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A Review of Image-Based and AI-Driven Water Level Monitoring: Methods, Datasets, and Deployment Considerations

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A Review of Image-Based and AI-Driven Water Level Monitoring: Methods, Datasets, and Deployment Considerations

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Abstract

Accurate and continuous water-level monitoring is essential for agriculture, flood management, and water resources planning. However, many rivers and agricultural canals remain ungauged because conventional sensing infrastructure is costly to install and maintain, limiting basin-scale water accounting and conservation policies such as water banking and leasing. Computer vision enables water-level estimation from ground-based cameras, unmanned aerial vehicles (UAVs), and satellites, offering a low-cost, non-contact alternative to conventional sensors. This review synthesizes 93 studies selected from 168 articles retrieved from five databases, following PRISMA 2020 guidelines. We summarize contact-based and non-contact sensing methods and examine image-based approaches, including traditional image processing, classical machine learning (ML), and deep learning (DL), alongside their imaging modalities and datasets. DL methods, particularly object detection, semantic segmentation, and transformer-based models, are more robust than earlier approaches under low light, reflections, and cluttered backgrounds, with several studies reporting field errors of approximately 1–3 cm. However, these results are not directly

comparable because studies differ in datasets, reference measurements, and evaluation metrics. Three major research gaps emerge: (1) fragmented datasets and inconsistent evaluation protocols; (2) limited cross-site validation and model generalization; and (3) insufficient long-term field evaluation and robustness to illumination changes, reflections, and camera displacement. Future research should prioritize standardized, publicly available multi-site datasets, common evaluation protocols, cross-site and seasonal testing, and adaptive models that maintain reliability under changing field conditions.

Keywords: Water level, Waterline detection, Computer vision, Deep learning, Classical machine learning, image processing

1 Introduction

Reliable water level estimation is fundamental to hydrological monitoring and effective water resources management. Key quantities such as stream discharge, reservoir storage, flood extent, and water allocation are rarely observed directly; they are instead derived from water level through established physical and empirical relationships [1]. As a result, uncertainties in water level measurements directly translate into errors in discharge estimation, water allocation, and flood prediction, particularly under dynamic flow conditions [2].

Although the terms *water level*, *water stage*, and *water surface elevation* are often used interchangeably in hydrological studies, they have distinct definitions based on the reference datum used. Water surface elevation (WSE) refers to the height of the water surface relative to a global or geodetic datum, enabling comparison across locations [3]. Water stage refers to the height of the water surface relative to a locally defined reference, such as the gauge datum at a specific gauging station [4]. The term water level is used more broadly to describe the vertical position of the water surface and, in practice, is often used interchangeably with stage when a consistent reference is implied [4]. Although WSE, water stage, and water level differ in their reference definitions, they describe the same physical quantity and can be related through constant offsets when the datums are properly defined.

The measurement of water level has evolved from manual observations to increasingly automated sensing systems. Early monitoring relied on people visually reading staff gauges, where an observer records the position of the water surface against a graduated scale at specific time intervals [5]. While simple and widely used, this approach is non-continuous, labor-intensive, and difficult to sustain in remote or hazardous environments [5]. The need for continuous and automated measurements led to the development of contact-based sensing technologies grounded in physical measurement principles. One of the most widely adopted approaches is the use of pressure transducers, which infer water level from the hydrostatic pressure exerted by the overlying water column, based on the relationship between pressure and fluid depth [6]. Another common method is the float-based system, in which a buoyant element rises and falls

with the water surface. Its vertical displacement is converted into a continuous measurement signal, often within a stilling well designed to reduce the influence of surface fluctuations. In addition, bubbler gauges estimate water level indirectly by measuring the air pressure required to force gas through a submerged outlet at a known elevation, where the back-pressure reflects the height of the water column above the outlet [7]. Although these methods provide continuous measurements with relatively high accuracy, their reliance on direct contact with water introduces significant operational challenges. Sensors are continuously exposed to sediment transport, floating debris, biofouling, corrosion, and ice formation, all of which can degrade performance and increase maintenance requirements. These limitations become particularly critical during high-flow and flood conditions, where both measurement reliability and physical durability are most challenged [8, 9].

To address the limitations of contact-based sensors, non-contact techniques were developed to measure water level without physical interaction with the water surface. Ultrasonic sensors estimate distance by emitting acoustic pulses and calculating the time delay of the reflected signal, assuming a known speed of sound in air [10]. A related approach uses radar sensors, which rely on electromagnetic waves for ranging and are generally less sensitive to variations in temperature, humidity, and atmospheric conditions. By avoiding direct exposure to water, these systems improve durability and operational safety, particularly in harsh or inaccessible environments. However, their performance can still be affected by surface roughness, wave activity, signal scattering, and installation geometry. In addition, radar-based systems, while more robust, are often more expensive to procure and deploy [11]. More broadly, both ultrasonic and radar sensors provide measurements at fixed locations, limiting their ability to capture spatial variability across larger or complex environments [12, 13]. Such variations can result from changes in channel geometry and slope, flow conditions, sediment accumulation, vegetation, gates, and other hydraulic structures, and inflows or diversions along the channel. Therefore, monitoring water-level variability across large or hydraulically complex water networks requires many sensor installations, with correspondingly high infrastructure and maintenance costs.

Computer vision offers a more recent, non-contact alternative that addresses several of these limitations. Instead of placing sensors in the water, image-based methods estimate water level from images or video captured by cameras, using the position of the water surface relative to reference features such as staff gauges, calibration targets, or fixed structures [5, 14]. Because cameras can be mounted away from the water, they avoid fouling and flood damage, provide a visual record that can be checked by an operator, and can make use of existing surveillance and webcam infrastructure. Beyond fixed ground-based cameras, imagery from unmanned aerial vehicles (UAVs) and satellites has extended visual monitoring to sites without fixed infrastructure, although at coarser spatial and temporal resolution [15, 16].

Early image-based approaches relied on classical image processing, in which the waterline is located with handcrafted rules such as intensity thresholding, edge detection, or line detection, and then converted to a physical water level using the gauge scale or a geometric calibration [17, 18]. These methods are computationally light and easy to interpret, and under controlled conditions they can achieve millimeter-level

accuracy [19]. However, because they depend on manually tuned features and thresholds, their performance degrades under changing illumination, reflections, shadows, occlusion, turbid water, and cluttered backgrounds, and they usually require site-specific adjustment [18]. These limitations restrict their robustness in long-term field deployment.

Recent advances in artificial intelligence (AI) have significantly enhanced the capability of image-based water level estimation. Classical machine learning and deep learning approaches shift the problem from rule-based detection to data-driven inference, enabling models to learn robust representations directly from visual data. Convolutional neural networks (CNNs), in particular, have been widely adopted for detecting and segmenting the water surface under complex conditions [20, 21], while temporal models leverage continuity in image sequences to improve stability and reduce noise [22]. More recently, transformer-based architectures have been applied to water level estimation; unlike CNNs, which analyze small local regions of an image, transformers use a self-attention mechanism that relates every part of the image to every other part, allowing them to capture the global context of the image, such as the full extent of the water surface and its relation to the gauge or riverbank. Building on this architecture, vision foundation models such as the Segment Anything Model (SAM) [23] are pretrained on very large and diverse image collections and can segment objects, including water, in new scenes with little or no additional training, which reduces the need for large site-specific labeled datasets and improves generalization across sites and imaging conditions [14, 24, 25]. Long-term field deployments have also begun to test these systems under operational conditions [26]. Collectively, these developments have transformed image-based approaches into scalable and low-maintenance alternatives to traditional sensing methods.

Research on image-based water level monitoring spans several disciplines, including hydrology, computer vision, and environmental monitoring. Although numerous studies have proposed and evaluated individual methods, a comprehensive understanding of their comparative performance, data requirements, and practical limitations remains limited. Previous reviews have covered parts of this landscape. Wu et al. [27] reviewed non-contact water level measurement based on computer vision and radar, Manfreda et al. [28] surveyed image-based river monitoring with an emphasis on surface velocity and discharge, Kossieris et al. [29] reviewed satellite-based inland water level monitoring, and Adikari et al. [15] focused on computer vision for flash flood forecasting. None of these reviews jointly examines image processing, classical ML, and DL methods for water level estimation alongside the imaging modalities, datasets, and deployment constraints that determine whether such methods can be used operationally, and none covers the rapid adoption of transformer and foundation-model approaches since 2023. This paper addresses this gap through a structured review of 93 studies selected following the PRISMA 2020 guidelines [30]. The aim is to provide a unified perspective on how water level can be estimated from visual data, linking methodological developments with data sources, sensing platforms, and practical deployment considerations. In doing so, the review seeks to clarify the strengths and limitations of existing approaches and to identify directions for future research.

The review investigates several important aspects of image-based water level monitoring, as outlined below:

- What image-based and AI-driven approaches have been used for water level estimation, and what are the principles and architectures underlying each approach?
- What measurement accuracy has been reported for image-based water level monitoring methods, and what challenges and limitations have hindered their widespread adoption?
- What are the different imaging modalities and devices used for water level monitoring?
- What datasets are available in the literature, and what are their characteristics and limitations for enabling robust and reproducible evaluation, and what accuracy has been reported for different methods in previously published studies?
- What are the key challenges and considerations that determine the applicability of these methods across diverse real-world environments?

2 Methodology and Literature Selection

This review follows the Preferred Reporting Items for Systematic Reviews (PRISMA 2020) reporting guidelines [30]. PRISMA is a widely used, evidence-based standard for reporting literature reviews transparently, so that readers can see how studies were found, which were excluded and why, and how the final set of studies was reached, and can reproduce the selection process. Its central element is a flow diagram that tracks the number of articles through four successive stages: (1) identification, in which articles are retrieved from the selected databases and duplicates are removed; (2) screening, in which the titles and abstracts of the remaining articles are checked against the eligibility criteria; (3) eligibility, in which the full texts of the retained articles are assessed in detail; and (4) inclusion, which gives the final number of studies analyzed in the review. At each stage, the number of excluded articles and the reasons for their exclusion are reported. The PRISMA flow diagram for this review is shown in Figure 1.

2.1 Search Strategy and Databases

Research articles were retrieved from five databases: Google Scholar, Semantic Scholar, IEEE Xplore, ScienceDirect, and Scopus. These databases were chosen because together they cover the hydrology, remote sensing, and computer vision literature relevant to image-based water level monitoring.

The first phase of the literature selection process involved identifying relevant keywords derived from the research objectives and questions: *water level monitoring*, *water level estimation*, *computer vision*, *deep learning*, *machine learning*, and *image processing*. Search strings were then constructed by combining each water level term with each method term using the Boolean operator AND. Examples include:

- “water level monitoring” AND “computer vision”
- “water level monitoring” AND “deep learning”
- “water level monitoring” AND “machine learning”

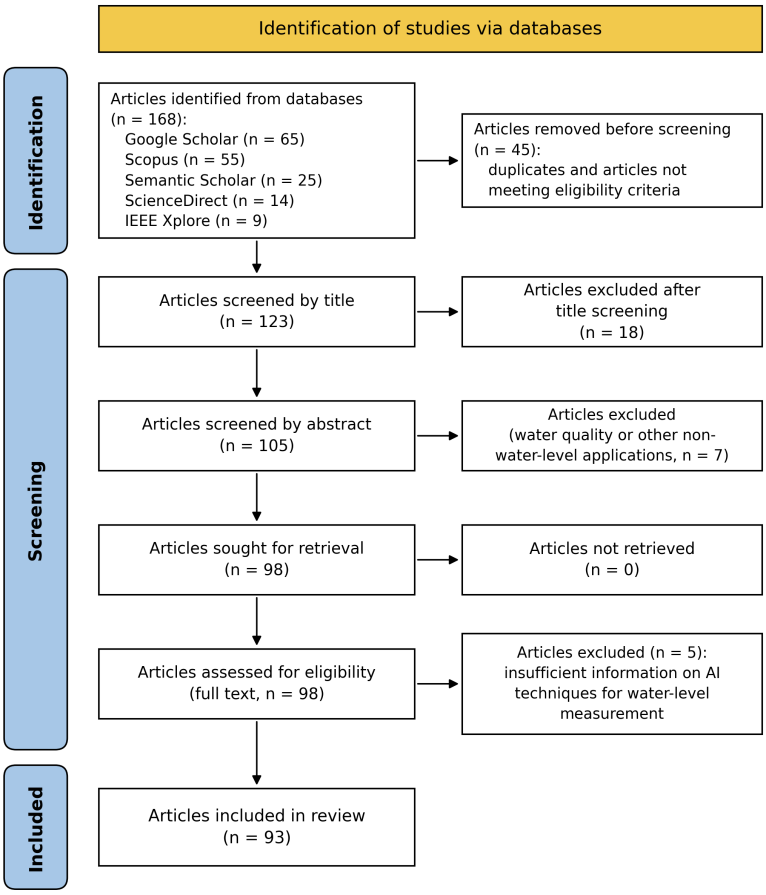


Fig. 1 PRISMA flow diagram of the literature identification, screening, eligibility assessment, and inclusion process.

- "water level monitoring" AND "image processing"
- "water level estimation" AND "computer vision"
- "water level estimation" AND "deep learning"
- "water level estimation" AND "machine learning"
- "water level estimation" AND "image processing"

Each search string was adapted to the syntax of the respective database. The articles retrieved by all search strings were combined, and duplicates were removed before screening.

2.2 Eligibility Criteria

Studies were included if they met all of the following criteria: (1) they were original research articles or full conference papers presenting a method and its experimental

validation; (2) they were published in English; (3) they estimated water level, or detected the water surface for the purpose of water level estimation, from images; (4) they developed or evaluated image processing, machine learning, or deep learning methods for water segmentation or water level detection, computer vision systems for real-time water level monitoring, or different imaging modalities and devices for water level estimation.

References cited in Sections 1 and 3 to describe measurement principles, sensing technologies, satellite missions, and previous reviews provide background context are not part of the review.

2.3 Screening and Selection

The database searches returned 168 research articles: 65 from Google Scholar, 55 from Scopus, 25 from Semantic Scholar, 14 from ScienceDirect, and 9 from IEEE Xplore. After duplicates and records that clearly did not meet the eligibility criteria were removed (n = 45), the titles of the remaining 123 articles were screened, and 18 articles were excluded. The abstracts of the remaining 105 articles were then screened, and 7 articles were excluded because they primarily addressed water quality monitoring or other water-related applications rather than water level. The full texts of the remaining 98 articles were assessed against the eligibility criteria, and 5 articles were excluded because they did not provide sufficient information on the application of AI techniques to water level measurement. In total, 93 studies were included in the review (Figure 1).

For each included study, we recorded the publication year, study location, water body type, imaging platform and modality, method category (image processing, machine learning, or deep learning), model architecture, dataset characteristics, and reported accuracy metrics. These data form the basis of Tables 1–4.

2.4 Bibliometric Overview

To characterize the thematic structure and evolution of the literature, a keyword co-occurrence network was constructed from the cited literature using VOSviewer (Figure 2). Title keywords were grouped into three methodological approaches (classical image processing, classical machine learning, and deep learning), two detection strategies (gauge-based and gauge-free), and two application settings (irrigation canals and other applications). Circle size indicates the number of titles in each category, lines indicate co-occurrence within the same title, and color and vertical position show the average publication year of the titles in each category. The network shows that deep learning is now the most frequently used approach (≈56 titles) and that the field has shifted from classical image processing through classical machine learning to deep learning, alongside a move from gauge-based to gauge-free detection. This progression indicates the structure of the review, which moves from classic image processing (Section 4), classic machine learning (Section 5), and deep learning (Section 6).

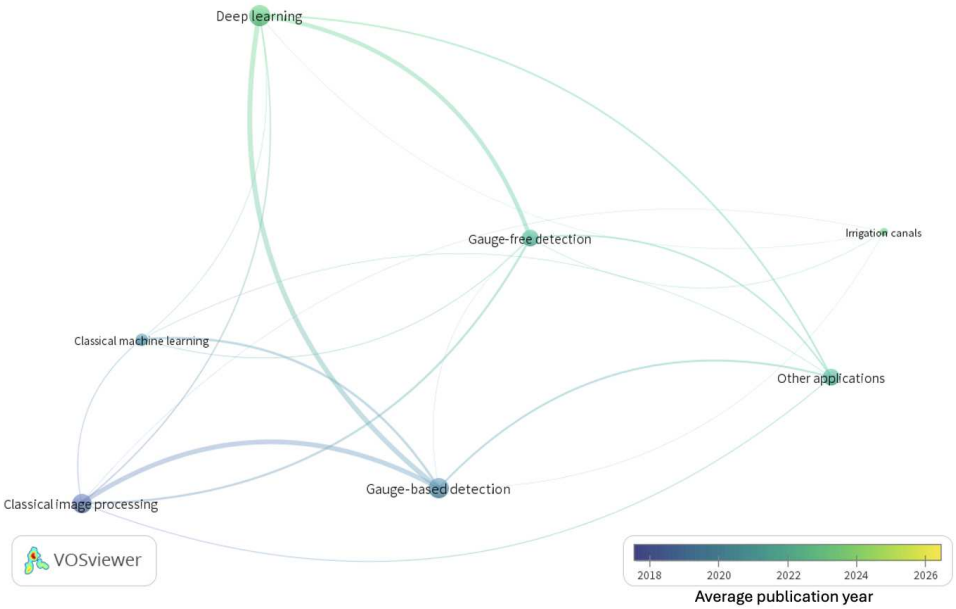


Fig. 2 Keyword co-occurrence network derived from the cited literature.

3 Water Level Monitoring Methods

As defined in Section 1, water level describes the vertical position of the water surface of a water body, such as a canal, river, reservoir, or lake, relative to a reference datum. Water level measurement approaches are primarily divided into two broad groups: (a) contact-based methods, in which the sensing element is placed in the water, and (b) non-contact methods, in which the water surface is observed remotely. Figure 3 presents the overall taxonomy of water level monitoring techniques, showing the transition from contact-based methods to non-contact methods based on sensors and computer vision.

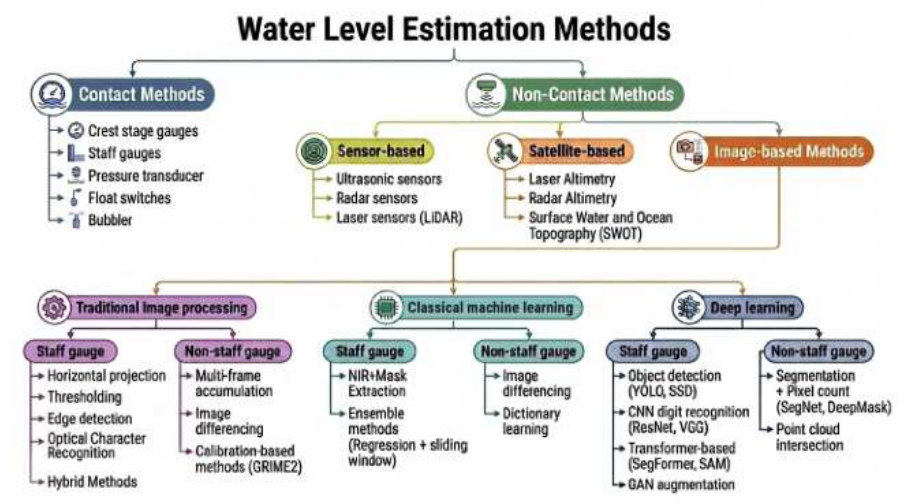


Fig. 3 Classification of water level monitoring techniques into contact-based and non-contact approaches.

3.1 Contact-based Methods

Contact-based methods use sensors or reference structures placed in the water to measure water level. These sensors range in complexity and are often designed for specific applications. Figure 4 shows the common contact-based methods, and their working principles are described below.

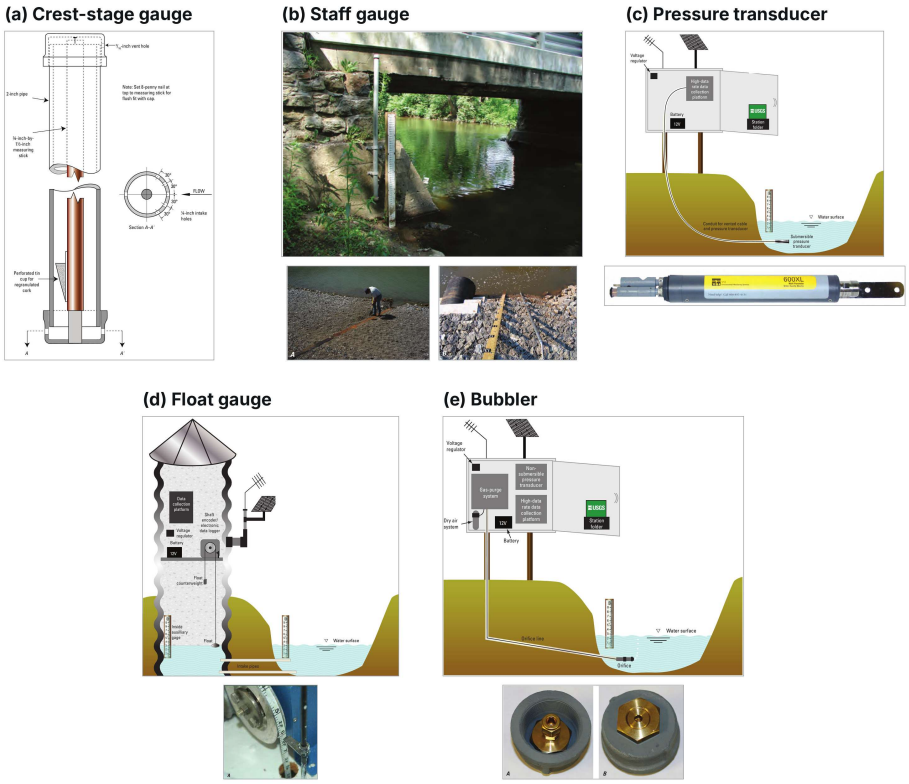


Fig. 4 Common contact-based water-level measurement methods: (a) crest-stage gauge, (b) staff gauge, (c) pressure transducer, (d) float gauge, and (e) bubbler. Source: U.S. Geological Survey (USGS) Technical Memorandum 3-A7.

3.1.1 Crest Stage Gauges

A crest-stage gauge is one of the simplest ways to measure water level [31]. The gauge consists of a vertical pipe containing a wooden staff and cork. Water enters through intake holes at the bottom of the pipe and rises inside it, and the cork floats on the rising water. When the water recedes, cork adheres to the staff at the highest water level reached, allowing the peak stage of an event to be read. The main disadvantages are that the intake holes can become clogged, insects can nest in the pipe, and cork can be washed out through the vent hole. In addition, the gauge records only the peak level, not a continuous time series.

3.1.2 Staff Gauges

A staff gauge is a graduated scale installed in the water that provides a direct visual indication of water level [4]. Staff gauges are among the most widely used reference devices and are routinely used to check and calibrate electronic level sensors. They

can be installed in almost any setting, including canals, lakes, and rivers. Their main limitations are that readings require an observer, the scale can corrode or become fouled, and the gauge cannot be monitored remotely without an additional device. Although the gauge itself is in contact with the water, reading it with a camera, as described in Sections 4–6, provides a hybrid measurement approach that combines a contact-based reference with non-contact remote observation.

3.1.3 Pressure Transducers

Pressure transducers measure water level from the pressure exerted on them by the overlying water column [32]. As the water level above the sensor increases, the pressure increases. The measured pressure is then converted to a water depth in meters or feet. Atmospheric pressure must be accounted for absolute (non-vented) transducers require separate barometric compensation, whereas differential (vented) transducers compensate for it directly through a vent tube.

3.1.4 Float Gauges

A float gauge consists of a tape or cable running over a pulley [33]. One end of the tape or cable is attached to a float in a stilling well while the other end is attached to a counter weight. The float rises and falls with the water level, and the water level can be read by means of an index and graduated tape or the pulley can be connected to a water-stage recorder or shaft encoder for continuous recording.

3.1.5 Bubblers

Bubblers [34] are hydrostatic water level measurement sensors that estimate water level by measuring the air pressure required to continuously force bubbles through the open end of a submerged dip tube. The measured back pressure equals the hydrostatic pressure exerted by the water column above the tube outlet. The water depth above the outlet is then obtained from the hydrostatic relationship $P = \rho g h$, where P is the gauge pressure (Pa), ρ is the water density ($\mathrm{kg\,m^{-3}}$; approximately 1000 $\mathrm{kg\,m^{-3}}$ for fresh water), g is the gravitational acceleration (9.81 $\mathrm{m\,s^{-2}}$), and h is the water depth above the sensor (m).

3.2 Non-contact Methods

Non-contact methods measure water level without placing the sensor in the water. They include ultrasonic, radar, laser, and satellite-based methods, as well as the image-based and AI methods that are the focus of this review. Non-contact sensors are advantageous in hazardous or harsh environments where direct contact with water could damage equipment or create safety risks. However, they remain susceptible to equipment failure, power outages, wind, and extreme weather, and they require careful calibration for accurate measurement.

3.2.1 Sensor-based Methods

Ultrasonic Sensors

Ultrasonic sensors were the first widely deployed non-contact technology in operational hydrometry [35]. These sensors estimate water level by transmitting acoustic pulses toward the water surface and measuring the time required for the reflected signal to return to the sensor. The distance to the water surface is then calculated using the known speed of sound in air. Because no components need to be submerged, ultrasonic sensors are relatively simple to install and maintain compared to contact-based gauges [36]. However, their performance is strongly influenced by environmental conditions. Variations in air temperature, humidity, wind, rainfall, and surface turbulence can affect sound propagation and introduce measurement errors. Consequently, ultrasonic sensors generally perform best in controlled environments such as reservoirs, culverts, and hydraulic structures, while their accuracy may deteriorate under highly turbulent or rapidly changing flow conditions [37].

Radar Sensors

Radar sensors were introduced to overcome several limitations associated with ultrasonic measurements. Similar to ultrasonic sensors, radar systems estimate the distance to the water surface using a time-of-flight principle, but instead of acoustic pulses they transmit electromagnetic waves. Since electromagnetic signals are largely unaffected by atmospheric conditions such as temperature and humidity, radar sensors typically provide more stable and reliable measurements across a wider range of environmental conditions [38]. Modern systems commonly employ frequency-modulated continuous-wave (FMCW) radar technology, which enables highly accurate water level measurements while maintaining reliable operation during rainfall, fog, and nighttime conditions. These advantages have made radar one of the most widely used non-contact technologies in modern hydrometric networks [39]. Nevertheless, measurement quality can still be affected by factors such as excessive surface roughness, strong wave activity, signal scattering, and unfavorable installation geometry, particularly during extreme flow events.

Laser Sensors

Laser sensors, including terrestrial laser rangefinders and LiDAR (Light Detection and Ranging) systems, provide another non-contact approach for water level monitoring. Similar to ultrasonic and radar sensors, they estimate the distance to the water surface by measuring the travel time of reflected near-infrared laser pulses [40]. Their narrow beam width enables highly precise measurements and detailed mapping of water surface elevations. However, their use in routine hydrometric monitoring remains limited. Measurement accuracy can be affected by weak reflections from rough, turbulent, or highly turbid water surfaces, while eye-safety requirements constrain laser power and operating range. As a result, laser-based systems are used primarily in research and specialized surveying applications rather than in permanent monitoring networks [41].

Satellite Altimetry

Satellite remote sensing has greatly expanded the ability to monitor water levels in regions where ground-based measurements are unavailable or difficult to maintain. This capability is particularly valuable given that a large portion of the world's rivers, lakes, and reservoirs remain ungauged or poorly monitored. Both laser altimeters (light detection and ranging, LiDAR) and radar altimeters (radio detection and ranging, RADAR) have been widely used to monitor water levels in inland lakes [29, 42]. Early radar altimeters operated primarily in low-resolution mode (LRM), which is suited to large water bodies. CryoSat-2 introduced the ability to switch between three modes: LRM, synthetic aperture radar (SAR), and SAR interferometry (SARIn), which allow for measurements with smaller footprints and the monitoring of smaller water bodies [43–46]. Sentinel-3 extended global observations in SAR mode, and Sentinel-6 further reduced measurement noise through a higher pulse repetition frequency [47, 48]. Several satellite altimetry-derived products for time-series lake-level data have been developed, such as DAHITI [49] and Hydroweb [3], which integrate data from multiple radar altimeters. Despite these advances, radar altimetry remains limited by large footprints and by the performance of retracking algorithms [46].

In contrast, laser altimetry, with its smaller footprint and higher along-track sampling density, is well suited to observing small lakes and reservoirs [50]. The Ice, Cloud, and Land Elevation Satellite (ICESat), the first laser altimeter, provided highly accurate lake level data for 100 lakes in the Tibetan Plateau (TP) region from 2003 to 2009, with an accuracy of approximately 10 cm for Qinghai Lake during the ice-free season [51, 52]. ICESat-2, launched in September 2018, carries the Advanced Topographic Laser Altimeter System (ATLAS) and provides substantially higher spatial resolution and denser sampling than the original ICESat [53]. Validation results of the ICESat-2 Along-Track Inland Surface Water Data (ATL13) product based on in-situ measurements indicate that ICESat-2 has significantly improved the ability of satellite altimetry to capture lake water levels, with lower uncertainty and bias than previous satellite methods [54]. The Global Ecosystem Dynamics Investigation (GEDI) lidar was designed to monitor forest structure and the global carbon cycle, but its elevation data have also been applied to inland waters. Comparative assessments show that GEDI elevations are less accurate than those of ICESat-2 [55]. A major recent advancement is the Surface Water and Ocean Topography (SWOT) mission, which employs Ka-band radar interferometry to generate two-dimensional measurements of water surface elevation, extent, and slope [56, 57]. Unlike conventional nadir altimeters, which observe only along the satellite ground track, SWOT provides spatially distributed observations across wide swaths, substantially improving the monitoring of rivers, lakes, reservoirs, and floodplains over large regions [56].

Despite their ability to provide observations over vast and often inaccessible areas, satellite-based methods have several limitations. Revisit intervals are often too long for continuous monitoring or rapid flood assessment, while spatial resolution and footprint size can restrict observations of narrow channels and small water bodies. Consequently, satellite observations are best viewed as a valuable complement to ground-based monitoring systems rather than a complete replacement. In contrast, ground camera-based methods offer a further non-contact alternative, in which cameras capture the

water surface images, together with a staff gauge or without staff-gauge, to estimate the water level from the images. These techniques include image-processing, classical machine-learning, and deep-learning methods. They allow remote measurement without installing sensors in the water and can provide continuous measurements at high temporal resolution, and record visual information on site. Image-based techniques are the main focus of this review and are discussed in detail in the following section.

4 Visual Data Acquisition and Image Processing Methods

4.1 Computer Vision for Water Level Monitoring

Computer vision, a subfield of artificial intelligence (AI), enables computers to process, analyze, and interpret visual information from digital images and videos. Through techniques such as image processing, feature extraction, and pattern recognition, computer vision converts visual information into meaningful numerical or symbolic representations that can support classification, detection, and quantitative estimation [58]. Practical applications of computer vision include autonomous driving [59], flood detection [60], facial recognition [61], and, in hydrology, staff gauge detection [62]. These techniques enable computers to learn and recognize patterns in images and videos, as illustrated in Figure 5. In human vision, the eye captures the scene of the staff gauge and the brain interprets this visual information to determine the water level. Computer vision follows the same two-stage process: a camera acts as the sensing device that captures the image, and a computer acts as the interpreting device that analyzes the image to estimate the water level, in the same way that the eye and brain work together in human perception. However, unlike the human brain, which uses previous knowledge and context to adjust to changing conditions, a computer vision approaches relies on patterns learned from its training data and may therefore be less accurate under conditions it has not seen before.

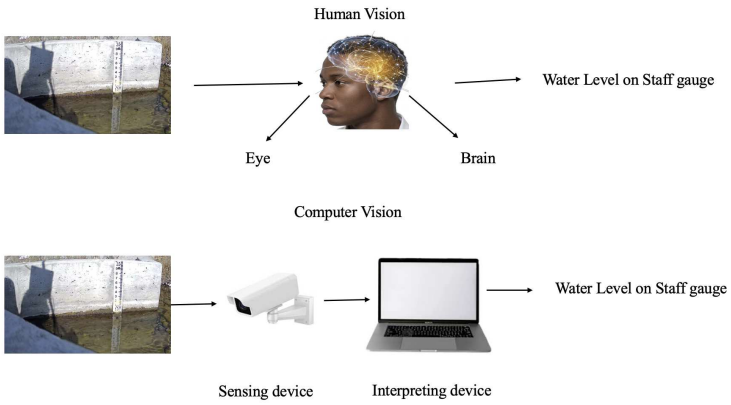


Fig. 5 Analogy between human vision and computer vision for reading water level from a staff gauge.

Computer vision techniques have been applied to water level monitoring since 1998, when Takagi et al. [63] developed a non-contact water level measuring system based on image processing. These techniques have since been used to measure water levels in various water bodies, including rivers, streams, ditches, and canals, using images captured with or without staff gauges [62, 64]. Image-based monitoring systems typically use visible-spectrum (RGB) cameras and, less commonly, near-infrared or thermal cameras [65–67].

Computer vision approaches for water level monitoring can generally be categorized into two main groups (1) image processing methods and (2) machine learning-based methods [17, 18, 68]. Image processing methods rely on techniques such as edge detection, thresholding, image segmentation, and feature extraction to identify water boundaries and estimate water levels. In contrast, machine learning-based approaches use algorithms that learn patterns and relationships directly from image data. These approaches can be further divided into classical machine learning methods, such as random forests, support vector machines, and multilayer perceptrons [69, 70], and deep learning methods, such as convolutional neural networks (CNNs)[71–74].

The following sections review the most commonly applied classical image processing, traditional machine learning, and deep learning techniques for image-based water level monitoring.

- **Thresholding:** One of the simplest and most common methods is thresholding, which converts grayscale images into binary (black and white) images [75]. A region of interest (ROI), such as a staff gauge in a river or canal, can be differentiated from background pixels by applying a threshold value. Choosing an appropriate threshold ensures that relevant pixels are correctly included or excluded [76].
- **Edge detection:** These techniques detect the boundaries of a staff gauge within an image. The Canny and Sobel operators are the most common. They identify the staff gauge by detecting sharp changes in pixel intensity, such as the markings on a gauge or the edges of the water body [27].
- **Convolutional neural networks (CNNs):** Within deep learning, CNNs have transformed vision-based water level monitoring. These networks automatically extract features and learn from image data, capturing variations in water surface patterns, reflections, and staff gauge markings. By learning spatial and contextual features from camera imagery, CNNs have become the most widely used approach in recent studies (Section 6).

4.2 Traditional Image Processing Methods

Traditional image processing methods use predefined mathematical operations and rule-based algorithms to process digital images and extract relevant visual information, such as edges, shapes, colors, and intensity variations. These methods typically analyze images individually, using pixel-level characteristics to identify features of interest. Image processing-based water level methods depend on handcrafted algorithms, so their accuracy is highly sensitive to environmental conditions, image quality, and the effectiveness of the chosen features [77]. They typically follow a standard workflow of

image acquisition, region of interest (ROI) identification, preprocessing, feature extraction, waterline detection, and mapping of image coordinates to physical water levels (Table 1). The ROI is usually defined around the staff gauge or calibration region and contains both water and non-water pixels, as illustrated in Figure 6 [78]. Within this region, various feature extraction schemes have been developed, which can be broadly classified into thresholding-based methods, multi-frame analysis methods, edge-based detection methods, and gauge-reading methods that recognize the markings on the staff gauge.

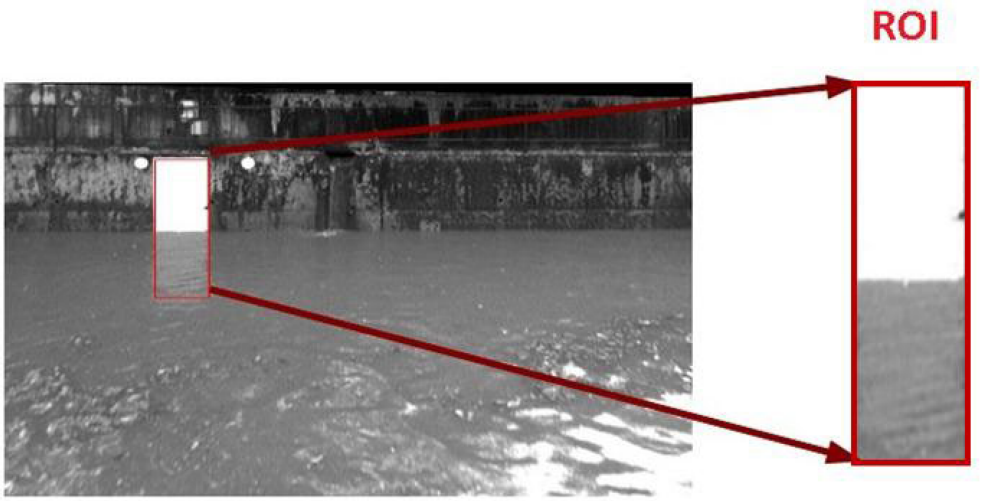


Fig. 6 Example of a region of interest (ROI) for water-level estimation. Source: https://doi.org/10.3390/w15183233, reproduced under the Creative Commons Attribution 4.0 International License (CC BY 4.0).

Thresholding-based methods estimate water levels by exploiting differences in pixel intensity or color between water and non-water regions. They generally transform images into binary masks by selecting an optimal threshold, with Otsu's maximum inter-class variance method being one of the most widely used [79–81]. Although thresholding methods offer computationally efficient and relatively simple implementation, their accuracy degrades under varying lighting conditions because of reflections, shadows, glare, and uneven intensity between the gauge and the water surface. For instance, [71] converted images from the RGB to the Hue-Saturation-Value (HSV) color space to enhance the separation between water and gauge regions. Similarly, [82] applied HSV-domain enhancement to increase the contrast between the water surface and the staff gauge, whereas [83] combined k-means clustering with region-growing techniques to improve water body segmentation. To reduce sensitivity to illumination changes at the acquisition stage, [66] used near-infrared (NIR) imaging to enhance the visibility of the staff gauge before detecting the waterline, although the approach

still relies on precise gauge detection and calibration. These modifications demonstrate that combining additional image characteristics can enhance threshold-based techniques, although they remain sensitive to site-specific conditions [18].

Multi-frame aggregation approaches mitigate some limitations of single-frame techniques by leveraging temporal information from consecutive images. Instead of relying solely on spatial differences, these techniques analyze variations caused by water movement while assuming that the water surface changes more than fixed objects such as staff gauges. Cumulative histograms and temporal intensity variations are processed to emphasize water-related features and produce projection curves from which the waterline is identified [84, 85]. Similarly, image differencing methods identify pixel intensity changes across consecutive frames that correspond to water surface movement, often enhanced through edge detection and morphological operations [86], while [87] estimated water level from temporal intensity variations using a histogram-based approach. These techniques perform best under high-flow or turbulent conditions, because surface movement provides additional information for separating water from its surroundings. However, their performance can degrade under low-flow conditions where insufficient temporal variation exists, as well as under camera movement or rapidly changing environmental conditions.

Edge-based techniques identify the waterline by detecting sharp changes in pixel intensity associated with the boundary between water and its surroundings. Because the boundary separating the water surface and staff gauge produces a strong edge feature, edge detection has been widely investigated for water level estimation. For instance, [88] proposed a water level detection system by applying a horizontal edge detector combined with a finite impulse response (FIR) filter to extract features under different lighting conditions. Similarly, [89] employed the Marr-Hildreth operator to detect the edge pixels of the ruler within ROI. However, distinguishing the water line from other edges, such as scale markings and structural boundaries, remains a major challenge. To address this issue, [18] proposed the maximum mean difference (MMD) method, which exploits the fact that the periodic pattern of a bicolor water gauge is visible only above the water surface. It computes the row-wise mean of the grayscale and edge images and, using a coarse-to-fine search, locates the water line as the position with the largest mean difference between the regions above and below it. Other studies have combined several detectors to compensate for the weaknesses of each. [90] localized the region of interest using edge maps from a pretrained edge detector and template matching, and then estimated the waterline through two parallel strategies: fitting a line to the detected edge points using linear regression, and a sliding-window search based on pixel intensity differences. These methods improve detection accuracy by combining multiple image characteristics but require carefully designed algorithms, careful integration, and parameter selection.

Gauge-reading methods measure water level by recognizing the numerical markings on the staff gauge and infer the water level from the known layout of the gauge scale. [62] integrated template matching with sequence verification to identify the digits on a gauge, exploiting the fixed order of the markings to correct detection errors caused by noise, missing characters, or partial occlusion. Compared with template matching alone, these sequence constraints improve reliability, although performance remains

dependent on clear visibility of the gauge markings, and recognition can degrade under poor lighting, blurred imagery, or partially submerged markings.

Beyond staff-gauge-based monitoring, classical image processing methods have also been used to extract water bodies directly from camera and remote sensing imagery. Unlike the gauge-based methods described above, which analyze a small region around a staff gauge to locate a single waterline position, these methods classify water pixels across the entire scene. For instance, [91] developed an automated threshold-based method for extracting rivers and lakes from Landsat imagery, producing a water extent map rather than a water level. For camera imagery, GRIME2 [19] offers an open-source tool that measures water levels without a staff gauge, using calibration targets and geometric transformations between image coordinates and real-world measurements. The workflow includes image preprocessing, calibration marker recognition, waterline extraction, and conversion of pixel-based measurements into physical water levels. Figure 7 shows a typical image processing pipeline for water level estimation, consisting of preprocessing, feature extraction (e.g., edge detection and thresholding), and feature projection.

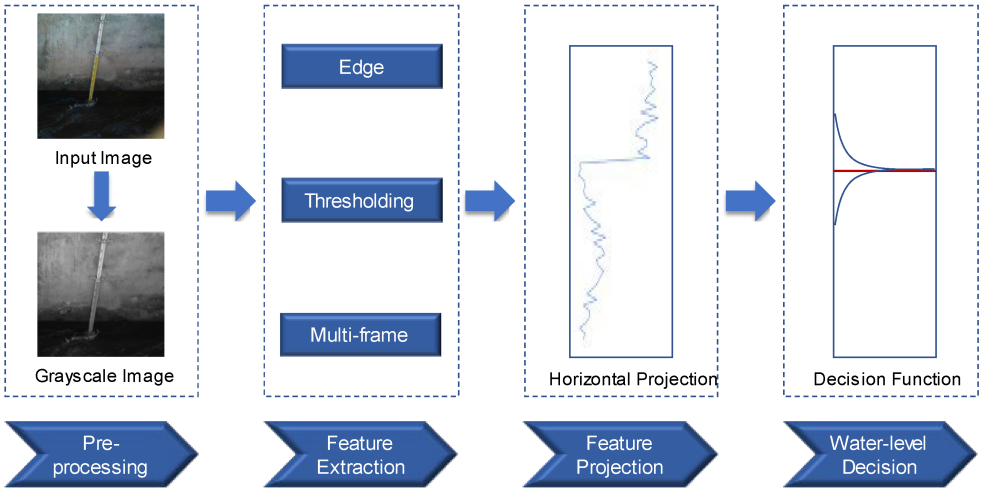


Fig. 7 Workflow of a classical image processing approach for water level detection. Source: https://doi.org/10.3390/w15183233, reproduced under the Creative Commons Attribution 4.0 International License (CC BY 4.0).

Overall, conventional image processing techniques have demonstrated the feasibility of automated water level monitoring and remain attractive because of their simplicity, transparency, and minimal computational requirements. However, their reliance on manually selected features and predefined thresholds limits their adaptability to diverse environmental conditions. Factors such as changing illumination, water reflections, camera displacement, complex backgrounds, and vegetation can significantly affect performance. These limitations have motivated the use of machine

learning methods, which learn decision rules from labelled data rather than relying solely on fixed thresholds and hand-tuned parameters.

5 Machine Learning-Based Techniques for Water Level Monitoring

Image-based water level detection has evolved from approaches relying primarily on classical image processing to those incorporating artificial intelligence (AI), particularly classical machine learning (ML) and deep learning (DL). While classical image processing applies predefined rules, such as edge detection and thresholding, classical ML methods learn a decision model, such as a random forest or support vector machine, from labelled training data, typically using handcrafted features as input. DL methods, in contrast, learn the features themselves directly from raw imagery and are discussed in Section 6. These categories are not mutually exclusive, as many ML- and DL-based frameworks integrate classical image processing algorithms for preprocessing, feature extraction, or postprocessing. More broadly, AI methods have been applied in hydrology to flood prediction [92, 93], water level and stage estimation [94], and assessing water availability at ungauged sites [95]. Camera-based water level estimation pipelines, both with and without a staff gauge, are illustrated in Figure 8, and the main image processing and classical ML methods, together with their reported performance and limitations, are summarized in Table 1.

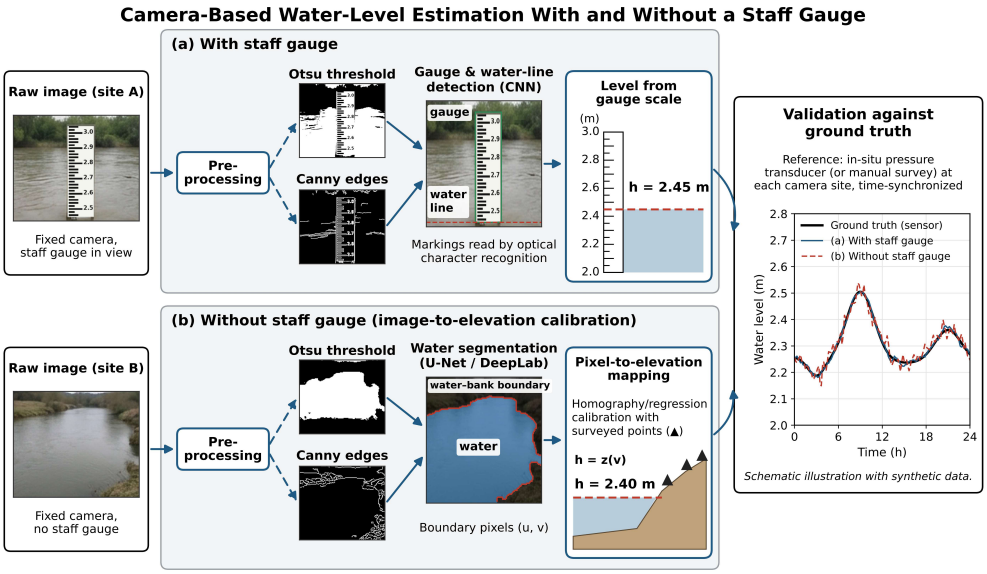


Fig. 8 Camera-based water level estimation pipelines (a) with a staff gauge (SG) and (b) without a staff gauge, using image-to-elevation calibration.

Compared with image processing and deep learning, relatively few studies have applied classical ML to camera-based water level monitoring. In these studies, trained models have mainly been used to segment the staff gauge or water region, recognize gauge markings, or locate the gauge before the waterline is extracted. [69] segmented the staff gauge using a two-class random forest classifier trained on texton features, applied Gaussian mixture model segmentation to separate bars and numerals, and recognized the gauge digits using an optical character recognition (OCR) module based on a random forest classifier. Similarly, [96] applied supervised random forest classification to smartphone images to highlight flooded regions before detecting the flooding line with edge-based methods and converting it to water level using photogrammetry. [64] combined threshold-based image processing with a trained Aggregated Channel Features (ACF) object detector, which located the staff gauge in night images before rule-based waterline extraction.

Another learning-based alternative is dictionary learning, which represents image patches as sparse combinations of learned basis functions. [97] used this approach to distinguish staff gauge from water regions, and compared it with a frame-difference method and a convolutional neural network. Compared with handcrafted rules, dictionary learning adapts better to diverse conditions while remaining less computationally expensive than deep learning, although it still requires representative training data and careful parameter tuning.

Overall, classical ML methods improve adaptability compared with image processing algorithms, but they still depend on handcrafted features and site-specific training data, which limits their generalization across monitoring locations. These shortcomings have motivated the adoption of deep learning methods, which automatically learn hierarchical feature representations directly from raw imagery and often achieve improved robustness under complex real-world conditions.

Table 1 Summary of classical image processing and classical machine learning techniques for water level monitoring.

Method	Reference	Key Technique	Metric	Notes / Limitations
Traditional image processing				
Thresholding methods	[79]	Maximum inter-class variance (Otsu) binarization on stage-camera images of a reference pole	MAE 0.27–2.20 cm; RE 3.42–19.95%	Low-cost wildlife camera; sensitive to noise, reflections, shadows, and flares
	[80]	Maximum inter-class variance (Otsu) binarization for real-time water level recognition	–	Also estimates surface velocity; sensitive to illumination changes
	[81]	Maximum inter-class variance (Otsu) binarization for reservoir water level monitoring	–	Common baseline; sensitive to reflections and shadows
	[82]	HSV color-space enhancement + recognition of ruler readings	Avg. measurement error ±0.90 cm	Improves contrast between gauge and water
	[83]	K-means clustering (RGB space) + region-growing algorithm	Event accuracy 89.29%; miss rate 11.76%	Unsupervised clustering used as a segmentation aid; selects water body after segmentation
NIR imaging	[66]	Near-infrared video imaging, ROI extraction, and NIR intensity response analysis	Resolution 1 mm	Reduces sensitivity to illumination changes; still relies on precise gauge detection and calibration
Multi-frame methods	[84]	Accumulated histogram with band-pass filter across multiple frames	–	Relies on water surface movement being more prominent than gauge changes
	[85]	Multi-frame binary images; reference level at the sharpest drop in the histogram; embedded real-time system	–	Effective under high-flow/fluctuating conditions; tested on a real river
	[86]	Image differencing + edge detection + morphological operations	∼1 cm	Detects water surface movement via temporal differences
	[87]	Histogram-based temporal analysis of intensity changes between consecutive frames	Average normalized cross-correlation (NCC) = 0.87	Degrades under camera movement or low surface motion
Edge-detection methods	[88]	Horizontal edge detector + FIR filter	–	Extracts features under varying lighting conditions
	[89]	Marr-Hildreth operator	–	Detects edge pixels of ruler within ROI
	[18]	Combines grayscale and edge features; coarse-to-fine detection via maximum mean difference (MMD)	Accuracy 1 cm; resolution 1 mm	Addresses similarity between water line and scale line edges
	[90]	Pretrained edge maps + template matching for ROI; ensemble of line fitting (linear regression) on edge points and sliding-window intensity search	MAE 4.8; MAPE 3.1%; R^2 0.92	Combines two branches for robustness; increases computational complexity
Gauge reading	[62]	Digit template matching + sequence verification of gauge markings	R^2 0.943	Robust to noise, scale, orientation, and partial occlusion; requires visible markings
Gauge-free calibration	[19]	GRIME2: calibration target-based geometric mapping from pixel to real-world units	±3 mm (lab); ±5 mm at 90% CI (field)	Open-source framework; includes preprocessing, waterline, and calibration marker detection
Classical machine learning				
Random forest	[69]	Random forest gauge segmentation on texton features + GMM segmentation + random forest-based OCR of gauge digits; quadratic water level function	–	Portable mobile-phone cameras; requires the gauge to be distinguishable from the background
	[96]	Random forest classification of flooded regions + Hough transform/Canny line detection + photogrammetric conversion with UAV-derived DEM	Classification accuracy 88.05%; water level difference <3 cm on average	Uses crowdsourced smartphone images; requires a high-resolution elevation model
Boosted object detector	[64]	Aggregated Channel Features (ACF) detector for gauge localization at night + multi-threshold frame classification + threshold- and morphology-based waterline extraction	Night ∼98.7%, day ∼84.8% of readings within ±3 cm	Edge-based frame quality check; day frames less reliable due to variable illumination
Dictionary learning	[97]	Sparse representation via dictionary learning on image patches; reconstruction error analysis	–	Separates water/non-water regions; compared with frame differencing and a CNN

6 Deep Learning-Based Techniques for Water Level Monitoring

Deep learning (DL), a subset of ML, has emerged as the dominant approach for image-based water level monitoring owing to its ability to automatically extract hierarchical feature representations from raw data. Unlike classical image processing and ML techniques that rely on handcrafted features, DL models learn both low-level and high-level

features through multiple hidden layers using backpropagation. This capability enables the extraction of spatial, contextual, and semantic information from complex scenes, making DL approaches more robust to variations in illumination, weather conditions, and water surface appearance. Figure 9 shows a general DL framework for water level monitoring, including dataset preparation, data splitting, model training, evaluation, and water level estimation for systems with and without staff gauges.

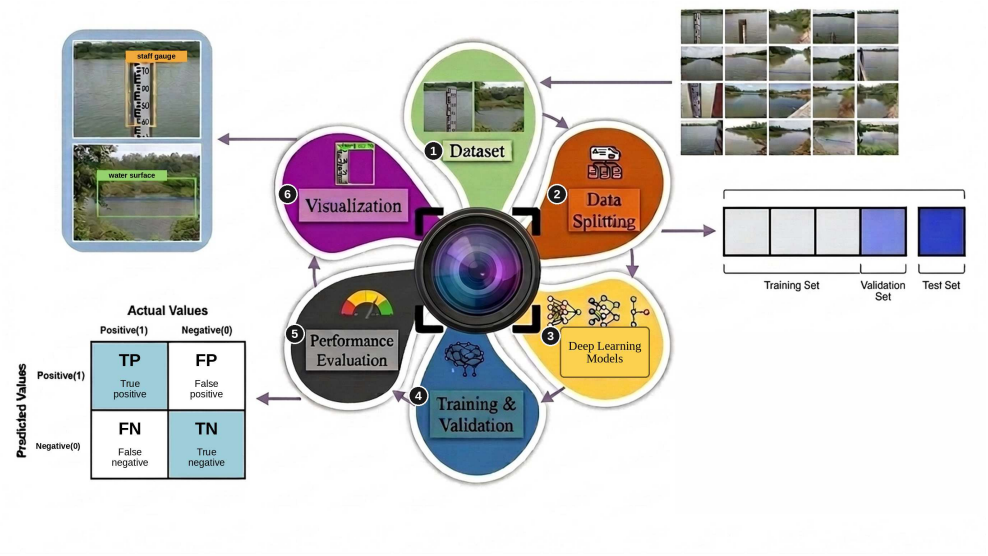


Fig. 9 Deep learning (DL) framework for water level estimation, from dataset preparation to water level estimation with and without a staff gauge.

Current DL-based approaches can be broadly categorized into object detection, semantic segmentation, regression or classification, and hybrid detection–segmentation networks. Although these frameworks differ in architecture, they typically follow a common pipeline in which an ROI is identified, relevant water or gauge features are extracted, and the detected features are mapped into physical water level measurements.

Object detection networks are among the most extensively deployed approaches for staff gauge monitoring because they automatically locate the gauge before measuring the water level. The YOLO (You Only Look Once) family of detectors [98] has attracted particular attention because of its high detection accuracy and real-time performance [68, 99–101]. Most YOLO-based frameworks first detect the staff-gauge or scale markings and then estimate the waterline relative to the detected region. Recent studies have further improved detection accuracy by incorporating attention mechanisms. For instance, [102] incorporated a Convolutional Block Attention Module (CBAM) into YOLOv7 to enhance feature representation and focus the network on the most informative regions of the gauge. Other studies have combined CNNs with image

enhancement, such as vertical shearing, gamma correction, and morphological filtering, to improve robustness under varying environmental conditions [94]. These advancements demonstrate that enhancing feature extraction before water level estimation improves detection accuracy under varying field conditions. Figure 10 illustrates the workflow of YOLO-based water level monitoring.

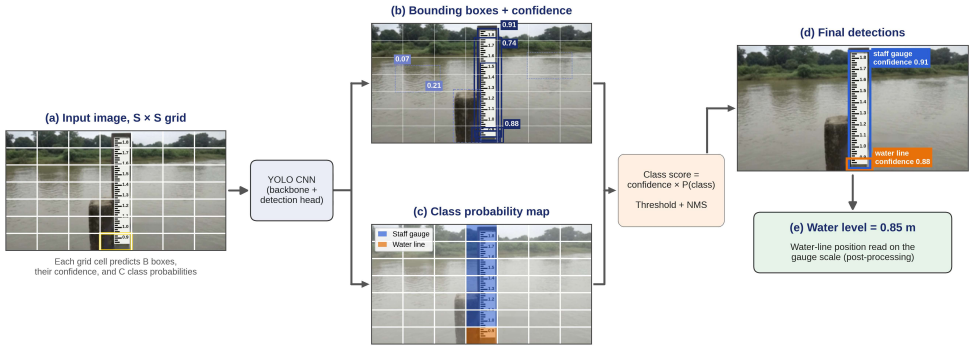


Fig. 10 Workflow of YOLO (You Only Look Once) object detection for water level monitoring.

CNN-based methods are among the most extensively studied because they effectively extract and learn hierarchical features directly from visual data. Residual networks, including ResNet-50 and variants such as ResNeXt and ResNetV2, have been widely used for both continuous water level regression and flood classification [103–105]. Compared with standard CNNs, residual architectures enable deeper networks through skip connections, improving feature learning while reducing training difficulties. CNNs have also been deployed to satellite imagery, web-based images, and crowd-sourced data. For example, DeepWaterMap [106] segments water bodies from surrounding land, snow, and cloud cover in multispectral Landsat imagery, and [107] applied a deep CNN with image segmentation to web camera images for flood detection and water level estimation. Other studies combine CNNs with ranking or classification schemes to estimate water levels or classify flood conditions from social media and crowd-sourced photographs [108, 109]. Hybrid frameworks that combine conventional image processing with deep learning have also emerged. For instance, [71] combined HSV-based segmentation, CNN-based digit recognition, and pixel-to-metric calibration to measure water levels, while [105] coupled classical preprocessing with CNN-based regression models for sensor-free monitoring. These studies show that classical image processing can complement deep learning by improving feature quality before prediction.

Transformer-based models have recently drawn attention because of their ability to model long-range spatial dependencies that are difficult for conventional CNNs to capture. Rather than depending solely on convolutional operations, transformer architectures leverage self-attention mechanisms to learn relationships across the entire

image. [110] used transformer-based segmentation models, namely the Segment Anything Model (SAM) [23], SegFormer [111], and MobileSAM [112], to extract water regions under diverse environmental conditions, and then applied random forest regression to estimate water level and discharge from the segmented water area. Compared with CNN-based segmentation models, transformers typically capture global context better, but they often require larger training datasets and more computational resources. Vision foundation models, which are pretrained on very large and diverse image collections, extend this trend. Because they can segment water with little or no site-specific training, they have been used to reduce dependence on site-specific labeled data [24], to measure water level with minimal retraining [25], and to refine water-line detection by coupling SAM with conventional water-line detection techniques [14]. Temporal information has also been combined with semantic segmentation to stabilize water level recognition across image sequences [22], and long-term field applications have begun to assess the robustness of AI image-based monitoring under operational conditions [26].

Table 2 summarizes representative DL methods for water level monitoring, their applications, and performance metrics. In terms of accuracy, most DL-based methods report water level errors in the range of approximately 1–3 cm, the highest accuracies, with errors below 1 cm, have been reported by methods that combine precise localization of the gauge or water region with accurate pixel-to-metric conversion. For example, [101] reported a maximum deviation of 0.8 cm from manual readings, [113] and [114] achieved errors below 1 cm by combining segmentation with a virtual gauge or with detection-based waterline modules, and [99] reported a systematic error of 7.7 mm, with 95% of daytime images within 1 cm. Other approaches achieved slightly lower but still competitive accuracy, such as [105] (MAE = 1.14 cm), [100] ($\pm$1.2 cm), and [110] (MAE = 1.03–2.33 cm). In addition, high classification or segmentation scores, such as accuracies above 98% [115] or IoU values above 0.97 [110, 113], do not necessarily translate into equally accurate water level estimates, since the final accuracy also depends on calibration and the conversion from image coordinates to physical units.

Overall, DL has significantly advanced automated water level monitoring by eliminating the need for handcrafted feature extraction and facilitating end-to-end learning directly from imagery. Although object detection and CNN-based methods remain the most widely adopted because of their efficiency and maturity, transformer-based and hybrid detection–segmentation approaches increasingly perform better under complex environmental conditions. Nonetheless, challenges related to dataset availability, computational requirements, and model generalization continue to motivate research into more resilient and transferable deep learning solutions.

Table 2 Summary of deep learning-based techniques for water level monitoring.

Method	Reference	Key Technique	Water Level Accuracy	Segmentation / Detection Metric	Notes / Limitations
YOLO-based detection	[99]	YOLOv5s detects the staff gauge and scale characters; waterline located by image processing	Systematic error = 7.7 mm; 95% of daytime images within 1 cm	–	Field station on a river in Beijing; accuracy drops for transparent water
	[68]	Improved YOLOv5m with attention for gauge segmentation + skew correction + linear regression of water level	Average error <2 cm	–	Tested under daytime, nighttime, occlusion, and lighting variations
	[101]	Temporal super-resolution + lightweight improved YOLOv5 for water level line detection	Mean relative accuracy = 98.5%; maximum deviation from manual readings = 0.8 cm	–	Indoor hydropower sump wells with poor lighting and water vapor
	[100]	DSC-YOLOv8n-seg for joint detection of water level line and gauge characters	Average error = ±1.2 cm	Precision = 93.1%; recall = 94.5%; mAP50:95 = 93.9%	Also estimates surface flow velocity; robust in low-light and nighttime scenes
	[102]	Improved YOLOv7 with CBAM	–	mAP = 87.26%; F1 = 75.6%	CBAM between backbone and head focuses the network on gauge regions
Object detection (SSD)	[116]	SSD trained on physical pool experiments to detect staff gauge regions	NSE = 0.98; R^2 = 0.99	–	Uses photographic principles and geometric mapping to compute water level
CNN with image enhancement	[94]	Vertical shearing, gamma correction, and morphological opening filters + CNN	ΔE = 3.3 cm; RMSE = 1.2	–	Improves robustness against image noise
CNN-based regression/ classification	[104]	CBAM-improved ResNet50 for classifying flood depth levels	–	Accuracy = 92.45%	Classifies urban waterlogging depth from images
	[103]	ResNet-50 virtual water gauge for real-time river water level monitoring	–	Accuracy = 83.6–96%	Learns hierarchical features from river surveillance imagery
	[105]	Conventional preprocessing + residual CNN with multi-branch feature aggregation	MAE = 1.14 cm	–	Sensor-free monitoring; fine-tuned for regression and classification
Web-image CNN segmentation	[107]	Deep CNN + image segmentation on web camera images	R^2 = 0.84–0.87; bias = 2.44–3.04 cm	Flood detection: accuracy >90%; IoU >80%; BF1 >70%	Water level estimation and flood detection under varying illumination and weather
Hybrid two-step approach	[71]	HSV-based segmentation + CNN digit recognition + quadratic pixel-to-metric mapping	–	Accuracy = 98.25%	Combines classical and deep learning techniques
IoT + instance segmentation	[77]	IoT-enabled cameras + Mask R-CNN segmentation	–	Accuracy = 0.86; F1 = 0.97	Addresses environmental distortion, poor lighting, and nighttime visibility; low-cost real-time flood monitoring
Semantic segmentation	[65]	SegNet, U-Net, and FCN water segmentation compared with continuous image subtraction	RMSE = 0.013–0.066 m (SegNet vs. gauge station)	Accuracy: SegNet = 97%, U-Net = 94%, FCN = 98%	SegNet outperformed the conventional image subtraction method
	[113]	Improved SegFormer-UNet water segmentation + virtual water gauge	Error <1 cm in field tests	Pixel accuracy = 99.10%; IoU = 98.34%	Virtual gauge removes the need for a physical staff gauge
	[115]	Canny edge detection + VGG16 and 2D CNN	–	Accuracy ≥98.3%; CNN = 99.99%	Enhances water boundary visibility for pixel-level segmentation
	[114]	Enhanced YOLOv4 (detection) + DeepLabv3+ (segmentation) + waterline detection modules	<1 cm	–	Addresses inaccurate edge localization and low measurement precision
Transformer-based segmentation	[110]	Fixed ROI + SegFormer [111], SAM [23], MobileSAM [112] + random forest regression	R^2 = 0.93–0.98; MAE = 1.03–2.33 cm	IoU ≈ 0.98 (MobileSAM), 0.97 (SAM), 0.90–0.93 (SegFormer)	Maps water pixels within the ROI to water level and discharge under diverse conditions

7 Imaging Modalities for Water Level Monitoring

Several imaging modalities, including RGB, near-infrared (NIR), and thermal infrared (TIR) imaging, have been used to estimate water levels under different environmental conditions. In addition, UAV, synthetic aperture radar (SAR), multispectral, and hyperspectral imagery are commonly used to map water extent. Table 3 lists representative studies, the water bodies they addressed, and the imagery and sensors they used.

7.1 RGB Images from Cameras

Among the different imaging modalities, RGB imagery is the most common for vision-based water level monitoring, used in the majority of the studies summarized in Table 3, due to its low cost, wide availability, and compatibility with both classical image-processing and deep-learning algorithms. Most current studies collect RGB images using fixed surveillance cameras, closed-circuit television (CCTV) systems, internet protocol (IP) cameras, or smartphones for continuous monitoring of rivers, canals, reservoirs, and urban waterways. Early vision-based monitoring systems relied on RGB images of staff gauges, in which the water level was estimated by detecting the intersection between the water surface and the graduated ruler using image-processing techniques [71, 88, 89].

More recent studies have used higher resolution RGB cameras to enhance the visibility of staff-gauge markings and numerical digits and thereby improve measurement accuracy. For instance, [117] used deep learning for automatic staff-gauge reading with a fixed RGB camera; [65] used RGB images acquired by surveillance cameras to identify the waterline on staff gauges under different illumination conditions. High-resolution RGB imagery supports the extraction of fine-scale features and can be used for object detection, semantic segmentation, and optical character recognition for water-level estimation.

RGB imagery is also used for water level estimation where staff gauges are not present [103, 104, 110]. These methods do not rely on a physical gauge, but estimate the water level by detecting natural shoreline boundaries or permanent structures, such as bridge piers, retaining walls or canal banks, that act as reference objects. For example, [73] estimated river levels by segmenting the water surface in river camera images and relating it to surveyed landmarks, and [94] used the surrounding infrastructure as reference features in live camera images. More recent deep learning methods extract water boundaries with semantic segmentation and map them to a virtual gauge, allowing continuous monitoring without installing physical gauges [65, 113].

7.2 Hyperspectral and Multispectral Imagery

Hyperspectral and multispectral imaging techniques have gained increasing attention for waterbody mapping and monitoring [118, 119], particularly in regions where ground-based observations are limited [120]. The primary difference between these two modalities lies in spectral resolution: hyperspectral images capture data across hundreds of narrow spectral bands, while multispectral images consist of a smaller number of broader bands.

These imaging techniques enable detailed spectral reflectance analysis, allowing differentiation between water, vegetation, and soil surfaces [121, 122]. Satellite multispectral missions, in particular, provide broad spatial coverage, regular revisits, and long historical archives, making them valuable for large-scale monitoring of surface water extent [123].

However, these systems have limitations. Hyperspectral sensors in particular are expensive and generate large volumes of partly redundant data that require careful calibration. Because both modalities are passive optical systems, they are also limited by cloud cover, haze, and the lack of nighttime acquisition [123]. Hyperspectral imagery captures finer spectral variations than multispectral imagery and can therefore discriminate surface materials more precisely, but it does not overcome these atmospheric limitations [124]. In addition, these modalities map water extent rather than measuring water level directly; level must be inferred by combining the mapped shoreline with topographic data.

7.3 Synthetic Aperture Radar (SAR) Imagery

Synthetic Aperture Radar (SAR) is an active remote sensing technology that operates in the microwave domain and provides high-resolution, all-weather imagery [125, 126]. Unlike optical systems, SAR can acquire data regardless of lighting conditions or cloud cover, making it particularly suitable for flood monitoring, wetland analysis, and inland waterbody mapping [127].

SAR imagery is widely used for flood and water extent mapping, especially where optical imagery is limited by cloud cover or low light [128]. Data from missions such as Sentinel-1 are commonly used for water body extraction and flood monitoring [127, 128], and super-resolution processing of Sentinel-1 data has recently been used to estimate water levels directly [16]. However, SAR imagery has several limitations for water monitoring. Speckle noise reduces the accuracy of water extraction [129], and wind-roughened water can appear bright while dry sand can appear dark, so a single global threshold may misclassify water and land [130, 131]. In addition, radar shadow and layover cause errors in urban and vegetated areas [132, 133], C-band signals have limited ability to detect water beneath vegetation [134], and narrow rivers may fall below the sensor's spatial resolution.

7.4 Near-Infrared and Thermal Infrared Imagery

Infrared imaging is used where visible light imaging becomes unreliable, such as at night or in poor weather. Two distinct modalities should be distinguished. Near-infrared (NIR) imaging (approximately 0.75–1.4 μm) records reflected radiation, usually with active infrared illumination, and is widely used in camera-based water level systems because water strongly absorbs NIR and therefore contrasts with gauges and banks [66, 67, 79]. Thermal infrared (TIR) cameras, in contrast, record radiation emitted by objects in the 8–14 μm range, representing surface temperature rather than reflected light [135].

Both modalities are deployed in automated monitoring stations and on UAV platforms. However, thermal imagery generally has lower spatial resolution than RGB or

NIR imagery, limiting its ability to resolve fine details such as staff gauge markings or small shoreline features, and thermal cameras remain considerably more expensive than conventional RGB cameras.

Table 3 Water level and surface water monitoring methods, water bodies studied, and sensor/imaging types.

S.No	Water Body	References	Location	Method / Approach	Image Type	Sensor Type
1	River	[65]	Yufeng Creek, Taiwan	Deep learning (SegNet & U-Net CNNs)	RGB	RGB camera
2	River / urban stream	[94]	Buffalo Bayou, USA	Fully Convolutional Network (FCN)	Video	Live camera
3	River	[136]	Wesenitz River, Germany	CNN (SegNet/FCN) with SfM photogrammetry	RGB	RGB camera + SfM
4	Reservoir tank (testbed)	[137]	Japan	YOLOv5 object detection (CNN)	RGB	RGB camera
5	River (complex environments)	[68]	China	Improved YOLOv5m (CNN)	RGB	RGB camera
6	River	[138]	Missouri River, USA	Multi-task CNN regression	RGB	Webcam
7	Reservoir	[20]	Myeonggyeong Reservoir, South Korea	U-Net segmentation + CNN/ResNet/EfficientNet classification	Video	CCTV
8	Watershed	[139]	Germany	Smartphone image-based photogrammetric measurement	RGB	Smartphone camera
9	River	[140]	Multiple rivers, UK and Ireland	Deep learning using CNN	RGB	RGB camera
10	Reservoir	[141]	Japan	WSN-integrated computer vision	RGB	Vision + wireless sensor network
11	Lakes, rivers, coastal water	[121]	Multiple countries	Automated Water Extraction Index (AWEI)	Multispectral	Landsat 5 TM
12	Coastal lagoon	[122]	Venice Lagoon, Italy	Modified NDWI (MNDWI) with sharpened SWIR band at 10 m	Multispectral	Sentinel-2 MSI
13	Global surface water	[123]	Global	Expert-system classification on Google Earth Engine	Multispectral	Landsat 5/7/8
14	River floodplain	[125]	River Dee, UK	Direct SAR flood extent mapping for flood risk	SAR	Spaceborne radar
15	Urban floods	[126]	River Severn, UK	SAR segmentation with LiDAR-based shadow/layover simulation	SAR (X-band)	TerraSAR-X + airborne LiDAR
16	River floods	[127]	Evros River, Greece and Turkey	Automatic thresholding, fuzzy-logic refinement, HAND masking	SAR (C-band)	Sentinel-1
17	Floods	[128]	Italy, Malawi, and Uganda	Normalized Difference Flood Index (NDFI) on SAR time series	SAR (C-band)	Sentinel-1
18	Global surface water	[142]	Global	MNDWI-based change detection on Google Earth Engine	Multispectral	Landsat 4/5/7/8
19	Urban stream	[67]	Portugal	Image processing for water level under bad weather	RGB / NIR	Camera with infrared capability

8 Datasets for Water Surface and Water Level Detection

Image-based datasets consist of digital images collected for training, testing, and evaluating deep learning and computer vision models. These datasets typically capture water bodies under varying conditions, often including visible references such as staff gauges, physical markers, or virtual stations to correlate images with ground-truth water level measurements. Table 4 summarizes the image-based datasets reported in the literature, their key features, and their applications.

Despite their importance, building such datasets remains challenging. One major limitation is the annotation process, which is labor-intensive and time-consuming, particularly for pixel-level segmentation or precise waterline extraction. Another challenge is ensuring sufficient diversity in the dataset, including variations in location, water body types, camera viewpoints, and environmental conditions. The lack of such diversity often leads to poor generalization and limits real-world deployment. Data augmentation, including generative adversarial network (GAN)-based synthesis of gauge images, has been proposed to partly offset limited training data [143]. The main datasets reported in the literature are described below.

8.1 ATLANTIS Texture (ATeX) Dataset

ATLANTIS (ArTificiaL And Natural waTer-bodIes dataSet) [144] is a semantic segmentation benchmark of 5,195 pixel-wise annotated images covering a wide range of natural and artificial water bodies, collected from online sources through the Flickr API under permissive licenses and refined through multi-stage filtering. The derived ATLANTIS Texture (ATeX) dataset represents the texture appearance of water in 15 types of water bodies, such as lakes, rivers, and swamps. It consists of 12,503 patches of 32×32 pixels, split into 8,753 training, 1,252 validation, and 2,498 test patches. Because ATeX targets water texture classification, it supports water surface recognition rather than direct water level estimation.

8.2 Eye of Horus Dataset

The Eye of Horus dataset [145] contains RGB river images paired with ground-truth water level measurements. The dataset was collected using a Raspberry Pi Zero W and an Arduino Nano system. A Raspberry Pi Camera Module 2 (Sony IMX219, 8 MP) captured images at a resolution of 1920×1440 pixels, while water levels were simultaneously measured using an HC-SR04 ultrasonic sensor. The dataset consists of 1,172 images, split into 812 training, 124 validation, and 236 testing samples.

8.3 Ningbo Staff-Gauge Dataset

The dataset of [68] consists of 2,556 images of a staff gauge captured at a single site in Ningbo, China, at 5-minute intervals over 10 days, of which 1,776 images were used for training and 780 for testing. The images cover a wide range of conditions, including sunny (17%), cloudy (16%), rainy (1.4%), night-time (37.9%), soiled gauge (26%), and other special situations (1.7%), such as rapid changes in water level and mud blockage.

Images were annotated with separate daytime and night-time gauge classes. Because all images come from a single site, the dataset is better suited to testing robustness under changing illumination and weather than to evaluating cross-site generalization, and it does not appear to be publicly released.

8.4 Barcode-Patterned Panel Dataset

This dataset [146] consists of RGB images of a stainless-steel barcode panel (155×40 cm, with seven black bars) used as a physical marker for water level estimation, where the number of bars visible above the water surface indicates the water level. It comprises 214 images captured in a pool, where water levels were varied by moving the panel and artificial rain was simulated in some captures, and 59 images captured in the Maués-Açu River, Brazil. In both settings, images were taken during the daytime from different positions and angles, and each image is annotated with the number of visible bars and a bounding box around the panel. In the original work, images were resized to 224×224 pixels for training.

8.5 River-Camera Dataset for Flood Event Monitoring

This dataset [73] was collected using four fixed cameras located along the rivers Severn and Avon in the United Kingdom, specifically at Diglis Lock (DIGL), Evesham (EVES), Strensham Lock (STRE), and Tewkesbury Marina (TEWK). The images capture a major flood event between November and December 2012. The dataset was acquired using Mobotix M24 HD cameras at a resolution of 2048×1536 pixels and contains 557 RGB images in total. Each image is annotated with landmarks to enable flood analysis and water level estimation.

8.6 River Segmentation Dataset

The River segmentation dataset [147] consists of RGB images with binary water segmentation masks. It contains 300 manually collected images from riverbank environments, with 225 images used for training. This dataset is particularly useful for direct river segmentation tasks. The image sizes vary, ranging from 118×158 to 2448×3264 pixels with a mean of approximately 550×826 pixels [147].

8.7 WATERDB Dataset

WATERDB [73] is a large-scale dataset containing RGB images with pixel-wise annotations for water and non-water regions. It is constructed by combining images from the ADE20K dataset [148] (water, sea, river, waterfall classes) and the COCO-Stuff dataset [149] (river, sea, and water-other classes). The dataset contains a total of 12,684 training images. As the images are taken from these two source datasets without being resampled to a common size, WATERDB does not have a fixed spatial resolution, images from COCO-Stuff are around 640×480 pixels, whereas ADE20K images vary in both size and aspect ratio. Therefore, images are usually rescaled during preprocessing before the segmentation.

8.8 Stage-Camera Ephemeral Streams Dataset

This dataset [79] consists of images captured using a consumer-grade wildlife camera (Bushwhacker D3 trail camera) focused on a white-painted steel pole used as a reference object. Images were collected in time-lapse mode at intervals ranging from 3 seconds to 24 hours. The dataset includes 16-megapixel RGB images and also incorporates nighttime near-infrared (NIR) imagery (850–940 nm). Images were captured every 30 minutes, enabling approximately two weeks of continuous monitoring before SD card storage limitations were reached.

8.9 Drone/UAV-Based Image Datasets

8.9.1 Aerial Drone Image Dataset for Flood Monitoring

This dataset [150] contains RGB images for object detection and water level estimation. It includes 47 flood images and 5 normal images, along with annotated objects such as 420 houses and 313 cars using bounding boxes and segmentation masks. A total of 627 object-level samples are used for water level estimation. Water level annotations range from 0 to 3 m based on object visibility and inundation depth, and include data collected from public sources and drone-based aerial imagery to improve generalization.

8.9.2 UAV Photogrammetry Dataset

This dataset [151] consists of UAV-based photogrammetry data collected using drone-mounted sensors, producing dense point clouds of river surfaces for water level estimation. The data is processed using Random Sample Consensus (RANSAC) to fit planar surfaces corresponding to water levels. Ground-truth annotations include reference altitude measurements, enabling accurate estimation of water surface elevation. This dataset provides a cost-effective alternative to in situ gauging for flood monitoring and hydrological analysis.

Table 4 Summary of image datasets reported in the literature for water surface and water level detection.

Dataset	Reference	Size / Split	Resolution / Sensors	Description / Key Features
ATLANTIS Texture (ATeX)	[144]	12,503 patches (8,753 train / 1,252 val / 2,498 test)	32×32 px	Derived from ATLANTIS (5,195 pixel-wise annotated images of natural/artificial waterbodies); covers 15 waterbodies (lake, river, swamp); collected via Flickr API under permissive license with multi-stage filtering; focused on water texture appearance
Eye of Horus	[145]	1,172 images (812 train / 124 val / 236 test)	1920×1440 px; Raspberry Pi Camera Module 2 (Sony IMX219, 8MP) + HC-SR04 ultrasonic sensor	RGB river images paired with ground-truth water level measurements; collected using Raspberry Pi Zero W and Arduino Nano system
Ningbo Staff-Gauge	[68]	2,556 images (1,776 train / 780 test); single site	Fixed surveillance camera	Staff-gauge images captured every 5 min over 10 days in Ningbo, China; sunny, cloudy, rainy, night-time (37.9%), and soiled-gauge (26%) conditions; separate day/night annotation classes; not publicly released
Barcode-Patterned Panel	[152]	Not specified	RGB camera	Images of stainless-steel barcode-patterned panels as physical water-level markers; captured in controlled pool and real river settings under varying environmental noise; annotations link barcode position to water level
River-Camera (Flood Event Monitoring)	[73]	557 images total	2048×1536 px; Mobotix M24 HD cameras	Collected from four fixed cameras on rivers Severn and Avon, UK (DIGL, EVES, STRE, TEWK); captures major flood event (Nov–Dec 2012); landmark-annotated for flood analysis and water level estimation
River Segmentation	[147]	300 images (225 train)	RGB camera	Manually collected riverbank images with binary water segmentation masks; useful for direct river segmentation tasks
WATERDB	[73]	12,684 images	RGB camera	Large-scale dataset with pixel-wise water/non-water annotations; combines ADE20K [148] (water, sea, river, waterfall classes) and COCO-Stuff [149] (river, sea, water-other classes)
Stage-Camera Ephemeral Streams	[79]	Continuous time-lapse (˜2 weeks)	16 MP RGB + NIR (850–940 nm)	Captured using consumer-grade wildlife camera (Bushwhacker D3 trail camera) on a white-painted steel reference pole; time-lapse intervals from 3 seconds to 24 hours; images every 30 minutes; includes nighttime NIR imagery
Aerial Drone Image Dataset (Flood Monitoring)	[150]	52 images (47 flood, 5 normal); 627 object-level samples	RGB (drone-based)	Object detection and water level estimation; 420 houses and 313 cars annotated (bounding boxes + segmentation masks); water level annotations 0–3 m based on object visibility/inundation depth; combines public and drone-collected sources
UAV Photogrammetry	[151]	Not specified (point cloud data)	UAV-mounted sensors	Dense point clouds of river surfaces processed via RANSAC to fit planar water-level surfaces; ground-truth reference altitude measurements; cost-effective alternative to in-situ gauging

9 Discussion

9.1 Methodological Trends

This review has examined how water level can be measured from visual data. Water level monitoring has developed from contact-based sensors, such as crest-stage gauges, staff gauges, pressure transducers, and bubblers, toward non-contact methods, and within non-contact methods from ultrasonic, radar, and laser ranging toward AI-driven image analysis. Within computer vision-based studies, a further shift is evident from handcrafted image processing to feature-based machine learning and then to deep learning (Figure 2). These developments share a common motivation: reducing reliance on physical contact with the water body and on manually engineered features, in favor of approaches that are more durable, scalable, and able to generalize across sites and conditions.

The review also clarifies the trade-off between methodological complexity, robustness, and deployment cost. Classical image processing techniques, including thresholding, multi-frame aggregation, and edge-based detection, remain attractive for their low computational cost and ease of implementation, but their dependence on manually tuned parameters makes them highly sensitive to illumination changes, reflections, and site-specific conditions. Machine learning techniques, such as ensemble feature extraction, template matching, optical character recognition, and dictionary learning, improve robustness over purely rule-based methods by learning relationships from extracted features, but they still depend on careful preprocessing. Deep learning methods, particularly YOLO-based object detection, residual CNNs, and transformer-based segmentation models such as SAM and SegFormer, largely remove the need for manual feature engineering by learning hierarchical representations directly from imagery. This has improved both accuracy and adaptability, especially under complex real-world conditions involving variable lighting and cluttered backgrounds.

9.2 Performance and Comparability

The reported accuracies of the reviewed methods overlap considerably (Tables 1 and 2). Calibration-target and NIR-based image processing systems report millimeter-level resolution and errors of a few millimeters under controlled conditions [19, 66], whereas threshold-based systems in the field report errors from below 1 cm to more than 2 cm depending on conditions [79]. Deep learning systems typically report errors of about 1–2 cm in the field [68, 105, 110], often under conditions in which image processing methods fail, such as low light, strong reflections, or cluttered backgrounds. Direct comparison of these figures is, however, unreliable. The studies use different sites, water body types, camera geometries, reference measurements, and metrics (MAE, RMSE, R^2, NSE, or classification accuracy), and many detection and segmentation studies report only mAP, IoU, or pixel accuracy, which do not translate directly into water level error. Very few studies evaluate several method families on the same dataset. The conclusion that DL outperforms earlier approaches under complex conditions is therefore supported by the qualitative pattern of results rather than by

controlled head-to-head comparison, and establishing common evaluation protocols is a priority for the field.

9.3 Datasets and Generalization

The review highlights a gap between algorithmic advancement and data infrastructure. The datasets described in Section 8, including ATLANTIS and ATeX, Eye of Horus, GaugeCam, the barcode-patterned panel dataset, the river-camera flood dataset, the river segmentation dataset, WATERDB, the stage-camera ephemeral streams dataset, and UAV-based collections, are individually valuable but collectively fragmented. They differ in imaging modality, site characteristics, annotation type, and scale, and most are limited to a small number of rivers, canals, or reservoirs. This fragmentation limits direct comparison across studies, prevents benchmarking under consistent conditions, and, most importantly, restricts the generalization of models trained at a single site when they are deployed elsewhere. Because illumination, shadows, reflections, and local occlusion vary substantially across locations and seasons, models that perform well in one environment frequently underperform in another. Dataset diversity and standardization are therefore a central bottleneck for the field.

9.4 Deployment Considerations

Beyond data availability, several practical factors determine whether image-based methods can be used operationally.

Calibration and geometry. Converting a detected waterline into a physical water level requires a stable relationship between image coordinates and elevation. Gauge-based systems obtain this from the scale markings, whereas gauge-free systems rely on calibration targets, surveyed ground control points, or homography [19, 136]. Camera movement caused by wind, vibration, or maintenance invalidates this calibration, so operational systems need either rigid mounting and periodic re-surveying or automatic detection and correction of camera displacement [86].

Environmental conditions. Camera orientation, temporary obstructions, water turbidity, surface turbulence, rain, fog, and image quality can all degrade waterline detection regardless of the underlying algorithm. Night-time operation is a particular challenge; NIR illumination provides one practical solution, and some gauge-reading systems perform better at night under infrared illumination than during the day [64, 79].

Computing and communication. Real-time monitoring at remote sites requires either transmitting images to a server or processing them on site. Edge computing and IoT architectures reduce bandwidth needs and latency [77, 110], but they constrain model size, which favors lightweight models such as MobileSAM or small YOLO variants over large foundation models.

Reliability and redundancy. Like other non-contact technologies, camera systems remain susceptible to power interruptions and equipment failure. Combining camera-based estimates with a conventional sensor provides redundancy and allows each to check the other [152]. Long-term field evaluations remain rare [26], and the

reviewed studies indicate that fully automatic adaptation to changing field conditions, without site-specific recalibration, has not yet been achieved.

Application settings. Most reviewed studies address rivers, urban streams, and reservoirs (Table 3). Agricultural irrigation canals, where low-cost level monitoring could directly improve water allocation, are rarely studied, even though their regular geometry and fixed structures make them well suited to camera-based measurement.

This gap between controlled experimental performance and sustained field reliability is one of the clearest barriers separating current research prototypes from operational hydrological monitoring networks.

9.5 Future Research Directions

Several research directions follow from these findings. First, the development of large, openly accessible, multi-site datasets spanning diverse hydraulic structures, seasons, and illumination conditions, together with common evaluation protocols, would allow meaningful cross-study comparison and directly address the generalization limitations identified above. Second, vision foundation models, transformer architectures, and self-supervised or transfer learning strategies offer a promising route to reducing dependence on large volumes of manually labeled, site-specific data while improving transferability across monitoring locations [24, 25]. Third, multi-sensor fusion, for example combining camera imagery with pressure transducers at the site scale [152] or UAV optical imagery with satellite SAR at the regional scale [13], can improve reliability and extend spatial coverage. Fourth, edge and cloud computing architectures could enable real-time, low-latency processing for autonomous monitoring in resource-limited or remote settings. In the longer term, research should extend single-purpose water level models toward multi-task computer vision systems that jointly estimate water level, surface velocity, discharge, and debris transport from a single image stream [28, 110], providing a richer basis for flood early warning and water resources management than water level alone.

10 Conclusions

This review consolidates a rapidly evolving and previously dispersed body of literature spanning hydrology, computer vision, and environmental monitoring into a unified account of image-based and AI-driven water level estimation. It shows that the field has advanced from classical image processing to classical machine learning and, most recently, to deep learning and transformer-based architectures capable of accurate, non-contact measurement. At the same time, it identifies dataset fragmentation, the lack of standardized evaluation, limited cross-site generalization, and sensitivity to environmental variability as the main obstacles to operational deployment. Addressing these challenges through open and diverse datasets, foundation-model-based learning, multi-sensor fusion, and edge-enabled real-time processing would move the field from largely site-specific research toward robust and scalable monitoring systems.

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