remove local outliers and a smooth structure of the space of the water area emerges. This is especially noticeable in the areas adjacent to the lake shore without having jagged edges due to localized variations in brightness. The resulting binary mask has a high geometric plausibility, with natural and continuous boundaries of lakes with no evident breaks and fractures. This mask is more similar to the real geographical features as compared to the traditional hard thresholding techniques. But

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the system failed to, in reality, detect all the water bodies in the two lakes as expected which shows that there are definitely limitations to traditional means.

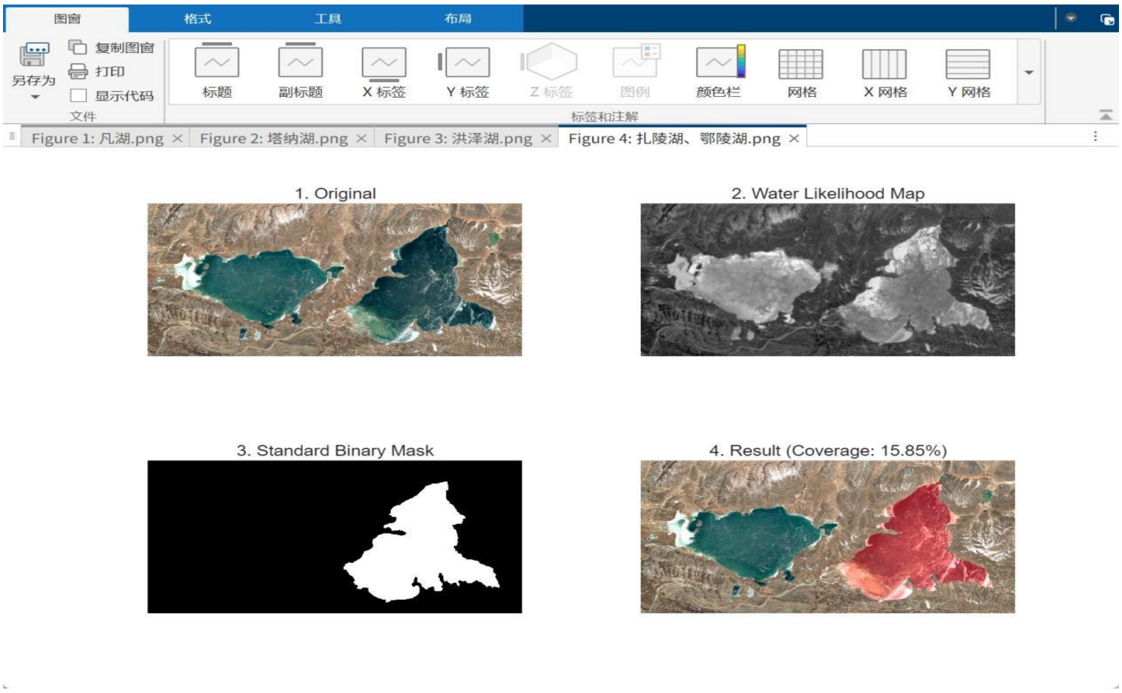

Figure 8. Zaling–Eling Lake processing result.

Cross-scene quantitative summary and comparison

The water coverage reported by the MATLAB output is summarized in Table 2. Coverage is the fraction of pixels assigned to water by the proposed method; it describes the algorithm's output and must not be interpreted as accuracy. Across the four scenes, coverage ranges from 15.85% to 41.26%, with a mean of 28.08%. The Zaling–Eling result also shows why coverage alone is insufficient: the largest-component rule retains the right-hand lake while excluding much of the disconnected left-hand lake.

Table 2. Water coverage reported by the proposed method.

Scene	**Estimated water coverage (%)**	**Observed interpretation**
Lake Van	24.71	A large, contiguous lake is retained with a coherent boundary.
Lake Tana	41.26	The main lake is retained; wetland and shoreline confusion remains possible.
Hongze Lake	30.49	The lake and connected channels are retained; some water-like land may remain.
Zaling–Eling Lake region	15.85	The largest-component rule excludes a valid disconnected lake.
Mean across four scenes	28.08	Descriptive output only; no ground-truth accuracy is implied.

Table 3 places the proposed pipeline beside common classical and deep-learning alternatives. This is a method-level comparison based on their data and operational requirements, not a numerical head-to-head experiment. A fair numerical comparison would require the original images, identical train/test partitions, independently prepared reference masks, and the same spatial resolution for all methods.

Table 3. Method-level comparison for water segmentation.

Method	**Data/training requirement**	**Relative advantage**	**Main limitation for the reported scenes**
Proposed NDWI–blue fusion+ Otsu + morphology	RGB image; no labeled training data	Transparent, lightweight, and thresholded separately for each image	Global threshold and largest-component rule are vulnerable to shadows, wetlands, and disconnected lakes
Method	**Data/training requirement**	**Relative advantage**	**Main limitation for the reported scenes**
Single-index thresholding (NDWI)	Green and NIR are preferred; RGB surrogate is possible	Simple, fast, and easy to reproduce	Sensitive to built surfaces, dark shadows, turbid water, and the absence of a true NIR band
MNDWI or AWEI	Multispectral imagery with NIR/SWIR bands	Often suppresses built-up land and shadow better than a visible-band index	Cannot be applied faithfully to the RGB-only exports used here
Region growing and morphological segmentation	No training; seed and similarity rules are required	Uses spatial continuity and can produce compact regions	Seed selection and fixed structural parameters may fail on fragmented or mixed shorelines
U-Net or DeepLab	Representative labeled images and substantially greater training resources	Can learn texture and context beyond hand-crafted spectral rules	Performance depends on annotation quality and domain match; training cost and interpretability are weaker

Adaptability and failure modes in complex scenes

The present method adapts automatically in two limited ways: both features are normalized for each image, and Otsu's threshold is recomputed from that image's smoothed score distribution. It does not learn environmental context and it does not adjust the fusion weights, Gaussian scale, or morphological element sizes. Thus, the word adaptive refers to histogram-based threshold selection, not full adaptation to different sensors, seasons, or land-cover compositions. A practical extension is to test the histogram for weak class separation and, when needed, switch to a local threshold or estimate thresholds by tiles before spatial reconciliation.

Several difficult cases remain. Shadows and dark roofs can be assigned high water scores, while vegetation and wetlands can overlap water in visible-band feature space. Bright sun glint, suspended sediment, and shallow water can produce false negatives. Mixed water–land pixels make shorelines unstable, and retaining only the largest component can discard valid ponds, tributaries, or a second lake. These problems can be reduced by using NIR/SWIR bands when available, adding shadow and vegetation masks, retaining multiple components through area and shape rules, and evaluating local thresholding. They are limitations of the current implementation, not capabilities already demonstrated by the four-scene test.

CONCLUSION

In this paper, a systematic exploration of a water body detection and standard binary mask generation framework of remote sensing images is carried out using classical computer vision techniques. The proposed approach offers consistent water body segmentation in a complex natural setting through the combination of NDWI and blue channel information to build up a continuous water body probability map, as well as the adaptive threshold, segmentation and multi-level optimization of morphological structures. The four-scene experiment shows qualitative feasibility under several water colors and background conditions, with estimated coverage between 15.85% and 41.26%. It does not establish pixel-level accuracy or broad generalization because independent reference masks and native sensor metadata were not available. The resulting mask of the body of water is highly geometrical in nature, continuous, and the total areas thereby offer a stable basis of further assessment and analysis of the water resource changes. The proposed method is compared to deep learning methods in that it does not need large-scale labeled data and there are additional advantages, such as a clear structure, high interpretability, and low-cost computation, which make it applicable to resource-constrained applications or those requiring high interpretability.

The main limitations are the small four-scene evaluation set, missing native image provenance and spatial resolution, absence of independent ground-truth masks, use of a global threshold, and the largest-connected-component assumption. Consequently, shadows, wetlands, vegetation, built structures, mixed shoreline pixels, and disconnected water bodies can still cause false detections or omissions. Further work should use georeferenced multispectral datasets with documented sensors and acquisition dates, prepare independent reference masks, report accuracy, precision, recall, F1-score, and IoU, and run matched comparisons with NDWI, MNDWI/AWEI, region-based methods, and representative U-Net or DeepLab baselines. Local threshold selection and component retention based on area, shape, and context should also be evaluated.

REFERENCES

1. McFeeters, S. K. (1996). The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. International Journal of Remote Sensing, 17(7), 1425–1432. https://doi.org/10.1080/01431169608948714
2. Xu, H. (2006). Modification of normalized difference water index (NDWI) to enhance open water features in remotely sensed imagery. International Journal of Remote Sensing, 27(14), 3025–3033. https://doi.org/10.1080/01431160600589179
3. Feyisa, G. L., Meilby, H., Fensholt, R., & Proud, S. R. (2014). Automated Water Extraction Index: A new technique for surface water mapping using Landsat imagery. Remote Sensing of Environment, 140, 23–35. https://doi.org/10.1016/j.rse.2013.08.029
4. Du, Z., Li, W., Zhou, D., Tian, L., Ling, F., Wang, H., & Gui, Y. (2016). Analysis of Landsat-8 OLI imagery for land surface water mapping. Remote Sensing Letters, 7(9), 873–882. https://www.mdpi.com/2072-4292/16/11/1984
5. Otsu, N. (1979). A threshold selection method from gray-level histograms. IEEE Transactions on Systems, Man, and Cybernetics, 9(1), 62–66. https://ieeexplore.ieee.org/document/4310076
6. Soille, P. (2003). Morphological Image Analysis: Principles and Applications. Springer. https://link.springer.com/book/10.1007/978-3-662-05088-0
7. Gonzalez, R. C., & Woods, R. E. (2018). Digital Image Processing (4th ed.). Pearson. https://books.google.com/books/about/Digital_Image_Processing.html?id =0F05vgAACAAJ
8. Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional networks for biomedical image segmentation. Medical Image Computing and Computer-Assisted Intervention, 234–241. https://link.springer.com/chapter/10.1007/978-3-319-24574-4_28
9. Chen, L. C., Papandreou, G., Kokkinos, I., Murphy, K., & Yuille, A. L. (2018). DeepLab: Semantic image segmentation with deep convolutional nets. IEEE Transactions on Pattern Analysis and Machine Intelligence, 40(4), 834–848. https://doi.org/10.1109/TPAMI.2017.2699184
10. Zhang, Y., Wang, Q., & Li, J. (2020). Water body extraction from remote sensing imagery based on improved spectral index. Remote Sensing, 12(4), 652. https://doi.org/10.3390/rs12040652
11. Li, J., Wang, S., & Zhang, Y. (2019). Automatic water detection in remote sensing images using morphological processing. ISPRS Journal of Photogrammetry and Remote Sensing, 154, 20–35. https://doi.org/10.1016/j.isprsjprs.2019.05.011
12. Tao, Z., Yang, Y., & Chen, X. (2021). Classical and deep learning-based methods for water extraction: A comparative study. Remote Sensing, 13(5), 901. https://doi.org/10.3390/rs13050901
13. Google. (2025). Google Earth [Computer software and imagery platform]. https://earth.google.com/