AUTOMATED DETECTION OF WATER SURFACES FROM SENTINEL-2 IMAGES AND PERFORMANCE ANALYSIS

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ABSTRACT: Water, which covers more than 50% of the Earth's surface, plays a crucial role in scientific research and is of immense importance in applications such as disaster prevention, urban planning, and water resource management. Precise and automatic detection of water bodies in remote sensing images has become a critical and challenging task in various studies. Therefore, to effectively address these various concerns, automated monitoring of water bodies is of paramount importance. To address the challenge of detecting water bodies in remotely sensed images, researchers have investigated various methods in previous studies. These approaches include the analysis of water indices, such as the Normalized Difference Water Index (NDWI), derived from the visible or infrared bands of satellite imagery. In addition, researchers have used k-means clustering analysis to identify patterns in land cover and segment regions with similar characteristics. Despite ongoing challenges such as distinguishing water spectral signatures from artifacts such as cloud and terrain shadows, our study aims to address these issues. The primary objective is to significantly improve the accuracy of water surface detection by constructing a comprehensive water database using existing digital and land cover maps. To achieve this, we used 1:5000 and 1:25000 digital maps of Korea to extract water properties, including rivers, lakes, and reservoirs. In addition, the inclusion of the 1:5000 and 1:50000 Land Cover Map of Korea was instrumental in extracting water properties from oceanic areas. Our research highlights the effectiveness of using the Water DB layer as the primary approach for efficiently extracting water surfaces from satellite imagery. This primary approach consists of two methods: the first involves the use of water indices through NDWI analysis, while the second employs unsupervised classification techniques, specifically the k-means clustering algorithm. During the water extraction process, we incorporated image segmentation and binary mask methods for image analysis. To evaluate the accuracy of our approach, we performed two evaluations using both reference data and our ground truth data. Visual interpretation involved comparing our results to the Global Surface Water (GSW) mask, which showed significant improvements in both quality and resolution. In addition, accuracy evaluation measures, including an overall accuracy (OA) of 90% and kappa values greater than 0.8, provide substantial evidence of the effectiveness of our methodology. In summary, our primary approach produced superior results compared to traditional methods used in previous studies and reference data, producing water mask results with improved resolution. Specifically, our first approach using (NDWI) analysis demonstrated higher accuracy than our second approach using k-means clustering for water detection. Overall, our approach consistently outperforms conventional methods.

1. INTRODUCTION

Changes in surface water can affect several critical factors, posing significant environmental challenges. Consequently, quantifying the extent of surface water as an integral component of the hydrological system, is important in several areas, including water resource management (including monitoring of surface reservoirs), climate modelling, biodiversity conservation, food security (including fisheries and agricultural), and human well-being (Bioresita et al, 2019). Considering these considerations, remote sensing technology has become a valuable tool for researchers involved in surface water monitoring. Over the past few decades and up to the present, numerous remote sensing satellites with enhanced sensing capabilities have been launched, elevating remote sensing to a pivotal role in the independent observation of water bodies from space (Schwatke et al., 2019). Remote sensing technologies, particularly optical satellites known for their high spatial and frequent revisits, play a critical role in improving data quality for water detection methods. Recent advances in remote sensing Earth observation satellites, exemplified by the Sentinel missions, provide an impressive combination of high spatial, spectral, and temporal resolution on global scale (Cordeiro et al., 2020).

Previous research using optical imagery to map water has mainly focused on methods that use water indices, such as the Normalized Difference Water Index (NDWI) (McFeeters, 1996; Cordeiro et al., 2020), and Modified Normalized Difference Water Index (MNDWI) (Xu, 2006; Cordeiro et al., 2020). These methods are based on concrete measures and have produced effective results. Sentinel-2 has firmly established itself as one of most suitable missions for accurate water body detection due to its compelling features, including unrestricted access, 13-band spectral resolution, and impressive spatial resolution 10 meters (Parajuli et al., 2022). As a result, techniques using water body indices such as NDWIs and MNDWIs with Sentinel-2 imagery consistently provide high accuracy especially for river extraction (Yang et al., 2017; Li et al., 2021).

Nevertheless, recent studies have shown that automatic water extraction, is typically carried out using conventional index-based methods combined with deep learning techniques (Parajuli et al., 2022). Furthermore, only a few publications on this subject have utilized multidimensional unsupervised techniques such as clustering (Cordeiro et al., 2020). The reason why clustering was used in some previous studies is because it has the potential to be a useful solution by combining multiple features, such as reflectance bands and water indices, using a single automated process (Cordeiro et al., 2020). Despite their apparent simplicity, traditional methods for extracting water through spectral indices and thresholding can encounter difficulties when accurately distinguishing water from features such as snow, mountains, buildings, and shadows due to the own limitations of pixel-wise computations (Zhou et al., 2017; Parajuli et al., 2022).

To overcome the limitations of previous water detection methods using Sentinel-2 image-based techniques, our study aims to develop an automated water detection method. We utilized all water related data for the entire Korean peninsula and combined them into a comprehensive water DB product. This product includes water features extracted from digital maps at scale of 1:5000 for South Korea area and 1:25000 for North Korea, as well as the 1:5000 and 1:50000 land cover map of Korea. We have used authenticity of the data, which comes directly from the Korean government map showing the real conditions of the ground. For our analysis, we integrated our water DB product with water index analysis, primarily using the Normalized Difference Water Index (NDWI). In this study NDWI analysis is crucial for extracting water and identifying water bodies from satellite imagery initially.

Furthermore, previous studies have explored integrating clustering methods into water detection research, often combined with other techniques such as water index analysis or deep learning approaches. Our study continues this trend by integrating our water DB product with water index analysis and utilizing clustering techniques such as the k-means algorithm, to enhance the results of previous research efforts. Consequently, our objective is to create high quality water masks for South Korea and North Korea by accurately delineate water regions from Sentinel-2 optical images. By combining two analyses and a product, we aim to present the results of our performance analysis applied to our automated water detection method and demonstrate its advancements over previous studies.

2. STUDY AREA AND DATA

The research focuses on a particular region of the Korean Peninsula, located in East Asia. The Korean Peninsula is geographically divided into two main entities: South Korea, which covers an area of approximately 100,210 km^2 and North Korea, which covers an area of approximately 120,540 km^2. Geographically, the Korean Peninsula has a diverse landscape. It is characterized by rugged mountain ranges along the eastern and western coasts, rolling hills and vast plains in the central region, and an extensive coastline dotted with bays, inlets, and islands. Notably, it has several major rivers and numerous inland reservoirs. Due to the diverse range of water features, including lakes, rivers, reservoirs, and coastal areas, of varying scales, the Korean region provides an ideal study area for water detection research. In the Figure 1. displays our study area using Sentinel-2 satellite images.

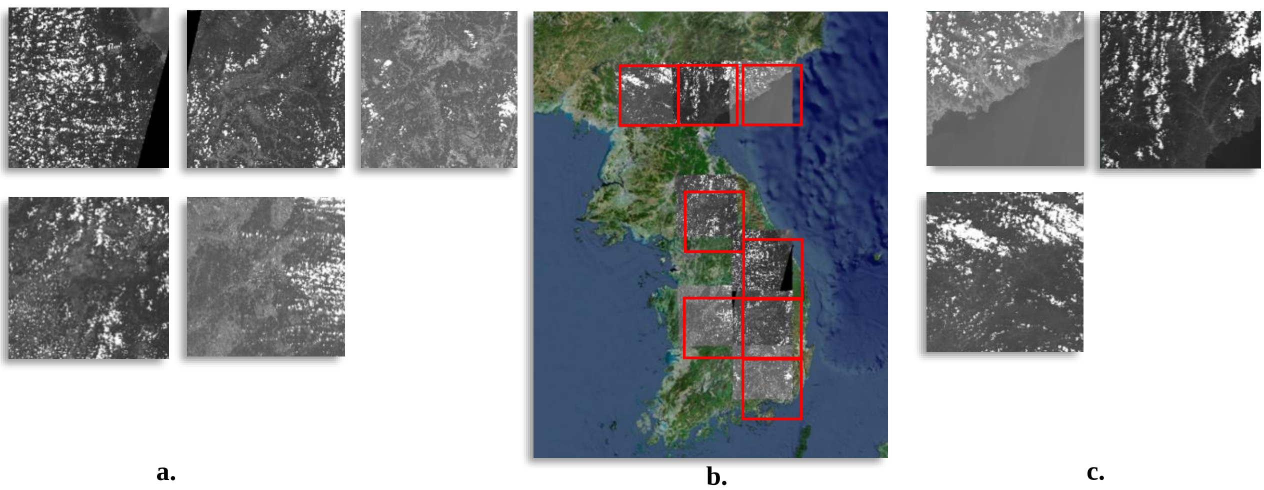


Figure 1. All the study area location with Sentinel-2 satellites images **a)** Five sample location for South Korean region. **b)** All study area location. **c)** Three sample location for North Korean region.

In our study, we employed water features to delineate and characterize various water regions within the Korean Peninsula, including rivers, lakes, reservoirs, and coastal areas. These features were extracted from 1:5000 scale digital maps over South Korean and 1:25000 scale digital maps over North Korean region-specific land cover maps, which formed our water DB product. For our primary dataset used to delineate water regions from satellite imagery, we relied on Sentinel-2 level 1C data. This dataset includes standard Top of Atmosphere (TOA) reflectance products that are freely available from the Sentinel Scientific Data Hub. Our approach focused on the near-infrared (NIR) and green bands of the 10-meter resolution Sentinel-2 imagery, which served as fundamental component of our methodology, including the application of the Normalized Difference Water Index (NDWI) for analysis. To provide comprehensive comparative analysis, we incorporated 20-meter resolution SWIR (Short-Wave Infrared) band imagery to perform Modified Normalized Difference Water Index (MNDWI) analysis. This comparative analysis complements the suite of water indices in our study. Our study included a total of eight sample images, each showing cloud cover. These images were carefully selected to represent eight different locations in both South and North Korea. The inclusion of cloud-covered images was intended to demonstrate the robustness of our approach in delineating water regions and generating high-resolution water masks, even in the presence of cloud cover. The selection of these specific data points was guided by their ability to accurately represent the water regions of the Korean peninsula, thereby increasing the reliability of our research results. In Table 1, our dataset for the sample study is presented. Coordinate corrections were applied to all our samples, realigning them to the EPSG: 5179 Korea 2000 coordinate system, which is aligned with the geographic coordinates of the Korean Peninsula.

Table 1. Detail sample data of Sentinel-2 satellite imagery.

Study area	Satellite	Type	Coordinate (UTM)	Acquisition date	Sample used
South Korea	Sentinel-2	L1C	EPSG:5179-Korea 2000	30/4/2023	Water extraction
South Korea				14/5/2023	
South Korea				2/5/2022	
South Korea				27/5/2022	
South Korea				16/6/2020	
North Korea				1/6/2020	
North Korea				29/5/2020	
North Korea				31/8/2018	

In addition, we strengthened our study by creating ground truth data for all of samples used in this research to increase the credibility of our approach. We created eight sets of ground truth data images to pair with the sample images in the accuracy evaluation section. These ground truth data sets were carefully created to reflect real-world conditions in the field, using the V-World base map as the foundation. We carefully aligned and matched the location of each sample to this base map, and then used a combination of manual drawing and editing techniques to delineate the water regions within our study area. In addition, to support other validation objectives, particularly the assessment of resolution through visual interpretation, we also incorporated reference data from Global Surface Water (GSW). This reference data has a 60-meter resolution of water mask and was precisely aligned to the locations of our sample data. The GSW dataset is constructed from collection of Landsat satellite imagery and includes a global representation of water regions, making it a valuable resource for our validation purpose.

2. METHODS

To support our automated water detection approach, we have developed a water DB product to help accurately delineate water bodies in satellite imagery. This innovative method uses government-provided maps from the Korean government, which faithfully represent the real condition in the Korean region. The water DB was constructed carefully by aggregating water features extracted from 1:5000 scale digital maps for South Korea area and 1:25000 scale digital maps for North Korea, supplemented by 1:5000 and 1:50000 land cover map specifically designed to highlight coastal areas. These extracted water features include represent lakes, reservoirs, rivers, and coastal areas within the Korean Peninsula. The workflow detailing the creation of our water DB product is illustrated in Figure 2 below. This process involves several key steps. First, the most time-consuming phase is the collection of water features across the entire Korean peninsula, which is known for its large inland water surface. This careful collection process is essential to building a comprehensive dataset. This is followed by careful extraction and polygonization of all features to a standardized format. We then merge the collected water features and categorize them into different water regions, which include rivers (including both large and small watercourse), lakes (including both small and large lakes as well as reservoirs), and coastal regions. Finally, we apply rasterization to polygon-based water layer that makes up the complete water database package. This results in the creation of the final water DB product, which serves as an asset for our automated water delineation process in our water detection method.

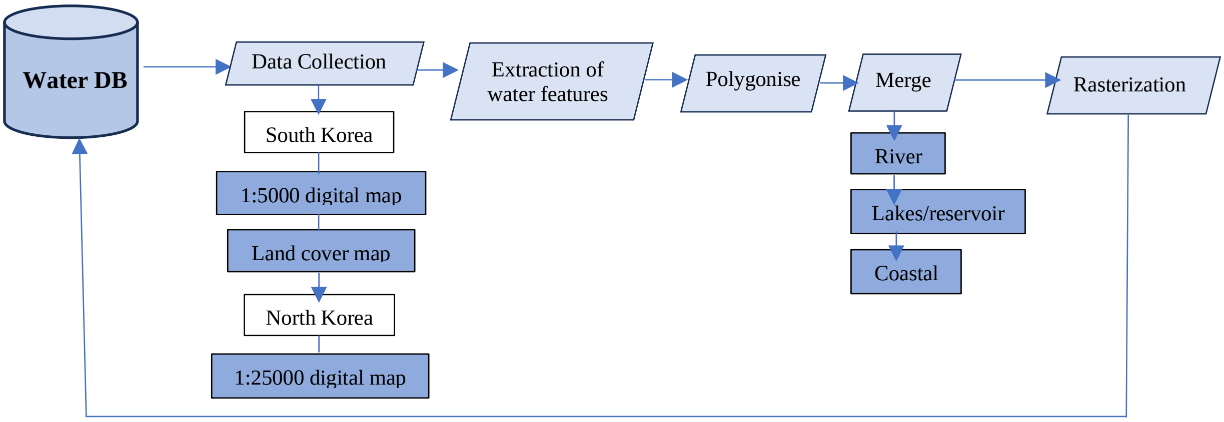


Figure 2. Process of making water DB product.

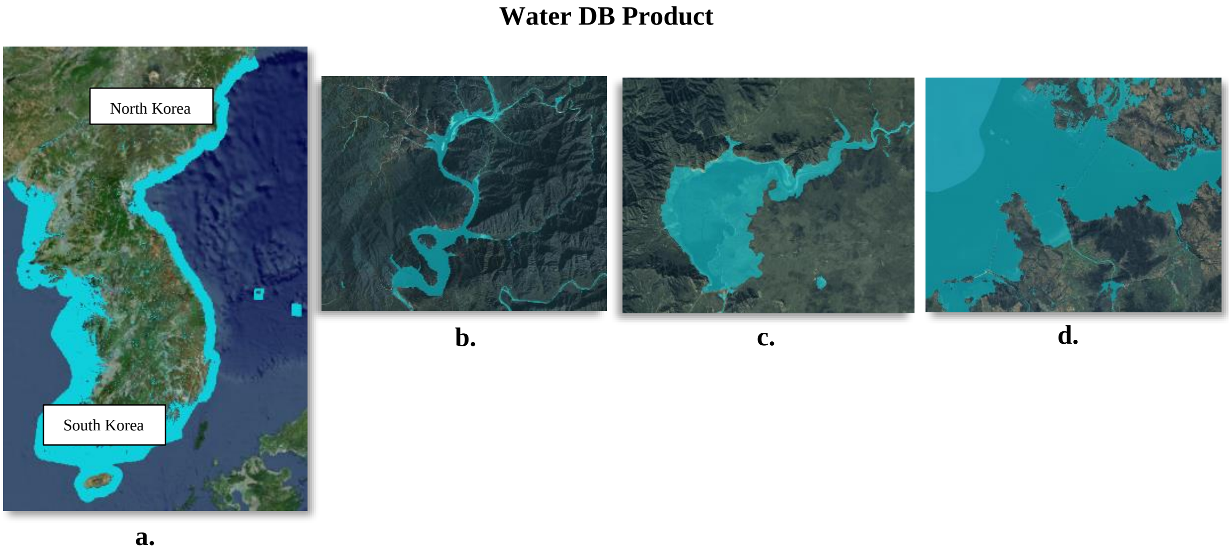
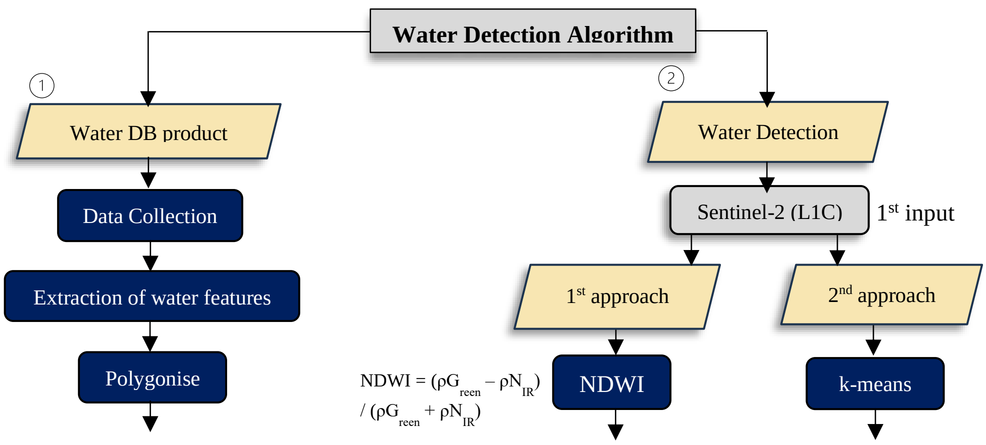


Figure 3. a) Appearance of whole package of water DB product with V-World map as a based map. **b)** water region that represent rivers area. **c)** Water region that represent lakes/reservoir. **d)** Water region that represent coastal area.

We have illustrated all the steps involved in our approaches in Figure 4. We mentioned before that our overall goal is to demonstrate that the fusion of traditional analysis techniques such as water index analysis and unsupervised classification analysis, with our primary product the water DB, can significantly improve the accuracy the water body delineation from satellite imagery compared to previous studies. In addition, we want to evaluate the performance of each of our two approaches. Our goal is to determine which method or approach provides better results and more accurate water body delineation.



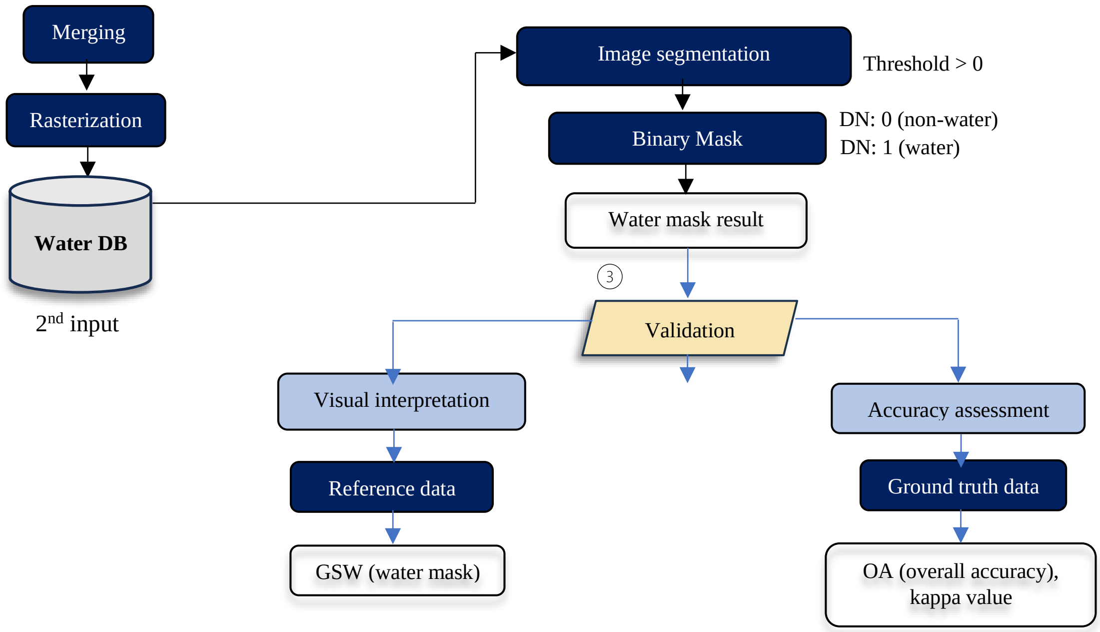


Figure 4. All the algorithm process for automated water detection.

As with many of the previous research studies that have relied on water index analysis for water detection, our approach follows a similar path, but with unique twist. In our method, we integrate traditional water index analysis with our innovative water DB product as a first process in our automated water detection approach. Our analysis focuses on the near-infrared and green bands of Sentinel-2 imagery, which provide a high resolution of 10 meters for Normalized Difference Water Index (NDWI) analysis.

$$\mathrm{NDWI} = (\rho G_{reen} - \rho N_{IR}) / (\rho G_{reen} + \rho N_{IR})$$

NDWI is typically used to enhance the contrast between water bodies and their surrounding surface features, effectively mitigates challenges such as mountain shadows caused by topographic variations and minimizes interference from artificial urban area (Acharya et al., 2018). Given our reliance on the water DB product, we found it unnecessary to include additional water indices, such as Modified Normalized Difference Water Index (MNDWI), in our research. The use of the water DB product greatly enhances our ability to accurately delineate water bodies from satellite imagery, which is the core of our methodology. This choice also supports our comparative analysis, where we evaluate the performance of our automated detection results against other studies. Once the water indices have successfully distinguished water bodies from other topographic features, we proceed to the second process of the analysis. In the next process, we combine the results NDWI analysis (the first input) with our water DB product (the second input) to initiate the water detection process. In this process, image segmentation techniques are used to generate a binary mask in the final analysis. This binary mask clearly delineates water bodies with a DN (digital number) value of 1 and non-water areas with a DN value 0, ultimately resulting in a water mask as the final output. This comprehensive approach represents our first approach for our automated water detection methods.

As mentioned above, our first approach was to delineate water bodies by integrating water index analysis, specifically NDWI, with our primary water DB product. In further analysis, previous studies have highlighted the effectiveness of unsupervised classification methods, such as clustering algorithms, in delineating water bodies from satellite imagery. This approach is widely adopted due to its ability to discriminate between water and non-water areas. However, it is important to recognize that this method has certain limitations and often require a combination with other techniques to improve accuracy and reduce misclassification. Following this concept, we have developed an approach that combines the k-means clustering algorithm from the unsupervised classification method with the incorporation of our water DB product. Initially, we apply multispectral Sentinel-2 images, including visible band and near-infrared (NIR) bands, to the k-means clustering algorithm. Within the k-means clustering process, we defined four classes representing water areas, land, terrain shadows and clouds to effectively distinguish water bodies differentiate the water area from the others land cover features in the first process. We then integrate the results from the first process into the second process, combining this output with our water DB as a second input. Same with our first approach, this second process uses image segmentation techniques and binary mask analysis to delineate water bodies within our satellite images samples. This method represents our second approach to refining and improving the accuracy and reliability of our automated water detection method.

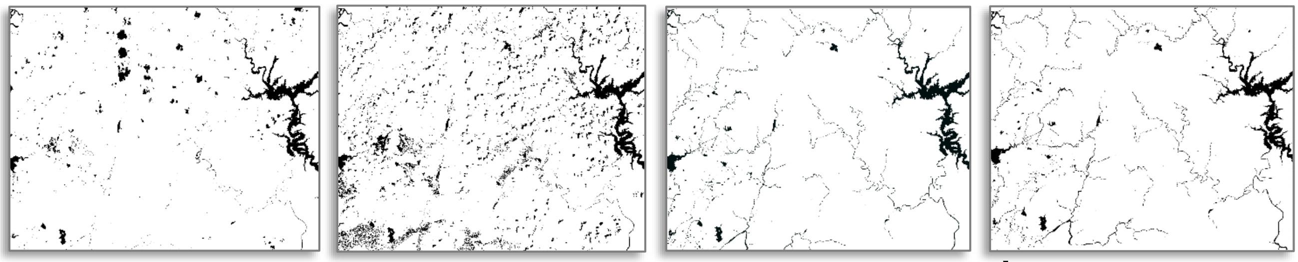
For the validation part of this study, our first validation focuses on comparing the performance of the results of our approach with our reference data. This validation involves a visual interpretation where we compare our water mask results with the reference data from GSW (Global Surface Water), which is known for its 60-meter resolution. This step allows us to visually assess the accuracy of our results. The final validation assesses the accuracy of our approach's results by comparing them to our ground truth data. We use a commission error matrix for this analysis, calculating overall accuracy (OA) and kappa values to provide empirical evidence of the effectiveness of our approach's performance.

Additionally, for further validation, we compared our approach to an alternative water index analysis, specifically the Modified Normalized Difference Water Index (MNDWI), which was not used in the primary analysis. The rationale for not using MNDWI initially was to emphasize the effectiveness of our comprehensive Water DB product. We believed that it might not be necessary to include MNDWI because we expected the results to be similar in quality to those obtained using NDWI. Our goal here is to confirm this hypothesis and validate the consistency of our approach.

3. RESULTS AND DISCUSSION

We have achieved successful water mask production using our automated water detection approaches. These results represent a significant improvement in the delineation of water bodies from satellite imagery, particularly Sentinel-2 satellite imagery. Our approach greatly improves the resolution of previous studies, which relied only on water index analysis and unsupervised classification techniques. To provide a visual comparation, we present the resolution comparison of our approach alongside traditional result in Figure 5. Our results show a significant improvement in the resolution of the water mask results. Our approach excels in delineating water bodies with remarkable detail, capturing even the smallest water flows. In addition, we have effectively mitigated noise and reduced misclassifications due to terrain shadows and other topographic features.

In Figure 6, we present the results of our visual interpretation validation, where we compare the results of our study with reference data from Global Surface Water (GSW), which offers a resolution of 60 meters. These results highlight the superiority of our approach in producing a more detailed water mask and achieving better resolution for water body detection. In addition, Table 2 presents accuracy metrics, including overall accuracy (OA) and kappa values, to compare our approach with the GSW reference data. While GSW maintains a respectable level of accuracy, our approach consistently outperforms it in terms of accuracy. It's worth noting that the kappa value for GSW's results is relatively low, despite its higher overall accuracy. This discrepancy is attributed to GSW's less detailed delineation of water regions and lower resolution compared to our results, resulting in a higher misclassification rate for small-scale water regions.



a. NDWI **b.** k-means **c.** 1st Approach **d.** 2nd Approach

Figure 5. The comparison of water detection result with Sentinel-2 of traditional methods and automated water detection method. a) From NDWI result. b) From k-means result. c) From 1st approach of this study. d) From 2nd approach of this study.

a. 1st Approach **b.** GSW water mask **c.** 2nd Approach

Figure 6. Visual interpretation validation of this study approach results and reference data from GSW water mask with same location with a V-World as based map. **a)** Result of 1st approach. **b)** GSW water mask. **c)** Result from 2nd approach.

However, when we compared the results of the first and the second approaches, as shown in Figure 7, we found that both methods produced commendable results with excellent resolution. However, it became apparent that the second approach had a slight error in classifying small land areas within narrow rivers as water bodies, whereas the first approach successfully delineated these small land features. This distinction is also reflected in the Table 3, which shows that our first approach consistently provides higher accuracy than the second approach. Furthermore, as mentioned earlier, we wanted to compare the results of our first approach using NDWI with an alternative approach substituting NDWI with MNDWI to demonstrate their equivalence in producing high quality results. The results of the comparison are presented in Table 4, which shows slight differences between the use of NDWI and MNDWI.

1st Approach 2nd Approach

Figure 7. The comparation result of 1st approach and 2nd approach with a V-world map as a based map.

Table 2. Comparation result of overall accuracy (OA) and kappa value of our approaches and reference data.

Sample name	GSW		1st Approach (Water DB + NDWI)		2nd Approach (Water DB + K-means)	
	OA (%)	Kappa	OA (%)	Kappa	OA (%)	Kappa
Sample1	94.97	0.33	98.27	0.82	98.32	0.83
Sample2	96.61	0.37	99.06	0.86	98.97	0.85
Sample3	96.35	0.16	95.95	0.47	95.68	0.46
Sample4	96.17	0.3	98.44	0.81	98.32	0.8
Sample5	92.25	0.38	98.36	0.88	97.92	0.85
Sample6	96.85	0.33	99.18	0.85	99.1	0.84
Sample7	90.58	0.44	98.72	0.92	99	0.94
Sample8	46.92	0.19	99.39	0.98	99.34	0.98

Table 3. Comparation result of 1st and 2nd approach for the accuracy assessment.

Sample name	1st Approach (Water DB + NDWI)		2nd Approach (Water DB + K-means)	
	OA (%)	Kappa	OA (%)	Kappa
Sample1	97.9	0.8	97.87	0.8
Sample2	99.06	0.86	98.97	0.85
Sample3	95.95	0.47	95.68	0.46
Sample4	98.44	0.81	98.32	0.8
Sample5	98.36	0.88	97.92	0.85
Sample6	99.18	0.85	99.1	0.84
Sample7	98.72	0.92	99	0.94
Sample8	99.39	0.98	99.34	0.98

Table 4. Comparation result of 1st and 2nd approach with original approach (with MNDWI).

Sample name	Approach method with MNDWI		1st Approach with NDWI	
	OA (%)	Kappa	OA (%)	Kappa
Sample1	97.55	0.7	97.9	0.8
Sample2	98.85	0.78	99.06	0.86
Sample3	96.55	0.46	95.95	0.47
Sample4	97.92	0.65	98.44	0.81
Sample5	98.23	0.86	98.36	0.88
Sample6	99.15	0.83	99.18	0.85
Sample7	98.61	0.91	98.72	0.92
Sample8	99.36	0.98	99.39	0.98

4. CONCLUSION

Our initial concept to develop the Water DB product as an integral part of our approach to improve water body delineation from satellite imagery has yielded promising results in our automated water detection methodology. The overall results indicate that our product has impressive resolution and excels at accurately delineating water bodies from Sentinel-2 imagery. We have successfully addressed challenging issues, such as distinguishing water from other land cover features, and effectively reduced the noise commonly encountered when delineating water bodies in satellite imagery, thereby mitigating misclassifications. In addition, our results demonstrate an improvement in water mask quality compared to the 60-meter resolution Global Water Mask (GSW) reference data, making it valuable for further research and water monitoring purposes. After evaluating both our first and second approaches, we conclude that the use of water index analysis proves to be more effective and accurate in delineating water bodies compared to the use of k-means clustering within our approach. Nevertheless, it is noteworthy that all our approaches, whether using water indices or k-means clustering, have consistently provided high accuracy. This underscores the significant contribution of our Water DB product to the water detection process, with the potential for broader application to different types of satellite imagery in future research.

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