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ADVANCES IN WATER SEGMENTATION: SYSTEMATIC LITERATURE SURVEY OF SATELLITE IMAGES

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Abstract

Satellite images play a vital role in environmental and climate monitoring, modelling hydrological systems, and managing disasters, however accurate segmentation of water bodies from satellite imagery remains challenging due to variations in resolution, spectral characteristics, and climate conditions.

A number of studies have been proposed for segmentation approach, there is still lack of systematic comparative study of performance of different approaches across different datasets and evaluating their readiness for real-time operational applications.

This systematic literature review (SLR) studies gradual advancements in water body segregation from satellite images over the past decade (2015–2024). A total 1,627 research paper and articles were identified in initial stage by spanning through seven major databases, out of which 48 high quality, open-access studies met our inclusion and quality assessment criteria. This review specifically categorizes water segregation approaches into conventional image processing approaches, modern approaches such as machine learning, deep learning, and multimodal hybrid approaches. Deep learning methods, such as variants of U-net and attention-based models, consistently overpower traditional methods, accomplishing average Intersection over Union (IoU) above 92% and precision exceeding 95% on datasets such as Sentinel-2 and Landsat-8, whereas, threshold-based and index-based methods achieved average IoUs of 78–85%, reflecting limitations in complex backgrounds. The most frequently used datasets for water segmentation are Sentinel-2, Landsat-8, Sentinel-1 SAR, WorldView, and GaoFen-2. These datasets were specifically selected by researcher and scholars for their work because they had good spatial resolution, spectral diversity, and availability. Apart from accuracy trends, the review highlights and elaborates emerging and promising techniques such as multimodal data amalgamation, lightweight deep networks for edge deployment, and Internet of Things (IoT) frameworks integrated with existing structure for real-time flood monitoring, creating smart water grids, and water management for various application like agriculture, power generation etc. The findings of this work provide a consolidated overview of segregation approaches and datasets, providing assistance for future research work leading to scalable, robust, and real-time water resource monitoring systems.

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Keywords: Satellite images, water segregation, Deep learning, IoU, Landsat-8, Sentinel-2

1. Introduction:

Over a span of time the world has been seeing a considerable increase in number of satellites [1]. This rise in number of satellites has led to cause of collection of huge set of satellite images. These images have high resolution and require higher capability processor to process such image. Earlier, processing techniques were inadequate for handling high-resolution satellite pictures [2]. In this research we are going to analyze such processing technique of delineation or segmentation. Segmentation is the idea is to break down the representation of an image into more understandable and controllable bits. Each segment is often assigned to objects or areas that share comparable features, such as color, texture, or intensity. Image segmentation is an important stage for numerous applications, which includes object recognition, image interpretation, and medical image analysis [3–5]. Despite these diverse approaches of water segmentation, past literature reviews or surveys in this field have often been descriptive rather than comparative, not having a structured performance analysis across datasets and segmentation techniques. In particular, there are very few discussions on how these approaches could be integrated for real-time or operational deployment, which is important for climate monitoring and disaster response systems. In our study we are mainly focusing on water segmentation techniques. Water body segmentation from satellite pictures is of great importance in various fields because of its variety of accomplishment. Some of them include environmental monitoring, hydrological studies, water resource management, urban planning, ecological studies, disaster management etc. [6, 7]. Fig.1 depicts these applications.

1. Monitoring Environment: Global variation in climate and human interference have resulted into significant reductions in surface water bodies of Lakes and rivers, which require management [8]. Water Segmentation has aided in understanding the global climate changes.

2. Hydrological studies: Water segregation helps in Calculating flow, transport of sediments, and contamination dispersion in the basins of rivers and ecosystems. It aids in water resource management authorities and officials with future strategy development and choice-making operations [9].

3. Urban Planning: Urbanization has significantly impacted the geography and overall health of surface water bodies. Frequent usage by humans could possibly lead to degradation of water quality. So, timely Understanding the geographical distribution of water body in urban settings is crucial for managing public health and living conditions [10].

4. Smart farming: Use of satellite imaging and water segmentation techniques has helped in agricultural regions mapping and crop health and moisture level evaluation. It also Enhances approaches of irrigation and water use by recognizing regions of water stress or surplus moisture [11].

5. Flood Prediction and Disaster management: Water segmentation helps in Locating flooded regions and determining the level of damage caused by flooding during natural catastrophes including hurricanes, high tides, and severe rains. It aids in providing fast

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information to emergency personnel and authorities to help with rescue efforts, evacuation strategies, and emergency assistance initiatives [12].

With growth Internet of Things (IoT) technologies, water segregation research can be fused to real-time monitoring frameworks. Such as, water segregated satellite imagery can be fused with edge-computing devices, in-situ sensors, and smart water grids to enable rapid flood detection, dynamic irrigation management, and continuous water quality assessment. This alignment with IoT-enabled systems positions water segmentation as a core component in future intelligent environmental management platforms.

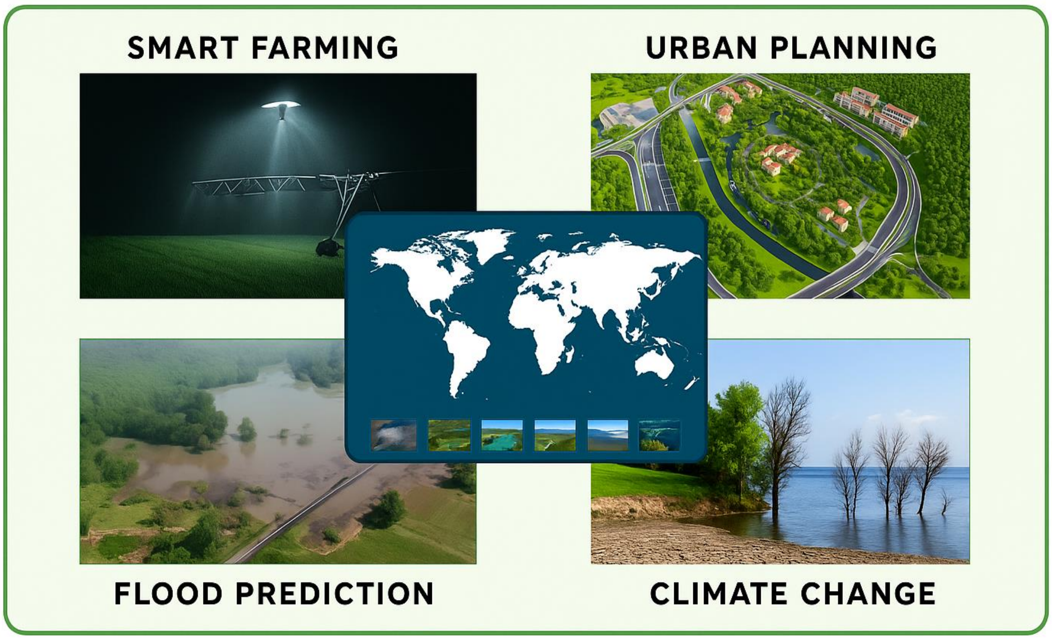

Fig.1: Application of Water-Segmentation Techniques

To address needs of efficient water segregation approaches, the present study undertakes a systematic literature review to:

(i) categorizing water segmentation approaches
(ii) analyzing and comparing their performance using consistent measurement metrics such as IoU, accuracy, and F1-score;
(iii) elaborating the strengths and limitations of widely used datasets; and
(iv) studying their applicability in IoT-based real-time monitoring scenarios.

These objectives are aligned with the research questions outlined in Section 3, ensuring that the review provides both a methodological synthesis and practical insights for operational use. This SLR mainly Focuses on giving an insight about Water Segmentation Techniques with a brief discussion of Background which briefs about the techniques that have been used so far water segmentation from the satellite images, moving ahead with standard procedure of systematic literature review which encompasses of first phase as Planning, second phase of conduction and last phase of reporting and result.

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2. Related Work

Segmentation is the method of splitting a picture into homogeneous fragments according to specific traits. The literature reports several attempts to separate certain spectral classes. [13] One such spectral class is water for segmentation which is useful for analysing its function in ecological services in the context of climate variation and global warming. [14] Water delineation or segmentation techniques can broadly be classified into conventional approaches and modern approaches. Conventional approaches include edge detection method, level set method, active contour model, random forest model, k- mean clustering and support vector machine whereas modern approaches include deep learning techniques, Attention Mechanisms and Multi-modal Fusion. [15, 16]

For better understanding and clarity, these water segmentation approaches can be classified further into four broad techniques:

(i) **Conventional image processing techniques** (such as thresholding, edge detection, level set, active contours).

(ii) **Machine learning techniques** (such as Random Forest, SVM, k-means).

(iii) **Deep learning methods** (such as CNN, U-Net, DeepLab).

(iv**) Fusion-based approaches** fusing multiple data modalities such as optical, SAR, and LiDAR.

This classification helps in a systematic comparison of strengths, limitations, and application contexts across different methodological families.

Edge detection can be classified as canny and sobel detection techniques.[15] Canny edge detection technique was named after its inventor John F. canny.[17] This detection techniques is efficient in extraction of water bodies from satellite pictures and it also performs well in multi scale edges.[18] Sobel edge detection is an approach for finding edges in satellite picture. It relies on abrupt variations in intensity, which correspond to border of objects in images. Sobel edge detection is rarely utilized for full-image segmentation, it is employed as a pre-processing step in segmentation. [17, 19] Another popular conventional method level set method which was being used for segmentation. The level set approach is good in segmenting objects with complicated forms and topologies. The level set approach uses a higher-dimensional function's zero level set to describe an object's changing boundary. It maintains a function whose zero-level set corresponds to the object boundary. [20, 21] Active contours also called snakes represents curves which grow to reconstruct object outlines in two dimensional images. Active contour algorithms can be into: parametric and geometric contour. [22, 23] Parametric active contours, also known as parametric snakes or deformable models, are a class of image segmentation techniques that utilize curves or surfaces to delineate object boundaries within images. Geometric active contours, also known as geometric deformable models, are a type of image segmentation approach that uses curves or surfaces to identify item boundaries within images.

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Water body segmentation using random forests is a machine learning strategy which employs random classifiers for detecting water pixels in a picture. It is an amalgamated learning approach that aggregate predictions from numerous decision trees trained on distinct subsets of data. [24] K-means clustering divides pixels in an illustration into two groups depending on their attributes, with one representing water and the other non-water areas. K-means allocates each pixel to the nearest cluster after repeatedly refining cluster centroids to minimize the distance between pixels and centroids. Following segmentation, water bodies may be detected by extracting the cluster corresponding to water, resulting in a binary map that distinguishes water from other components in the picture. [25]

Water segmentation with Support Vector Machine (SVM) entails training a classifier to differentiate among water and no water pixels relying on retrieved attributes. SVM learns a decision boundary to split into two categories in feature space, allowing for precise pixel categorization in an image. [26] Modern techniques provide higher efficiency and robustness. One of the advanced techniques is Deep learning algorithms which has transformed water segmentation, with greater performance in capturing complicated patterns and spatial correlations. These are some typical deep learning approaches for water segmentation [15]:

• Convolutional Neural Networks (CNNs) for segmentation entail training a neural network to pick up characteristics from incoming pictures and generate pixel-level masks of segmentation that separate water from non-water regions. CNNs can reliably identify water bodies by iteratively optimizing network parameters using training data, making them useful for various applications. [6]

• Water segmentation with U-Net involves developing a U-shaped convolutional neural network on image data, where input data and matching ground truth segmentation masks are combined. The network learns to map input pictures to their corresponding pixel-level water segmentation masks by optimizing parameters with the goal of minimizing a certain loss function, such as binary cross-entropy. [27]

• DeepLab uses dilated convolutions and atrous spatial pyramid pooling (ASPP) to collect information, allowing for precise segmentation of bodies of water at different scales and resolutions. [15]

• Mask R-CNN integrates detection of objects with instance segmentation to identify and delineate separate water bodies in a scene. It can generate exact segmentation masks as well as identify objects. [15]

Another modern technique is attention techniques can be categorised as self-attention or spatial attention. It improves the discriminating capacity of deep learning models by focusing on key visual areas, allowing for more accurate segmentation of water bodies against complicated backdrops. [28, 29]

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The third technique is multi-modal fusion that combines data from many sources, such as optical images, LiDAR, and SAR, to produce a composite dataset. Relevant characteristics are retrieved from each modality, and a segmentation model is trained to use this multimodal data. The model is verified and fine-tuned for precise water delineation, yielding strong segmentation results. [30, 31]

Different literature articles give comparative evidence that indicates that conventional approaches such as NDWI, Sobel edge detection, and level set models are efficient computationally and require less data, they often underperform in complex scenarios, having overall accuracies in the range of 75–85% on diverse datasets. [17,21,23] While Machine learning models such as Random Forests and SVM improve accuracy of classification (often exceeding 90%) but require carefully engineered input features. [24,25] Deep learning models, such as variants of U-Net, have excelled as the most consistent high performers, with many studies reporting IoU scores above 92% and accuracies exceeding 95% on datasets such as Sentinel-2 and Landsat-8.[15,27] Fusion-based approaches show strong potential for challenging conditions (e.g., cloud cover, turbid waters), with some studies achieving over 98% accuracy by combining optical and SAR data, but they need high computational resources and data integration pipelines.[30,31]. Recent analysis has shown the emergence of attention mechanisms and lightweight deep networks whose objective is to improve segregation precision while decreasing computational complexity, enabling deployment on edge devices for IoT-based monitoring systems. Furthermore, multimodal fusion leveraging complementary datasets is gaining traction for robust, all-weather water segmentation, particularly in flood mapping applications.[31] The techniques of water segmentation observed in past one decade has been depicted in Fig.2. In our survey efforts have been made to analyse the trends in the field of water segmentation along with popular datasets and techniques for segmentation. Table 1 outlines a comparison summarizing strengths, weaknesses and performance of various models.

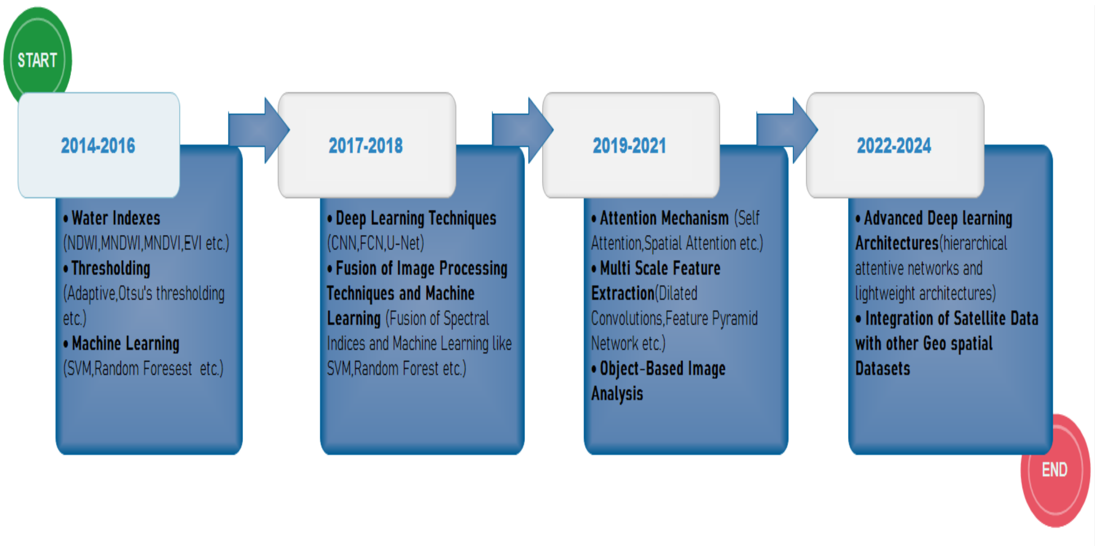

Fig.2: Trends of Water-Segmentation Techniques

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Table 1. Comparative analysis of techniques

CATEGORY	TECHNIQUES	STRENGTHS	LIMITATIONS	ACCURACY
TRADITIONAL IMAGE PROCESSING	NDWI, MNDWI, Otsu thresholding, edge detection, Level set, Active contours	Simple, computationally efficient, low data requirements, easy to implement	Sensitive to noise, poor performance in heterogeneous backgrounds, struggles with mixed pixels	Accuracy: 75–85% IoU: 0.70–0.80
MACHINE LEARNING	Random Forest (RF), Support Vector Machine (SVM), k-means clustering	Handles non-linear relationships, better generalization than thresholding, adaptable to different datasets	Requires feature engineering, performance depends on input features and training data quality	Accuracy: 85–93% IoU: 0.80–0.88
DEEP LEARNING	U-Net, ResU-Net, DeepLabv3+, CNN-based models, Mask R-CNN	High precision, automatic feature extraction, robust to noise and variations, adaptable to multiple resolutions	Requires large labeled datasets, higher computational cost	Accuracy: 92–99% IoU: 0.90–0.98
FUSION-BASED	Optical + SAR fusion, Optical + LiDAR, Multimodal attention networks	All-weather capability, improved robustness under cloud cover and turbidity, captures complementary information	Complex preprocessing, large storage needs, high computational demand	Accuracy: 94–99% IoU: 0.92–0.98

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3. Systematic Literature Survey

Various studies have been conducted which focus on surveys on water segmentation methods and approaches. These assessments emphasized the need for more precise and efficient detection approaches that employ modern technology such as Deep Learning. Previous literature studies lacked a clear structure and adhered to specific norms; thus, this study used a systematic literature review approach. The systematic literature review (SLR) method has become norm for conducting reviews. It is a framework for identifying, evaluating, and interpreting existing research findings while also answering predetermined research questions. The approach has been utilized in a number of studies across several fields. Various researchers for instance Aqthobirrobbany [32] carried a systematic Literature survey (SLR) for breast cancer detection on thermal pictures while other researcher Iskandar [33] carried a SLR on Knowledge management system and its current issues for future research. These researches have used systematic literature review (SLR) which mainly consist of three phases. First phase is planning proceeding with conduction phase and last phase is the reporting phase. Entire SLR followed for our study is explained in table 2 with brief discussion about each phase.

Table 2. Outline of SLR structure

PHASE	STEP	REMARK
First Phase	PLANNING PHASE	RESEARCH QUESTIONS ARE FRAMED
Second Phase	CONDUCTION PHASE	SEARCH STRING FORMATION
		SELECTION CRITERIA
		QUALITY ASSESSMENT
		DATA EXTRACTION AND SYNTHESIS
Final Phase	REPORTING AND RESULT PHASE	ANALYSIS AND RESULT EACH RESEARCH QUESTION

3.1 First phase: Planning Phase

In Planning phase, it is recognized that performing a systematic literature review (SLR) is necessary for Water segmentation techniques using satellite images. Review standards are carefully crafted so that clear focus could be maintained. During this phase in our study, research questions (RQs) were defined based on the scope and objectives of the review by identifying important ideas, examining existing literature, and developing specific research questions. During this procedure, researchers want to address gaps, trends, and empirical discoveries connected to the selected issue. Research Question (RQs) formulated for our study mentioned in table 3.

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Table 3. Research Questions

ID	RESEARCH QUESTIONS
Q1	WHAT NUMBER OF PAPERS REGARDING WATER SEGMENTATION ARE WRITTEN AND PUBLISHED ANNUALLY?
Q2	WHICH GENRE OF PUBLICATIONS HAS THE GREATEST RESEARCH INTO WATER SEGMENTATION METHODS?
Q3	HOW DOES WRITER'S WORK CONTRIBUTE TO THE FIELD OF WATER SEGMENTATION TECHNIQUES?
Q4	WHAT DATASET IS BEING USED FOR WATER DELINEATION OR SEGMENTATION USING SATELLITE IMAGERY?
Q5	WHICH TECHNIQUES ARE EMPLOYED FOR WATER SEGMENTATION FROM SATELLITE IMAGES, AND WHICH APPROACH IS MORE COMMONLY USED?
Q6	WHICH TECHNIQUE HAS THE HIGHEST EFFICIENCY IN RECOGNIZING WATER BODIES USING SATELLITE IMAGES?

3.2 Second phase: Conduction Phase

Conducting activities include search strategy and data synthesis which further comprises of selection of data along with data extraction. The search strategy includes defining of search phrases or search keywords and the search method to attain objectives of SLR. Our search phrase is framed with the help of research question which were formed in planning phase. [33] The search strategy was constructed using the procedures below:

1. We first figured out our research related Search Phrases and then moved ahead to find search keywords from the research questions provided.
2. Generating search phrases utilizing the Boolean operator (AND and OR).

The search phrases for our search process were tailored according to unique requirements of each database. Table 4 explains each search string for specific databases. Our research focuses on open access articles published over a decade, such as journals and conference proceedings. Open-access articles were given priority to ensure that all reviewed studies are reproducible and accessible to researchers, policymakers, and practitioners without subscription barriers. This approach is particularly important for environmental monitoring applications, where stakeholders in developing regions may not have institutional access to paywalled journals. We acknowledge that this restriction may have excluded relevant high-quality studies, introducing a potential selection bias; however, it enhances the transparency and practical utility of the review's findings.

Criteria for data selection Search phrases was designed to have broad spectrum so as maximum research article could be reached out. Journals relevant to our study were kept for further reference for the purposes of data selection. We pinned down the metrics that would help us to rule out article that were not relevant to our study. These metrics are provided in Table 5.

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The beginning of the search phase we got 1627 research articles. After using our rules for selection criteria in Table 5, we limited the list to 48 articles. Articles that did not fit with the research aims or did not match the criteria were eliminated. It is also important to consider that by confining our study to open-access sources, we may have overlooked any relevant research published in non-open-access publications. However, the broad database search and rigorous selection procedure used assured that

Table 4. Databases and Search String

NO.	DATABASES	SEARCH STRING
DS1	IEEEXPLORE	” WATER” AND (” SEGMENTATION” OR” EXTRACTION”) AND” SATELLITE IMAGE”
DS2	WILEY	” WATER” AND (” SEGMENTATION” OR” EXTRACTION”)” IN TITLE AND”” SATELLITE IMAGE”” ANYWHERE
DS3	SPRINGERLINK	” WATER SEGMENTATION” OR” WATER EXTRACTION” AND” SATELLITE IMAGE
DS4	SCIENCEDIRECT	” WATER SEGMENTATION” AND” SATELLITE IMAGE”
DS5	NATURE	” WATER SEGMENTATION” OR” WATER EXTRACTION” AND” SATELLITE IMAGE”
DS6	TAYLOR AND FRANCIS	[PUBLICATION TITLE:” WATER”] AND [[PUBLICATION TITLE:” SEGMENTATION”] OR [PUBLICATION TITLE:” EXTRACTION”]] AND [ALL: SATELLITE IMAGE]
DS7	MDPI	” WATER SEGMENTATION” OR” WATER EXTRACTION” AND” SATELLITE IMAGE”

Table 5. Selection Criteria

NO.	SELECTION CRITERIA
SC1	ARTICLE MUST BE ENGLISH JOURNAL OR A CONFERENCE PROCEEDING
SC2	RESEARCH MUST BELONG TO DURATION BETWEEN 2000 TO 2024
SC3	FREE ACCESSIBLE PAPER
NO.	**QUALITY ASSESSMENT CRITERIA**

QAC1	HOW MANY DATA RESOURCES INCLUDED IN OUR STUDY ARE RELEVANT TO OUR REVIEW?
QAC2	THE RESEARCH ARTICLE MUST DISCUSS HOW THEY GATHER DATA AND TECHNIQUES USED.

the study thoroughly addressed the important trends and breakthroughs in the field of Water segmentation diagnosis utilizing Satellite data. The quality of the literature was also evaluated beside the selection factors. Guidelines for quality were developed to identify possible inaccuracies in outcomes of studies. Table 5 demonstrates the quality assessment criteria along with selection criteria. The quality evaluation follows the summary quality checklist for investigations established by Kitchenham [34]and Raymon [35]. We picked research quality assessment criteria based on how they impact on SLR quality. Two quality assessment criteria (QAC) are used to evaluate methodological rigor and relevance. QAC1 (Score of Relevance) assessed the degree to which a paper's datasets and segmentation techniques aligned with the scope of this review. Scores were assigned as: 0 = minimal/no relevance, 1 = partial relevance, 2 = fully relevant. QAC2 (Methodological Transparency) measured the clarity and completeness of descriptions regarding data sources and applied segmentation methods. Scores were assigned as: 0 = insufficient detail, 1 = partial description, 2 = comprehensive methodological explanation. Only studies achieving QAC1 ≥ 1 and QAC2 ≥ 1 were included in the final synthesis. This approach follows the quality evaluation guidelines adapted from Kitchenham [34] and Dinter et al. [35] for systematic reviews in technical domains. The final outcome after applying selection criteria (SC)and quality assessment criteria (QAC) is presented in Table 6.

3.2.1 Data Extraction and Data Synthesis

Data extraction comprises an organized collection and extraction of the pertinent information from chosen studies to answer study's research question. The analysis of 48 articles results in the extraction of data and synthesis techniques to obtain substantial data. The data extracted from researches are

Extraction element 1: Source (journal or conference) with complete citation, year of Publication.

Extraction element 2: Study Type (SLR, Meta-Analysis MA) and Scope (research trends or technology evaluation questions).

Extraction element 3: Main subject matter, overview of the study, including important research questions and responses. Research issue or subject, quality assessment.

Extraction element 4: Analyse design and methodology like data collection and techniques employed.

Extraction element 5: Outcomes and results.

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Data synthesis means evaluating and combining specific study data to produce novel perspectives, uncover trends, and make inferences concerning the research topic or issue. The goal is to gather useful knowledge from acquired data, uncover commonalities or patterns across research, and give a thorough picture of the issue being investigated

Table 6. Final Outcome after selection and quality assessment criteria

Database	All result	SC1	SC2	SC3	QAC1	QAC2
DS1	127	126	96	8	4	2
DS2	2	2	2	1	0	0
DS3	811	541	449	6	2	0
DS4	582	536	450	133	18	17
DS5	19	19	19	17	2	1
DS6	54	54	50	9	9	9
DS7	32	24	24	24	21	19
Total	1627	1302	1090	198	56	48

In above table 6 SpringerLink database initially yielded 811 articles, but at end only two met both the open-access requirement and QAC thresholds. The main reasons for exclusion were: (i) paid access restricting reproducibility,

(ii) focus on unrelated application domains such as medical imaging or non-environmental computer vision, and (iii) absence of explicit water body segmentation methodology in the full text.

Similar filtering patterns were observed across other databases, though the reduction was less drastic. For example, IEEE Xplore decreased from 127 results to 2 after applying the same criteria, and ScienceDirect dropped from 582 to 17 after quality screening. These reductions reflect the combined impact of the open-access restriction and strict methodological relevance checks applied consistently to all databases, ensuring that the included literature directly supports the research questions. The flow of records through the identification, screening, eligibility, and inclusion stages is depicted in Fig.3, with numerical details provided in Table 6.

Table 7. Research Questions Relevant to Extraction

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EXTRACTION ID	RESEARCH QUESTIONS
Extraction element 1	Q1, Q2
Extraction element 2	Q3
Extraction element 3	Q3
Extraction element 4	Q4, Q5
Extraction element 5	Q6

To provide a structured synthesis of our findings, each data extraction element was explicitly mapped to the corresponding research question. Table 7 presents this mapping, ensuring that every extracted component directly addresses the objectives outlined in the planning phase. This alignment helps maintain consistency between the SLR framework and the analysis process.

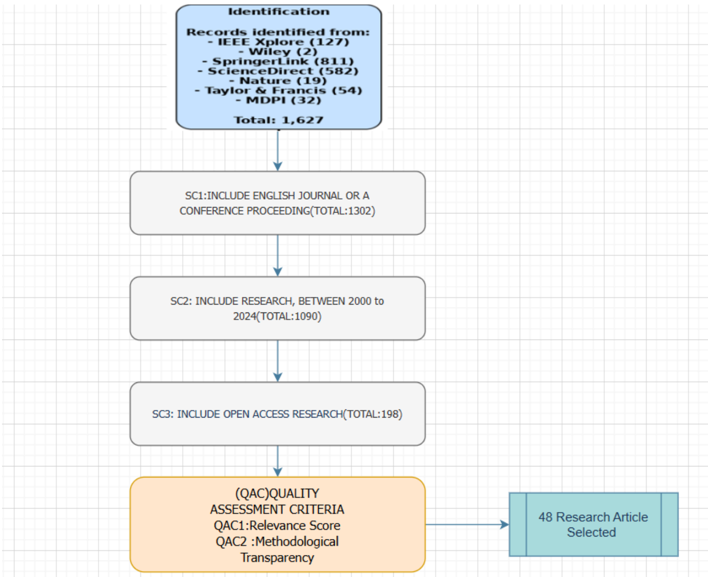

Fig.3: PRISMA flow diagram

3.3 Final phase: Reporting and Result Phase

The reporting step of a systematic literature review (SLR) involves incorporating the findings from the selected studies and recording them in a concise and thorough style. Table 8 is a brief analysis of the findings of final 48 selected research articles in context with the research questions, aims, and larger literature.

Table 8. List of 48 selected article

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REFERENCE	PRIMARY AUTHOR YEAR OF PUBLICATION	METHOD	FINDINGS AND REMARKS
[36]	Kunhao yuan,2021	MC-WBDN	mIoU = 73.56
[28]	Xinyu zhang,2022	MRSE-Net	F1-score = 0.9400
[37]	Gonzalo mateo,2021	FCNN-Based Flood Detection Model	Recall Total Water = 96.03
[38]	S. D. Jawak,2015	Modified NDWI	Total average (RMSE)m^2 = 240.03
[39]	Junjie li,2023	Sentinel-1 And Sentinel-2 Fused Data for Time-Series Surface Water Maps.	Accuracy of Water Reaches 95.8%
[40]	Xin luo,2021	Structured WatNet model based	mIoU = 73.56
[41]	Ujwala bhangale,2020	Normalized Difference Water Index (NDWI)	Visualize Consistencies Between Two Data and Verify Presence or Absence of Water Bodies in Certain Regions
[42]	Vivek kumar gautam,2015	Water ratio index (WRI), normalised difference water index (NDWI), modified normalised difference water index (MNDWI), supervised classification and wetness component of K-T transformation	NDWI = 64.83% WRI = 85.17% K-T = 77.10% Supervised Classification = 83.78%
[43]	Mohammad aghdami-nia,2022	U-Net	IoU = 98.87%, Accuracy = 99.43%
[44]	Jikang wan,2023	EDCM (efficientnetv2 and deeplabv3 + comprehensive model)	Highest Accuracy in All Selected Test Areas, Reaching More Than 95.28%.
[45]	Vitor S. Martins,2020	DNN algorithm (Deep neural network)	Accuracy = 93.33%

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[46]	Ian olthof,2022	Multi-Sensor Dynamic Surface Water Monitoring System	Enhance Floodplain Mapping in Canada
[47]	Zhaofei wen,2021	A New ensemble way of using WIs that integrates five widely used WIs is proposed, namely the CDWI	F1-scores by CDWI = 67%
[48]	Hafiza wajiha khalid,2021	LST Based Water Extraction Index (LBWEI)	Highest Accuracy = 97.63%
[49]	Xinyan li,2021	category-based approach spatiotemporal dependence (STD) model	Accuracy of up to 98%
[50]	Kai li,2021	Pixel-Based CNN, Pixel-Based DNN, AND U-NET	Pixel-Based CNN = 99.90%, Pixel-Based DNN = 96.98%, U-NET = 93.70%
[51]	James worden,2020	Logistic regression model using an optical surface water index (MNDWI)	Accuracy of 93.0%
[52]	Nosheen abid,2021	Convolutional Neural Networks (CNN)	Highest Efficiency 91%
[53]	Xiucheng yang,2018	The modified normalized difference water index (MNDWI) and the automated water extraction index (AWEI)	Highest Accuracy 98.66%
[54]	Gulcan sarp,2017	Support Vector Machine (SVM) Classification and Spectral Water Indexing MNDWI, NDWI and AWEI	Approximately One Fifth Lake Lost Its Surface Area
[55]	Yongtao yu,2022	Hierarchical attentive high-resolution network, abbreviated as WaterHRNet	Average Precision was 98.44%, Average Recall was 97.84%, Average IoU was 96.35%, And Average F1-Score was 98.14%.

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[56]	Wangping li,2022	(MEDPSO) Coupling Discrete Particle Swarm Optimization Algorithm with Maximum Entropy Model	Highest, With an Overall Accuracy Of 99.4%
[57]	Guizhou zheng,2023	Fully convolutional adversarial network (FANet)	IoU of 0.8564 and F1-Score of 0.9031%
[58]	Jingming wang,2022	Flood Water Body Extraction Convolutional Neural Network (FWENET)	Precision = 0.98 , Recall = 0.9842 , F1 = 0.9871, IoU = 0.9744
[59]	Chuan xu,2021	Object-Based Classification	Kappa Accuracy Assessment = 0.90
[60]	C. Bipin,2021	Spatial Search and A Three-Level Model-Based Approach	Accuracy of 94%
[61]	Bo liu,2023	Multi-Scalefeatures Extraction Network (MSFENet)	High F1-score = 95.70% and Kappa Coefficient = 94.97%
[62]	Donghui ma,2023	Water Index and Swin Transformer Ensemble (WISTE)	Highest Accuracy 97.85%
[30]	Rongfang wang,2024	A Multi-Modality Fusion and GatedMulti-Filter U-Net	Accuracy Of Chengdu = 96.11%, Accuracy of GF-2 = 93.63%
[63]	Xufeng wei,2020	Swarm Optimization with Linear Feature Enhancement (SMDPSO+LFE)	Accuracy Higher Than 94.5%
[64]	Wei jiang,2021	Fusion of SWI and Otsu algorithm	A Novel Approach for Rapid and Accurate Water Body Extraction
[65]	Jie yu,2023	Boundary-Guided Semantic Context Network	Qtpl Dataset Accuracy is 98.97% And Loveda Dataset Accuracy is 95.70%
[66]	Paramate horkaew,2017	Entropy-Based Fusion of Water Indices and DSM Derivatives	98.25% accuracy

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[67]	Tri dev acharya,2019	NB, RPART, NNET, SVM, RF and GBM Algorithms	Overall Accuracy above 90%
[68]	Yanjun wang,2021	Lightweight Deep Neural Network Method (MobileNetV2)	F1-score and Kappa were 0.64 and 0.61 for GF-2 and for Worldview-2 0.82 and 0.81, for UAV 0.98 and 0.98
[29]	Xin lyu,2023	MSAFNET: Multiscale Successive Attention Fusion Network	QTPL dataset, MSAFNET 99.14% ,98.97% for F1 and Accuracy. LOVEDA, MSAFNET, with F1 and Accuracy 97.69% and 95.87%
[69]	Zhaobin wang,2020	Multi-Scale Lake Water Extraction Network (MSLWENet)	Accuracy = 98.53%
[70]	Wei jian,2018	Multilayer Perceptron Neural Network	Accuracy of MLP ranges from 98.25–100%
[71]	Xin lyu,2022	Multiscale Normalization Attention Network	SW dataset Accuracy = 94.44%, QTPL dataset Accuracy = 98.47%
[72]	Yijieweng,2023	OCNET	Accuracy (ACC) can reach 85%
[6]	Zhili zhang,2021	Multi-Feature Extraction And Combination Network (MECNet)	IoU = 0.9064
[73]	Longhai xiong,2018	Subpixel Surface Water Extraction (SSWE)	The SSWE demonstrates high accuracy in extracting surface water, particularly in optically complex aquatic environments
[74]	Joshua billson,2023	Deep Convolutional Networks and Pixelwise Category Transplantation	Incorporating multispectral bands improves performance over visible-spectrum models by an average of 4.193 mIoU.
[75]	Xiaohong yang,2020	Multiscale Spatiotemporal Super-Resolution Mapping	KAPPA = 0.8984 and Accuracy = 95.06%

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[10]	Liwei li,2019	Fully Convolutional Networks (FCN) model	FCN model to extract water bodies from VHR images
[76]	Jiahang liu,2022	Domain Adaptation-Based Network Embedding Selective Self-Attention and Multi-Scale Feature Fusion	F1=92.56, mIoU =83.99
[77]	Linan bao,2021	Features Analysis and Dual-Threshold Graph Cut Model	Accuracy = 99.88%

3.3.1 Annual trends for Research in Water Segmentation: Q1

The present investigation examines 48 papers that address water segmentation in satellite images. Over the last decade, study patterns in water segmentation in satellite images have been impacted by developments in remote sensing technology, image processing techniques, and the growing demand for precise and efficient means of monitoring water bodies. Researchers are increasingly focusing on combining multi-source satellite data, such as optical, thermal, and radar imaging, to increase the accuracy and reliability of water segmentation algorithms. The fusion of data from several sensors allows for improved distinction of water bodies under diverse environmental circumstances, improving overall classification performance. Fig.4 gives a glimpse of number of articles published in last decade.

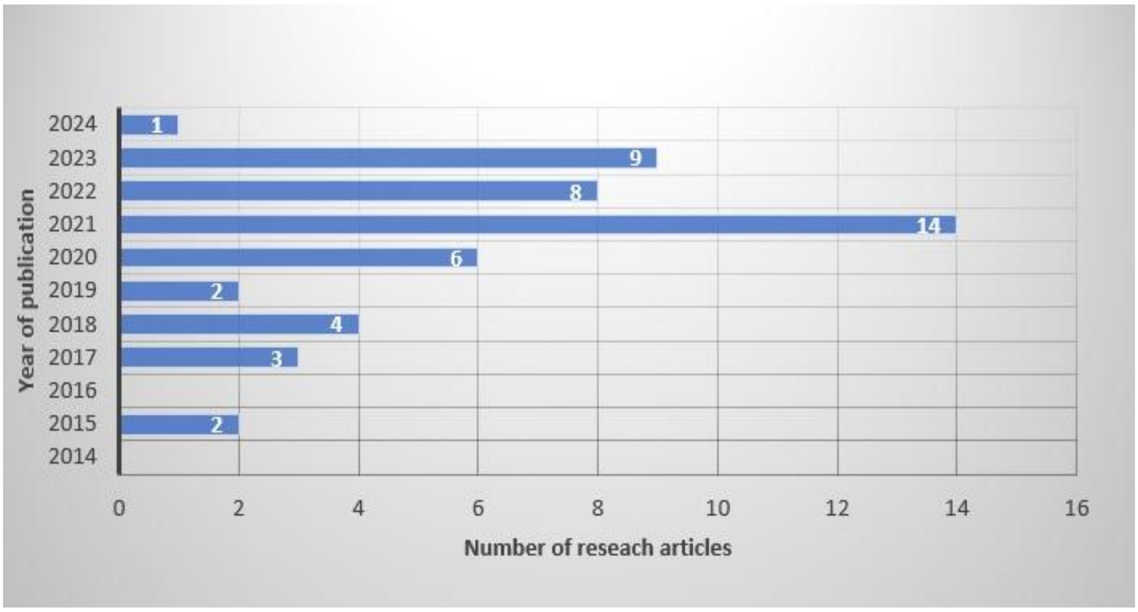

Fig.4: Annual Trends

3.3.2 Research Domains in the field of Water Segmentation: Q2

Water segmentation research spans several disciplines and multidisciplinary fields in which the identification, delineation, and analysis of water bodies are critical. Forty- Eight articles are

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collected and classified based on domains. This particularly intends to offer solutions to research questions (Q2). There are majorly two broad domains of publications: journal articles and conference proceedings. The current study discovered that journal is much more common than conference proceedings in the field of segmentation. The journal article can either be a survey paper or a case study or informative paper which contains a novel finding. Fig.5 depicts the distribution of each of these domains that were found in our study of 48 papers whereas Fig.6 depicts the number of papers published in conference or journals.

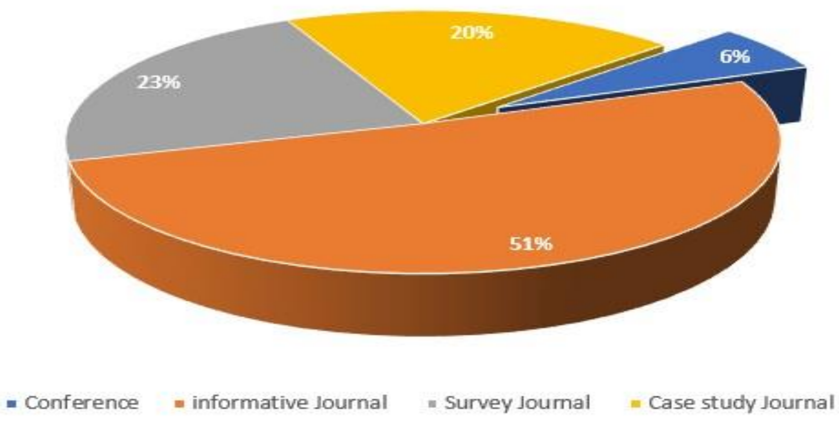

Fig.5: Domains of Research

3.3.3 Research Contribution in the field of Water Segmentation: Q3

This section tries to examine how each study's objectives are attained while also answering the research questions (Q3) by highlighting research contributions. The writers of each literature claim that their recommended approach produces successful results, however this study must correctly identify the literature in order to validate the results. As a result, it is important to mention that the primary purpose of this work is to evaluate the proposed methodology and methodologies for addressing the research topic. There are no stand-alone approaches, as most proposed methods are modifications or additions to existing ones.

3.3.4 Dataset Employed in the field of Water Segmentation: Q4

Multiple satellite imaging datasets are utilized by the 48 research articles for water segmentation purposes owing to their accessibility, spatial resolution, spectral bands, as well as temporal coverage. Here are a few of the most popular satellite imaging datasets utilized in a decade for water segmentation process:

1. Landsat: Landsat satellites offer multi-spectral images at a modest spatial resolution (30 meters) with a revisit duration of 16 days. The Landsat program, run by NASA and the USGS, provides data continuity that spans many decades, making it useful for long-term water

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monitoring and research. Landsat imagery is publicly available via a variety of data portals and repositories, including the USGS Earth Explorer, GloVis, and the Landsat Level-1 Data Products website. Users may obtain Landsat data from several missions, such as Landsat 1-5 (MSS and TM sensors) and Landsat 7-9 (ETM+ and OLI/TIRS sensors).

2. Sentinel 2: The European Space Agency's (ESA) Sentinel-2 mission produces high-resolution multi spectral imaging with a spatial resolution of 10 meters for visible and near-infrared bands and 20 meters for red edge and shortwave infrared bands. Sentinel-2's frequent revisits and worldwide coverage make it ideal for dynamic water feature recognition and change detection analysis.

3. Sentinel-1 SAR (Synthetic Aperture Radar): Sentinel-1 SAR satellites, primarily operated by ESA, have all-weather imaging abilities and offer high-resolution radar images ideal for detecting water in hazy or occluded locations. SAR data is sensitive to ground roughness and may penetrate plants, and making it useful for mapping wetlands, rivers, and coastal areas.

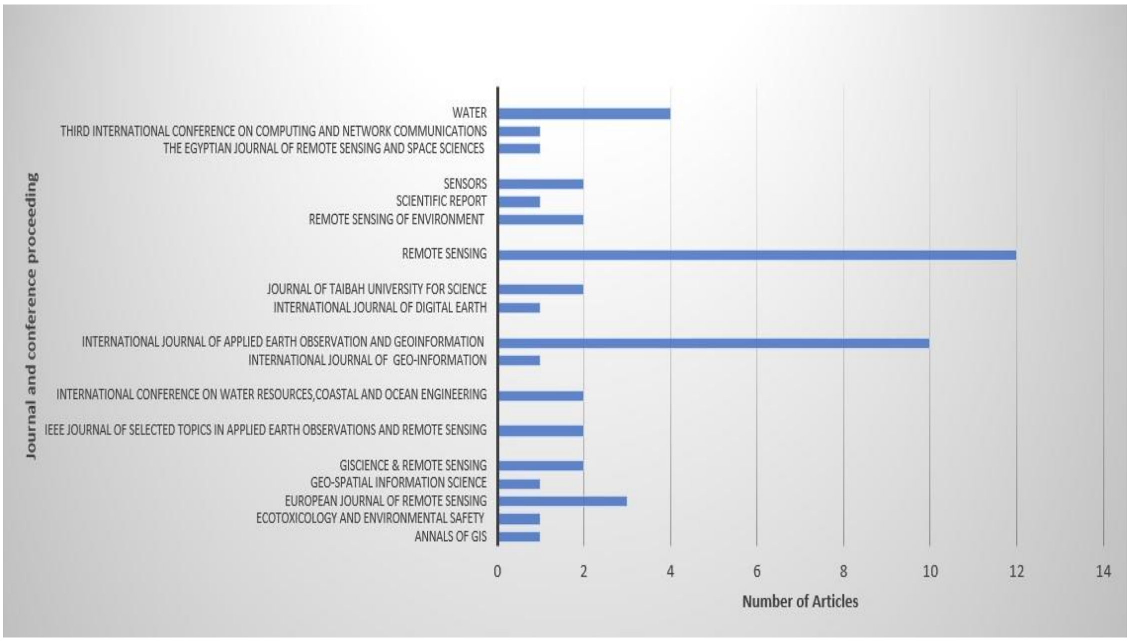

Fig.6: Article in Journals or conferences

4. WorldView Series (WorldView-2, WorldView-3): The WorldView series of satellites handled by DigitalGlobe. WorldView satellites provide extremely high-resolution images (up to 30 cm) and multispectral capabilities, making them ideal for comprehensive water feature mapping, urban planning, and local environmental monitoring.

5. GaoFen-2 (GF-2): The China Center for Resources Satellite Data and Applications (CRESDA) operates the high-resolution optical satellite GaoFen-2 (GF-2). The satellite's multispectral images offer spatial resolutions ranging from 0.8 to 3.2 meters, depending on the imaging mode and spectral bands. The GF-2 spacecraft has many sensors, including a

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panchromatic camera and four multispectral cameras that record pictures in a variety of spectral bands, including visible, near-infrared, and shortwave infrared.

The research article reviewed used a diverse set of satellite datasets, ranging from freely accessible medium-resolution such as Landsat and Sentinel to commercial very-high-resolution platforms like WorldView and Gaofen. These datasets differ significantly in spatial resolution, revisit time, which directly influence their suitability for water body segmentation tasks. To provide direct comparison, Table 9 summarizes the key characteristics, advantages, and limitations of each dataset referenced in this review.

Table 9. Summary of commonly used datasets for water body segmentation

DATASET	SPATIAL RESOLUTION	REVISIT TIME	ADVANTAGES	LIMITATIONS	ACCESSIBILITY
LANDSAT-8/9	30 m (optical), 100 m (thermal)	16 days	Long historical archive, consistent calibration	Lower revisit than Sentinel series	Open & free (USGS EarthExplorer)
SENTINEL-2	10–60 m	5 days	High resolution, rich spectral detail	Cloud-sensitive	Open & free (Copernicus Hub)
SENTINEL-1	10 m	6–12 days	All-weather, day/night imaging	Speckle noise, requires preprocessing	Open & free (Copernicus Hub)
MODIS	250–1,000 m	Daily	Daily coverage, global monitoring	Coarse resolution	Open & free (NASA LAADS DAAC)
ALOS PALSAR	10–100 m	46 days	Penetrates vegetation, good for wetlands	Long revisit time	Partially open (JAXA)
WORLDVIEW-2/3	0.3–1.8 m	1–4 days	Extremely high resolution for small-scale mapping	Commercial cost, smaller swath width	Paid (Maxar)
GAOFEN-1/2/6	0.8–2 m (panchromatic)	4–5 days	High spatial detail, multiple spectral bands	Limited international access, licensing required	Restricted / Paid (China National Space Admin)

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3.3.5 Techniques Employed in the field of Water Segmentation: Q5

During the last decade, different water segmentation approaches have been developed and implemented to satellite imagery, taking advantage of advances in remote sensing technologies and image processing. Mentioning a few of water segmentation methods that have become more popular over the last decade: Threshold techniques, Machine learning algorithms, object-based image analysis, Data fusion and integration, Deep learning algorithms etc. A trend of techniques is shown during decade using a graph plot in Fig.7. In recent years, the most prevalent water segmentation strategy has been

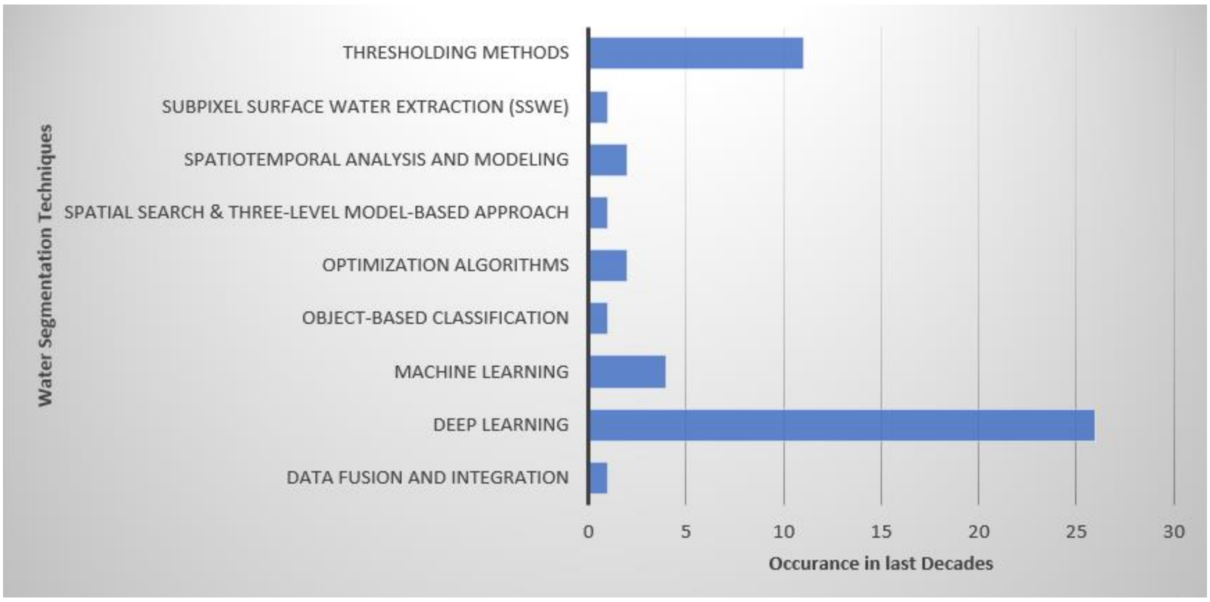

Fig.7: Trend of techniques

to use machine learning algorithms and deep learning approaches, notably CNN-based models. Deep learning has demonstrated promising results in autonomously locating and defining water features from satellite data. However, the selection of segmentation approach is determined by a variety of parameters, including data properties, spatial resolution, computing resources, as well as application requirements. To acquire the best segmentation findings, researchers frequently mix and tailor various approaches to specific study areas and aims.

3.3.6 Techniques with highest efficiency in the field of Water Segmentation: Q6

Determining the most efficient approach for detecting water bodies using satellite pictures is dependent on a number of factors, including the unique properties of the satellite images, the climatic circumstances, the analytic objectives, and the computational resources available. To identify the most effective water segmentation approaches, we synthesised reported performance metrics from the top-performing methods in the reviewed literature. The segmentation approach is closely related to the dataset characteristics summarised in Section 3.3.4 (Table 9). Optical datasets with high spatial resolution, such as Sentinel-2, Landsat-8/9, and WorldView, tend to favour deep learning architectures like U-Net and ResU-Net, which can exploit fine-grained spectral and spatial features. Conversely, SAR datasets such as

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Sentinel-1 and ALOS PALSAR benefit from models robust to speckle noise, including DeepLabv3+ and fusion-based CNNs integrating optical and radar inputs. Coarser but high-temporal-resolution datasets like MODIS are better suited for lightweight, threshold-based or machine learning methods when rapid monitoring is prioritised over fine detail. This alignment between dataset properties and algorithm performance provides a practical framework for selecting efficient techniques in operational contexts. Further table 10 summarises these techniques, the datasets used, input modalities, reported accuracy or segmentation scores (IoU/F1), and key strengths and limitations. The studies span both optical and radar (SAR) data sources, as well as fusion-based approaches combining multiple modalities.

Table 10. Comparative performance of top water segregation approaches across datasets

METHOD	DATASET	INPUT TYPE	ACCURACY	STRENGTHS	LIMITATIONS	METHOD
U-NET	Sentinel-2	Optical multispectral	IoU: 0.92, F1: 0.95	High accuracy, good for small water bodies, robust to moderate cloud cover	Requires large labeled dataset for training	U-Net
RESU-NET	Landsat-8	Optical multispectral	IoU: 0.90, F1: 0.94	Captures fine boundaries with residual connections	Sensitive to atmospheric noise	ResU-Net
DEEPLABV3+	Sentinel-1 (SAR)	Radar backscatter	IoU: 0.88, F1: 0.91	Works in all weather, robust to cloud cover	Struggles with mixed land-water pixels in urban areas	DeepLabv3+
RANDOM FOREST	Landsat-8	Optical multispectral	Accuracy = 0.89	Fast, interpretable, works with small datasets	Less effective for irregular shorelines	Random Forest

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OTSU THRESHOLDING	Sentinel-2	Optical multispectral	Accuracy = 0.85	Simple, no training required	Poor in shadow/cloud conditions	Otsu Thresholding
FUSION CNN-SAR + OPTICAL	Sentinel-1 + Sentinel-2	Radar + Optical	IoU: 0.93, F1: 0.96	Combines spectral + structural info, robust to noise	High computational cost	Fusion CNN-SAR + Optical

Study and analysis of the top methods in this literature shows a clear picture of performance hierarchy. Deep learning models such as U-Net, ResU-Net, and fusion-based CNNs integrating optical and SAR data, achieved average IoU scores between 0.91–0.96 and F1-scores above 0.94, much better than both traditional and classical machine learning methods. Thresholding and index-based methods (e.g., NDWI, Otsu) typically yielded IoU scores of 0.78–0.85 and accuracies below 90% in heterogeneous features. Machine learning models such as Random Forest and SVM improved over thresholding, with IoUs in the 0.80–0.88 range, but required careful feature engineering. Fusion models offered the best robustness under challenging conditions such as cloud cover and turbidity, reaching up to 0.96 IoU and 99% accuracy. This evidence suggests that, for operational contexts, deep learning, especially fusion-enhanced architectures provide the optimal balance of accuracy and adaptability, while lightweight threshold-based models remain useful for rapid, low-resource monitoring.

4 Conclusion and Future work

This review elaborated findings from 48 research studies on water body segregation, classifying techniques into traditional approach, machine learning model, deep learning models, and fusion-based approaches. Comparative analysis (Tables 9 and 10) found that deep learning models, such as U-Net, ResU-Net, and fusion CNN models integrating optical and SAR inputs, has the highest accuracy, with IoU reaching up to 0.96. These approaches have consistently overpowered traditional thresholding and classical machine learning techniques, especially in complex scenarios or under variable climatic conditions.

Dataset selected also emerged as a critical performance evaluator. Dataset such as Sentinel-2 and Landsat-8/9 were the most commonly used, who offered a balance of spatial resolution, spectral coverage, and accessibility. Sentinel-1 SAR proved best for flood mapping in cloudy areas, while very-high-resolution datasets from WorldView and Gaofen were excellent in small-scale mapping despite cost and constraints of accessibility.

Three emerging research trends were identified:

1. Data amalgamation of multi-sensor inputs (e.g., optical, SAR, LiDAR) for improved robustness.
2. Deep learning lightweight models optimised for real-time or edge-device deployment.

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3. Fusion with IoT-enabled monitoring systems, enabling automated, near-real-time water segmentation for flood forecasting and resource management.

4.1 Future research recommendations

- Developing cross-modal transfer learning frameworks to leverage knowledge between regions and sensors.
- Expanding labelled benchmark datasets for underrepresented geographies, particularly in the Global South.
- Designing computationally efficient models for deployment in IoT and edge-computing environments.
- Investigating uncertainty quantification in segmentation outputs to improve decision-making reliability.

4.2 IoT integration potential

The integration of water segmentation models with IoT-based monitoring frameworks offers a transformative pathway for real-time environmental management. Edge devices equipped with embedded AI can process satellite or UAV-acquired imagery locally, reducing latency and enabling rapid flood alerts. Coupling segmentation outputs with smart water grids, sensor networks, and automated control systems can facilitate dynamic water allocation, early flood warning, and adaptive reservoir management. Such IoT-enabled workflows are especially valuable in data-scarce or high-risk regions, bridging the gap between remote sensing analytics and actionable, field-level interventions.

By consolidating performance evidence and linking dataset characteristics to methodological strengths, this review provides a practical reference for researchers and practitioners selecting appropriate segmentation strategies for operational water monitoring systems.

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