

Article

Hybrid IoT-VIoT System for Real-Time Water-Level Monitoring Using Computer Vision

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Abstract

Efficient water resource management is critically important for arid regions such as southern Kazakhstan. This paper presents a hybrid Internet of Things (IoT) and Vision-based Internet of Things (VIoT) architecture for real-time monitoring of water levels in irrigation channels. The proposed system integrates an ultrasonic water-level sensor, an IP camera with edge-based computer vision processing on a Raspberry Pi, wireless communication, an autonomous solar power supply, and discharge estimation using Manning's equation. The VIoT subsystem applies image processing techniques, including gauge calibration, Canny edge detection, and pixel-to-metric conversion, to automatically estimate water level from captured video frames. Water-level measurements obtained from IoT sensors and video-based analysis are combined through synchronised data fusion to improve monitoring accuracy and reliability. The hybrid approach leverages the complementary strengths of IoT and VIoT by combining continuous quantitative sensing with visual verification capabilities. Field experiments conducted on the Merke River in the Zhambyl region of Kazakhstan over a 14-day observation period demonstrated stable real-time operation with RMSE = 0.311 cm, MAE = 0.279 cm, and Pearson $r = 0.99$ between the ultrasonic sensor and the vision-based estimates. Sensitivity analysis indicated that water level is the most influential parameter in Manning-based discharge estimation, confirming the importance of accurate level detection. The proposed system improves reliability by cross-checking independent data sources, making it applicable to monitoring water levels in agricultural regions.



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1. Introduction

Water scarcity and flood risks are among the most pressing issues in the arid zones of Central Asia. In the southern regions of Kazakhstan, including the Zhambyl region, agriculture fully depends on the rational use of limited water resources. Given that a large share of water resources is allocated to agricultural needs, especially during the dry summer season, continuous monitoring of small rivers and canals is crucial to ensuring efficient

irrigation. However, the region's existing hydrological infrastructure requires modern solutions to manage water resources effectively. Despite advances in information systems, most observation stations still rely on manual measurements or analogue devices, resulting in data gaps and inaccuracies. Such data collection methods often result in distorted or lost information. These problems call for the modernisation of monitoring systems based on digital technologies. In response to this challenge, researchers and government agencies are turning to the Internet of Things (IoT) and smart agriculture technologies to improve water management [1–3].

IoT systems enable the deployment of low-cost distributed sensor networks that provide real-time measurements of water level, discharge proxies, and environmental parameters. For example, precision irrigation systems use IoT sensors to monitor soil moisture, weather conditions, and water levels in canals, enabling data-driven decisions on water distribution [4–8]. Traditional IoT sensor nodes, such as ultrasonic and pressure sensors, measure water height or velocity with high accuracy and can transmit data continuously over a wireless network [9,10]. These devices are energy efficient and operate reliably in darkness and rain. Ultrasonic sensors, in particular, measure water levels based on the time of flight of a reflected sound pulse. They are inexpensive, non-contact, and suitable for harsh or hard-to-reach locations.

Several recent studies have demonstrated the capabilities of sensor-based IoT systems in hydrological monitoring. Paper [11] presents an IoT-based deep learning approach that improves measurement robustness and operational reliability compared with conventional submersible and ultrasonic sensors. Unlike traditional contact-based sensors, which are susceptible to sediment accumulation, mechanical degradation, and signal instability under adverse environmental conditions, the proposed Mask R-CNN-based method enables accurate water-gauge segmentation under varying illumination and weather conditions. Experimental results demonstrated stable water-level estimation performance during both daytime and nighttime operation, while maintaining reliable detection capability in the presence of shadows, rainfall, reflections, and partial gauge occlusions. In addition, the vision-based approach reduces maintenance requirements and minimises measurement interruptions, which are commonly associated with conventional flood-monitoring sensors deployed in harsh outdoor environments. Reference [12] presents LevelWAN, a low-cost, open IoT system for water-level monitoring based on ultrasonic sensors and LoRaWAN communication. The system has been tested for three years and has demonstrated measurement accuracy of approximately 1 cm. The solution is energy efficient, easy to install, and suitable for long-term monitoring in rivers and canals. The authors note that the absence of a video module limits its use under interference conditions. Research presented in [13] proposes an autonomous real-time system for monitoring water level and flow on the Sakarya River in Turkey. The station uses an ultrasonic sensor, solar power, and GSM-based data transmission to provide continuous level measurement and flow calculation using the Manning formula. The results obtained showed high accuracy, with a level deviation of about 0.1% and a correlation with control measurements reaching 0.92. The system demonstrated stable operation in autonomous mode, but the lack of a video module limits the possibilities for data verification. The authors of [14] present an intelligent IoT system for water resource management that uses water-level, flow, and quality sensors. The system performs real-time monitoring and automatic pump control via NodeMCU. The use of machine learning allows leaks to be detected and consumption to be predicted, reducing water losses by up to 30%. The solution contributes to sustainable and energy-efficient water management in smart cities and rural areas.

One of the most arduous challenges faced by most residential units is water overflow. The paper [15] proposes a smart IoT-based system for monitoring and managing water

levels in overhead tanks and sumps. Though water is an essential resource, people often turn the motor on only when the taps run dry and turn it off only after the tank overflows, resulting in unnecessary wastage. The proposed system uses an ultrasonic sensor connected to an ESP8266 Wi-Fi module to measure water levels continuously. When the level falls below a user-defined minimum threshold, a red LED is activated to indicate that the motor should be switched on. When the level exceeds the maximum threshold, a green LED is activated to indicate that the motor should be switched off. The ESP8266 firmware is developed using the Arduino IDE, and sensor readings are transmitted to the Adafruit IO cloud platform over Wi-Fi. Water-level data is displayed in real time as a line graph and gauge metres with configurable thresholds. This eliminates the need to inspect the tank physically, prevents overflow, and protects the pump from damage caused by running the motor with insufficient water in the sump. These principles are implemented in a low-cost IoT water monitoring system proposed in [16]. The system is based on an ESP8266 microcontroller with an ultrasonic sensor, powered by a solar panel and a 12-volt battery, and provides round-the-clock data collection even in remote areas. Thus, modern sensor-based IoT solutions are reliable tools for automated monitoring and can reduce reliance on manual stage-gauge observations. However, sensor data is primarily quantitative. IoT systems do not provide visual context and, in some cases, require calibration. For example, ultrasonic sensors are sensitive to air temperature [17,18]. It does not provide visual context and does not allow detection of phenomena such as blockages, coastal erosion, or water pollution. In addition, sensor clogging or misalignment can result in false data. This raises the need to supplement sensor networks with a camera that provides visual verification and enables anomaly detection.

The convergence of IoT and Visual IoT (VIoT) opens up new opportunities for remote monitoring and interpretation of hydrological conditions, in addition to numerical measurements. When these technologies are combined, each has its own unique advantages. Thus, in [19], the authors proposed an automatic solution for monitoring river water levels using computer vision, processing images from water-level gauges captured by a VIoT device. In [20], a water-level recognition model was developed using deep learning on closed-circuit television (CCTV) footage. The model focuses on real-time water-level recognition in agricultural reservoirs without automated water-level gauges, with potential future expansion to flood-forecasting applications. The results of these studies show that VIoT can serve as an effective monitoring tool, creating a “Virtual eye” on the river. VIoT systems can provide rich information. A single camera can track not only the water level on a gauge, but also surface currents, debris, or the condition of the banks.

Modern Computer Vision (CV) algorithms have achieved an accuracy of several centimetres, comparable to that of instrumental measurements. Alongside the development of IoT, computer vision methods are advancing, enabling water bodies to be monitored using conventional cameras. The simplest example is the automatic reading of a stage gauge installed in a riverbed or canal [21,22]. In [23], the authors present the “Eye of Horus” system, a computer vision-based deep segmentation solution for real-time water-level measurement. Using cameras, LiDAR data, and SegFormer, PSPNet, and TransUNet models, the authors achieved high accuracy compared to ultrasonic sensors. The method provides reliable monitoring but requires stable camera installation and calibration, which limits its application in challenging natural conditions. This study addresses this gap by proposing a hybrid VIoT architecture that integrates numerical measurements and visual observations into a single system. The main idea is to use the complementary advantages of each modality. Several authors have pointed out the benefits of such integration. In [24], the authors propose a non-contact approach based on analysing images of a staff gauge and converting pixel values into real-world water-level measurements. This method

aligns with modern trends in agricultural digitalisation and reduces reliance on traditional sensors. However, the results indicate limited system accuracy due to external factors, particularly lighting conditions and variability in colour characteristics. These issues lead to segmentation errors and reduce measurement reliability. Overall, the study demonstrates the potential of computer vision techniques, but further improvements to the algorithms are required to enhance system robustness and accuracy.

Despite the active development of IoT- and VIoT-based water-level monitoring systems, most existing studies focus either on sensor-based monitoring or visual image analysis in isolation. Sensor-only systems provide continuous quantitative measurements but do not support visual inspection of flow conditions or gauge readings. Computer vision systems, in turn, are highly dependent on lighting conditions, camera lens contamination, weather, and flow turbulence. An analysis of the reviewed literature reveals that most published hybrid systems focus on the architectural integration of devices and data transmission, while formalised models for combining sensor and visual measurements, mechanisms for analysing measurement discrepancies, and decision-making algorithms remain insufficiently developed. Furthermore, existing research lacks systems that simultaneously combine ultrasonic water-level monitoring with visual gauge-based verification, cross-validation of sensor and visual measurements, local edge data processing, an autonomous solar power supply, and real-time water-flow calculation using Manning's formula. Thus, the primary research gap is the lack of a systematic approach to cross-validating sensor- and vision-based water-level measurements in hybrid monitoring systems for small irrigation channels in arid regions.

The scientific contribution of this paper extends beyond the engineering integration of IoT and VIoT components. Unlike existing research, the developed system employs a rule-based approach to integrate data from ultrasonic sensors and visual inspection modules, enabling cross-validation of water-level measurements from two independent sources. The proposed approach integrates ultrasonic water-level measurement, visual determination of water level using a calibrated gauge, analysis of discrepancies between sensor and visual measurements, verification of water level before hydraulic calculations, and real-time water flow estimation using Manning's formula—all within a single unified monitoring platform. Unlike many existing hybrid systems in which IoT and computer vision modules operate independently, the proposed system employs a rule-based cross-validation procedure that compares measurements from both modalities, thereby improving monitoring reliability under real-world conditions such as unstable lighting, flow turbulence, and potential sensor interference. The proposed architecture further integrates autonomous solar power, local edge processing on a Raspberry Pi, and real-time data visualisation, forming a unified platform tailored for irrigation channels and small rivers in arid agricultural regions. In our paper, we integrate IoT and visual observation technologies into a single architecture, thereby achieving higher reliability. If one modality fails, for example, due to sensor contamination or lens glare, the other compensates. Unlike other systems, our system is designed for the realities of rural arid regions, such as inexpensive equipment, solar power, wireless communication, minimal maintenance, and the ability to monitor water levels in real time. Thus, the literature makes it clear that sensor and visual systems have limitations individually, especially under extreme conditions. Sensor networks are cheaper and simpler but require visual verification [25]. Visual systems provide rich data but depend on lighting and energy. Table 1 shows that sensor-only systems minimise power consumption and data traffic but lack visual context. Vision-only systems provide maximum context awareness, but increase bandwidth and energy requirements. The proposed hybrid configuration occupies an intermediate position and is designed to exchange additional complexity for the possibility of cross-validation.

Table 1. Comparison of sensor-based, visual and hybrid water monitoring systems.

Criterion	Sensor-Based IoT System	Visual System (VIoT)	Proposed Hybrid System
Power Consumption	Low	High	High, requires solar power
Data Traffic	Low (data packets)	High (if images are transmitted)	Medium (data + event-based snapshots, e.g., threshold crossing, anomaly detection)
Data type	Quantitative (level, speed)	Visual (context, stream status)	Combined (numerical and visual)
Sustainability	Operates in all weather; possible clogging/overheating	Depends on light, fog, lens cleanliness	Enhanced: one modality compensates for failure of the other
Maintenance	Calibration, sensor cleaning	Camera cleaning, power, connectivity	Both procedures required
Use in remote areas	Limited by communication and power	Requires communication and power; sensitive to dust and heat.	Limited by communication and power; sensitive to dust and heat

These factors motivate the development of hybrid solutions that combine the advantages of both data types. In addition, the specifics of rural and arid regions should be taken into account. The main contributions of this study are: (1) a hybrid IoT–VIoT architecture integrating an ultrasonic sensor and a calibrated vision-based gauge reader on a single autonomous platform for small irrigation channels; (2) a rule-based fusion procedure (Algorithm 1) that cross-validates the two channels via inverse-error weighting and flags anomalies before they enter hydraulic calculations; (3) field-validated discharge estimation from camera-derived water levels using Manning’s equation, calibrated against the velocity–area reference method; and (4) a quantitative evaluation of accuracy, statistical agreement, and parameter sensitivity, benchmarked against published low-cost systems. The remainder of the paper is organised as follows. Section 2 presents the system design and methods. Section 3 describes the experimental setup and sensitivity analysis. Section 4 discusses the results and limitations. Finally, Section 5 presents the conclusions.

2. Materials and Methods

The study was conducted in accordance with the design and validation methodology, which comprises five consecutive stages. Firstly, the requirements for autonomous monitoring of water levels in irrigation canals were determined through a literature review and the identification of research gaps. Secondly, to meet these requirements, the architecture of the hybrid IoT–VIoT system was developed, combining subsystems for sensing, peripheral computing, communications and autonomous power supply. Third, a rules-based model for merging sensors and video surveillance systems, and a cost estimation method based on personnel data, have been developed. Fourth, a working prototype was implemented and deployed for field testing at a representative monitoring site on the Merke River. Fifth, the system was evaluated through paired comparisons of sensor readings, cross-validation of the reset based on Manning’s readings using the velocity-and-area determination method, statistical matching analysis, and individual sensitivity analysis of the reset model. This step-by-step design ensures that each component meets the identified need and that the claimed accuracy is assessed against an independent hydrometric benchmark, rather than against independently obtained data. The remainder of this section describes in detail the system architecture (Figure 1), the model for merging sensory and visual equipment, the hydraulic assessment method, and the verification algorithm.

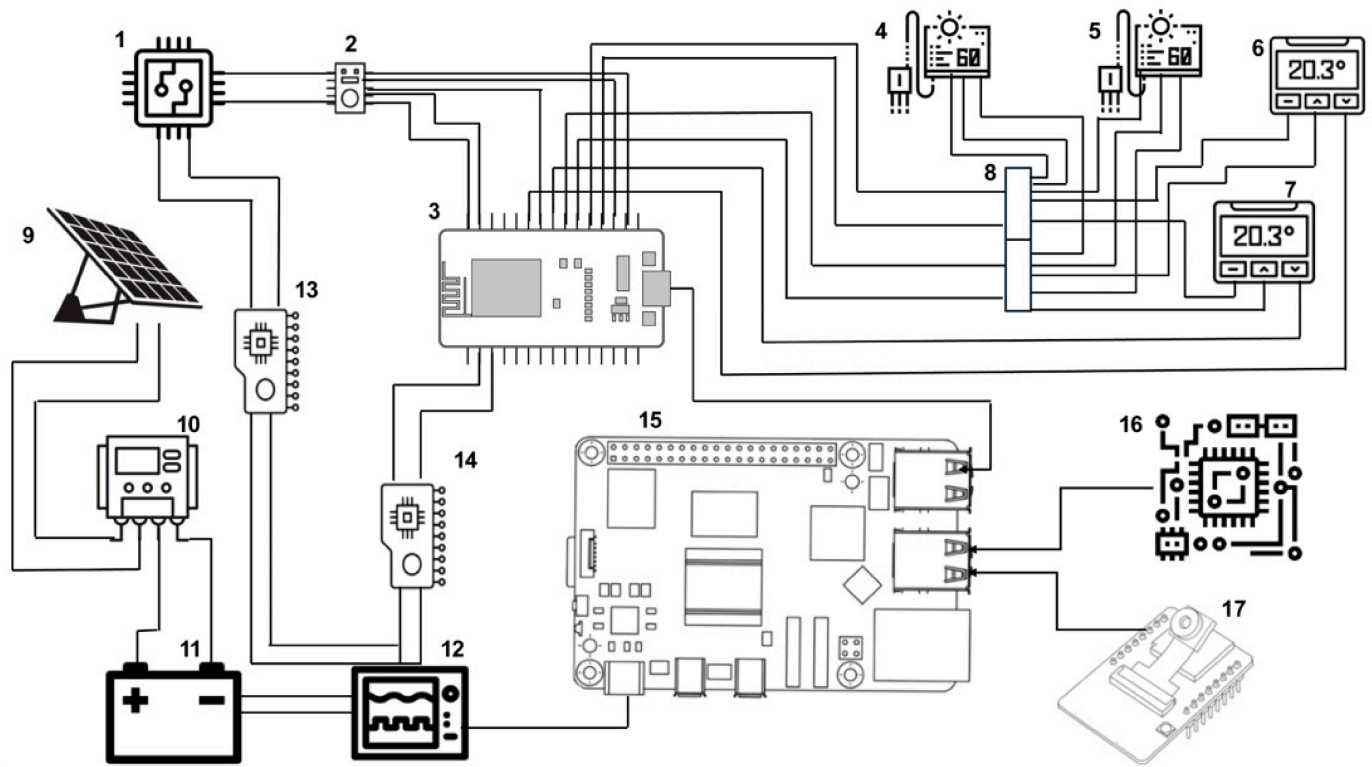


Figure 1. Hybrid architecture. 1—Ultrasonic water-level sensor; 2—Multi-client wired data transmission; 3—Microcontroller; 4, 5—Temperature sensors; 6, 7—Temperature and humidity sensors; 8—Terminal block; 9—Solar panel; 10—Solar charge controllers; 11—Batteries for solar panels; 12—Battery protection board; 13, 14—Boost converters; 15—Microcomputer; 16—Radar flow metre; 17—Microcontroller with camera.

Our proposed solution is a multi-level VIoT hybrid architecture that integrates traditional sensors with computer vision-based video surveillance into a single system. Figure 1 illustrates the system architecture developed for real-time monitoring of water levels and flow rates in small rivers and canals.

The system architecture is built on a distributed modular principle and includes measurement, computing, communications, and power subsystems. The central element of the architecture is the ESP8266 microcontroller (3), which collects and synchronises data from connected sensors and measurement modules. An ultrasonic water-level sensor (1), as well as temperature sensors (4, 5) and temperature/humidity sensors (6, 7), are connected to the microcontroller via a multichannel transmission line (2). Signal switching is implemented via a distribution node (8), ensuring modular connection of the sensor components. Local computing is performed by a Raspberry Pi microcomputer (15), which is used for data aggregation, image processing, and interaction with the system's server. Connected to the computing node are a radar flow metre (16), which provides flow parameter monitoring, and an ESP32-CAM video module (17), which is designed for real-time monitoring of the hydrometric gauge and for implementing computer vision algorithms. The power subsystem includes a solar panel (9), a charge controller (10), a battery (11), a battery protection board (12), and step-up voltage converters (13, 14). This configuration ensures autonomous power supply for the system and stable operation of computing and sensor components in the field. The presented architecture enables simultaneous use of contact sensor measurements, video monitoring, and local analytical data processing, thereby increasing the stability and reliability of the hydrological parameter monitoring system.

The sensor node is based on a microcontroller (MCU) with analogue and digital interfaces. The prototype uses an ESP8266 board, which is characterised by low power consumption and a built-in Wi-Fi modem. A JSN-SR04T ultrasonic water-level sensor is connected to it. Measurements are taken at fixed intervals or when an event occurs, such as a sudden change in level. A temperature sensor is also connected next to the ultrasonic sensor to compensate for the effect of temperature on the speed of sound and to monitor weather conditions. If the rating curve (stage-discharge curve) is known, the flow rate is calculated based on the level. The design focuses on modularity, scalability, and autonomy, making it particularly suitable for rural areas. Sensor nodes and a video camera form the lower level of data collection, exchanging information via Wi-Fi or a 4G network with cloud services. The system is designed to operate autonomously using solar energy and to provide real-time data to users via a web panel. The autonomous power supply architecture of the proposed system is consistent with the broader trend of integrating renewable energy sources into remote monitoring infrastructure. The energy autonomy of the system can be further enhanced by integrating complementary renewable sources, such as the small-scale sail-based wind power system proposed in [26], which enables efficient energy generation at low wind speeds in open arid environments with limited solar irradiance.

The proposed architecture's main block is the Data Collection Layer. This layer contains all devices installed in the field that collect primary data. The hybrid system uses two main types of devices. Our water-level monitoring system enables continuous, accurate acquisition of water-level data, ensuring more precise estimates of both instantaneous and cumulative discharge. The proposed system is not limited to the engineering integration of IoT sensors and VIoT devices. Its methodological contribution is a rule-based model that merges sensor data and computer vision to verify water-level measurements under real-world field conditions. In the proposed approach, the water level is determined from two independent sources, an ultrasonic sensor and a computer vision module. The ultrasonic sensor provides a numerical value for the water level, whilst the VIoT module estimates it from a calibrated image of a measuring rod. Thus, the system performs a cross-check between the sensor measurements and those from computer vision before using the data for hydraulic calculations.

Let h_s be the water level measured by the ultrasonic sensor, and h_v be the water level determined by the computer vision method. The difference between the two measurements is defined as follows:

$$\Delta h = |h_s - h_v| \quad (1)$$

The adaptive discrepancy threshold is defined as:

$$T_d = \alpha(e_s + e_v) \quad (2)$$

where e_s is the measurement error of the ultrasonic sensor, e_v is the measurement error of the computer vision module, and α is a scaling coefficient controlling the tolerance to discrepancies between the two measurement channels.

$$w_s = \frac{1}{e_s + \delta} \quad (3)$$

$$w_v = \frac{1}{e_v + \delta} \quad (4)$$

where w_s and w_v are reliability-based weighting coefficients, and δ is a small positive constant used to avoid division by zero.

If the following condition is satisfied $\Delta h \leq T_d$, the fused water level is calculated as:

$$h^* = \frac{w_s h_s + w_v h_v}{w_s + w_v} \quad (5)$$

where w_s and w_v are inversely proportional to the measurement errors of the ultrasonic sensor and computer vision module, respectively. If $\Delta h > T_d$, the system flags the measurement as inconsistent and records the anomaly. In this case, both values, h_s and h_v , are stored for further verification of sensor stability, image quality, camera position and environmental conditions. The resulting water-level value h^* is used to calculate the channel's hydraulic parameters.

In the mountainous section of the watershed, runoff is formed under steep-gradient conditions. Subsequently, it enters an engineered open channel with a U-shaped cross-section constructed from monolithic reinforced concrete blocks, with internal dimensions of 1×1 m (Figure 2). Within this section, the hydraulic behaviour is governed by open-channel flow mechanics. The flow regime can be described as free-surface flow, in which discharge capacity depends on the hydraulic radius, flow depth, channel slope, and surface roughness coefficient (commonly expressed by Manning's equation).

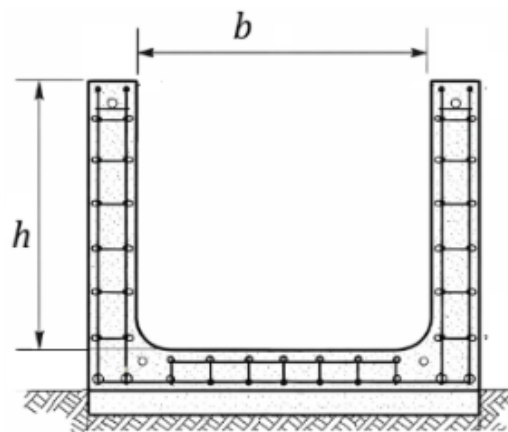


Figure 2. U-shaped reinforced concrete channel.

Given the regular geometric cross-section and controlled headworks conditions, the site provides a stable hydraulic control section suitable for validating the accuracy of water-level measurements. Under quasi-uniform flow conditions, variations in water level directly correspond to fluctuations in discharge, enabling reliable calibration of the monitoring system against hydraulic reference measurements.

To calculate the hydraulic parameters from Computer Vision data, we used Manning's equation for open channels [27]. At each time instant t , the installed camera records the water level $h(t)$, m . The calculations are based on known constant channel parameters: rectangular cross-sectional geometry; channel width B , m ; Manning roughness coefficient n . For concrete-lined irrigation channels typical of Kazakhstan, $n = 0.015$; channel bed slope S_0 (or hydraulic slope I).

The hydraulic slope was determined through inverse calculation using Manning's equation based on discharge values obtained by the velocity–area method. The resulting value $I = 0.00724$ was used to construct the stage–discharge calibration relationship. The parameters n and I are based on typical hydraulic characteristics of the channel and the results of control field measurements. Manning's equation is expressed as:

$$Q = \frac{1}{n} A \cdot R^{\frac{2}{3}} \cdot I^{\frac{1}{2}} \quad (6)$$

where Q —water discharge, m^3/s ; A —wetted cross-sectional area (flow area), m^2 ; R —hydraulic radius, m ; I —hydraulic slope (energy gradient), dimensionless; n —(empirical; units are often omitted in practice).

Hydraulic parameters were calculated as follows. For a rectangular open channel, the flow (wetted) cross-sectional area as a function of water level is: $A(h) = B \cdot h$ and the wetted perimeter is $P(h) = B + 2 \cdot h$. Accordingly, the hydraulic radius is:

$$R(t) = \frac{A(t)}{P(t)} = \frac{B \cdot h(t)}{B + 2 \cdot h(t)} \quad (7)$$

After computing $A(h)$ and $R(h)$, the discharge as a function of water level is obtained from Manning's equation:

$$Q(h) = \frac{1}{n} \cdot A(h) \cdot R(h)^{2/3} \cdot I^{1/2} \quad (8)$$

For a discrete time step Δt , the incremental water volume is:

$$V_i = Q(h_i) \cdot \Delta t \quad (9)$$

and the daily/monthly cumulative volume is calculated as:

$$V_{\Sigma} = \sum Q(h_i) \cdot \Delta t \quad (10)$$

Δt —measurement time step, s.

This formulation is a key component of the proposed system when only water-level data derived from the video camera is available. Based on Manning's equation for a rectangular channel, a rating curve relating discharge Q to water level h was constructed. The table is used to estimate operational discharge from water-level measurements obtained by the video-based monitoring system at the gauging post. The calculation of water flow using Manning's formula depends on the parameters n , I , and water level h . In the developed system, the water level is determined using computer vision based on video monitoring of the hydro-rail, ensuring high measurement accuracy. To reduce the effects of random fluctuations, the camera takes a series of images and then averages the measurements. The main uncertainty in the water flow calculation concerns the selection of the Manning roughness coefficient n and the determination of the hydraulic slope I , which were assumed constant for the canal section under consideration in this study.

The hybrid verification procedure is formalised in Algorithm 1. At each cycle, the system checks temporal synchronisation between the ultrasonic sensor and vision readings, evaluates their discrepancy against a scaled error threshold, and produces either a weighted fused estimate or an anomaly flag with diagnostic information.

Algorithm 1 Reliability-aware hybrid sensor–vision fusion

Input: $h_s(t), h_v(t), e_s, e_v, \Delta t_{sync}, \alpha, \delta$

Output: $h^*(t)$ —verified fused water level, or NULL if anomaly is detected

- 1: Initialise synchronisation and fusion parameters
 - 2: Set $\Delta t_{sync} = 0.1 \text{ s}$, $\alpha = 1.5$, $\delta = 10^{-6}$
 - 3: for each monitoring cycle t **do**
 - 4: Acquire $h_s(t_s)$ from the ultrasonic sensor node
 - 5: Acquire $h_v(t_v)$ from the computer-vision pipeline
 - 6: **if** $|t_s - t_v| > \Delta t_{sync}$ **then**
 - 7: log("desynchronization detected")
-

Algorithm 1 *Cont.*

```

8:    $h^*(t) \leftarrow \text{NULL}$ 
9:   return  $h^*(t)$ 
10: end if
11:  $\Delta h \leftarrow |h_s - h_v|$ 
12:  $T_d \leftarrow \alpha \cdot (e_s + e_v)$ 
13: if  $\Delta h \leq T_d$  then
14:    $w_s \leftarrow 1/(e_s + \delta)$ 
15:    $w_v \leftarrow 1/(e_v + \delta)$ 
16:    $h^*(t) \leftarrow (w_s + h_s + w_v h_v)/(w_s + w_v)$ 
17:    $Q(h^*) \leftarrow \text{Manning}(h^*(t))$ 
18:   publish( $h^*(t)$ ,  $Q(h^*)$ )
19: else Acquire  $h$ 
20:   flag_anomaly( $t$ ,  $h_s$ ,  $h_v$ ,  $\Delta h$ ,  $T_d$ )
21:   store_snapshot(camera_frame, sensor_log)
22:   trigger_diagnostic(LENS_DIRTY, SENSOR_TILT, DEBRIS)
23:    $h^*(t) \leftarrow \text{NULL}$ 
24: end if
25: end for
26: return  $h^*(t)$ 

```

The fusion in line 16 assigns each channel a weight inversely proportional to its calibrated error, so that the more precise modality dominates the fused estimate. The threshold multiplier $\alpha = 1.5$ was selected empirically to balance anomaly sensitivity against tolerance to turbulence-induced fluctuations. Only verified values $h^*(t)$ are passed to Manning's equation for discharge estimation, preventing single-modality faults from propagating into flow rate calculations.

3. Results

3.1. Computational Results

The computation was performed using the following input parameters: channel width $B = 6.85$ m, Manning roughness coefficient $n = 0.015$, hydraulic slope $I = 0.00724$, and water-level range $h = 0.226 \dots 0.264$ m. The discharge was computed using formula:

$$Q = \frac{1}{n} A \cdot R^{2/3} \sqrt{I} \quad (11)$$

where $A = B \cdot h$, $R = A/P$ and $P = B + 2 \cdot h$.

Table 2 presents the hydraulic parameter values for several characteristic water levels recorded by the hydrographic station's video monitoring system. Each row in the table corresponds to a single measured water level h , obtained by the computer vision system from processing images of the hydrographic screed. The calculations were performed for a rectangular channel cross-section with constant parameters: channel width $B = 6.85$; Manning roughness coefficient $n = 0.015$; and hydraulic slope $I = 0.00724$.

The obtained discharge values correspond to steady uniform flow conditions and are used to construct the rating curve $Q(h)$. Table 2 allows determining water flow based on the measured level without directly measuring the flow rate and can be used in automated monitoring systems to convert continuous water-level measurements into instantaneous flow values. The rating curve $Q(h)$ describes the functional relationship between discharge Q and water level (stage) h at the selected channel section (Figure 2). This stage–discharge relationship enables operational estimation of flow rate based solely on measured water-

level data. For the given parameters $B = 6.85$ m, $h = 0.2483$ m (camera reading), and $n = 0.015$, $I = 0.00724$, the hydraulic characteristics are calculated as follows:

$$A = B \cdot h = 6.85 \times 0.2483 = 1.7008 \text{ m}^2$$

The hydraulic radius was: $P = B + 2 \cdot h = 6.85 + 2 \times 0.2483 = 7.3466$ m

$$R = \frac{1.7008}{7.3466} = 0.2315 \text{ m}$$

Using Manning's equation:

$$Q_{Man} = \frac{1}{0.015} \cdot 1.7008 \cdot 0.2315^{\frac{2}{3}} \cdot 0.00724^{\frac{1}{2}} \approx 3.6377 \text{ m}^3/\text{s}$$

flow rate, velocity–area-dependent method: $Q_{ref} = 3.6840 \text{ m}^3/\text{s}$.

Table 3 presents a comparative analysis of water flow determined using two methods: the velocity–area method and the Manning formula.

Table 2. Calibration relationship between water level and discharge (rating curve).

h, m	A, m ²	P, m	R, m	Q, m ³ /s
0.226	1.548	7.302	0.212	3.1224
0.247	1.692	7.344	0.230	3.6069
0.256	1.754	7.362	0.238	3.8224
0.264	1.808	7.378	0.245	4.0177
$h_{avg} = 0.2483$	$A_{avg} = 1.7008$	$P_{avg} = 7.3466$	$R_{avg} \approx 0.231$	$Q_{avg} \approx 3.6377$

Table 3. Comparison of discharge calculation methods.

Calculation Method	Discharge, m ³ /s
Velocity–area method	3.6840
Manning method	3.6377

The velocity–area method was used as a control field method for measuring water flow. The discharge obtained by the velocity–area method was $Q_{ref} = 3.6840 \text{ m}^3/\text{s}$. The discharge calculated using Manning's equation was $Q_{Man} = 3.6377 \text{ m}^3/\text{s}$. The absolute difference between the two methods is $\Delta Q = |Q_{ref} - Q_{Man}| = |3.6840 - 3.6377| = 0.0463 \text{ m}^3/\text{s}$. The relative deviation is:

$$\delta = \frac{\Delta Q}{Q_{ref}} \cdot 100\% = \frac{0.0463}{3.6840} \cdot 100\% = 1.26\%$$

In the developed water-level monitoring system, discharge is determined using the measured water level h obtained from the video camera and the channel's known hydraulic parameters. The calculation is performed using Manning's equation, where the geometric characteristics of the cross-section are expressed as functions of water level. This approach enables automated estimation of instantaneous discharge and cumulative water volume without direct velocity measurements. The Manning-based calculation yielded $Q = 3.6377 \text{ m}^3/\text{s}$, with a relative deviation of less than 2% compared to the velocity–area method. The resulting relative discrepancy of approximately 1.26% indicates good consistency between the Manning-based hydraulic calculation and the reference velocity–area measurements under the field conditions considered. However, it should be noted that the velocity–area measurements were partially used for calibration of the hydraulic slope

parameter I . Therefore, this comparison should be interpreted as a calibration consistency assessment rather than a fully independent experimental validation.

An independent validation dataset consisting of additional field measurements, not used to calibrate the hydraulic slope parameter, was used to assess the Manning-based discharge estimation model. The hydraulic slope parameter ($I = 0.00724$) remained fixed during validation and was not adjusted. Reference discharge values Q_{ref} were obtained using the velocity–area method, while Q_{Man} values were calculated from camera-derived water levels using Manning’s equation. The relative deviation was calculated as:

$$\Delta Q = \frac{|Q_{ref} - Q_{Man}|}{Q_{raf}} \times 100\% \quad (12)$$

The obtained relative deviations ranged from approximately 1.6% to 2.2%, indicating acceptable agreement between the Manning-based hydraulic calculations and independent field hydrometric measurements under different operating conditions.

The obtained results demonstrate the practical applicability and internal consistency of the proposed monitoring approach for the investigated channel section. At the same time, to expand the model’s scope in the future, additional independent validation can be performed using a separate set of field measurements of water flow.

Field validation of the developed water-level monitoring system was conducted on the Merke River at the main irrigation canal. The monitoring site is located at coordinates (42.786479° N, 73.226999° E) in the WGS84 coordinate system, as shown in Figure 3. The river originates from glacial springs and serves as the main source of agricultural water supply in the region. The hydrological regime is characterised by pronounced seasonal variability in discharge and stage, driven predominantly by snowmelt and glacial meltwater. Peak flows typically occur during the spring–summer period, while reduced discharge is observed during late autumn and winter. The selected monitoring site is representative of small mountain rivers and irrigation canals typical of southern Kazakhstan, where autonomous monitoring systems are critically required due to spatial distribution and limited infrastructure.



Figure 3. Installation location system for testing the system on the Merke River.

Figure 4 below illustrates the camera-mounting geometry for monitoring the water level with a water gauge.

The diagram shows two possible camera positions and their corresponding fields of view. The upper position at a 26° angle is too steep, resulting in significant perspective

distortion and reduced measurement accuracy. The lower position with a 19° field of view provides a more optimal geometry for reliable water-level determination. The camera is mounted at a height of approximately 3.0 m above the gauge's zero mark, with a horizontal distance of 8.7 m to the observation target. The diagram also shows the measurable water-level range of 0 to 150 cm and the effect of the camera's installation height on the gauge's visible portion. Using a lens with a focal length of 12 mm provides sufficient spatial resolution while simultaneously offering a full view of the measured area. This configuration provides an optimal balance among field of view, measurement accuracy, and stability of the real-time water-level monitoring system. To ensure the reproducibility of the experimental results, the main parameters of the deployed monitoring system are presented in Table 4. The configuration reflects the actual hardware and software settings used during the field inspection campaign at the Merke River site.

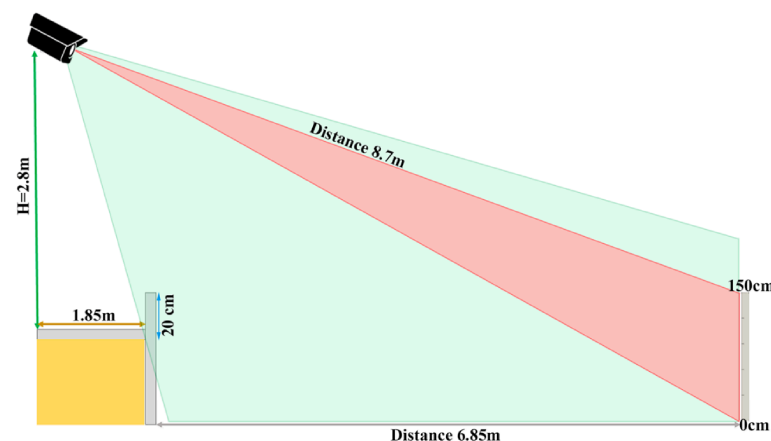


Figure 4. Geometric configuration of camera placement for staff gauge-based water-level estimation.

Table 4. Implementation parameters of the deployed hybrid monitoring system.

Parameter	Value
Camera	Hikvision IP camera (RTSP protocol)
Video stream resolution	1920×1080 pixels
Effective processing frame rate	20–25 FPS
Edge processing time per frame	≈ 42 ms (Raspberry Pi 5)
Median filtering buffer	21 consecutive measurements
Ultrasonic water-level sensor	JSN-SR04T
Network latency (Wi-Fi)	< 1 s
Data aggregation interval	Averaging every 60 s
Data synchronisation method	System-time timestamps
Region of interest (ROI)	Staff gauge vicinity
Power supply	12 V; active mode 85 mA, sleep mode 12 mA; battery autonomy 14 h
Monitoring site	Merke River (42.786479° N, 73.226999° E), Zhambyl region, Kazakhstan

The surveillance camera was positioned to capture both the water gauge and the flow surface simultaneously. The resulting images were used to automatically determine the water level using image processing algorithms and pre-calibration of the gauge. The image processing pipeline is presented in Figure 5.

The measurement process involves several stages, including calibration of the water gauge, region-of-interest (ROI) selection, edge detection using the Canny detector, noise filtering, and determination of the water surface line. After determining the coordinates of the water line, the pixel values are converted to real metric units using the gauge's

predefined upper and lower reference points. This approach enables automatic real-time water-level calculation and tracking of its changes under various hydrological conditions.

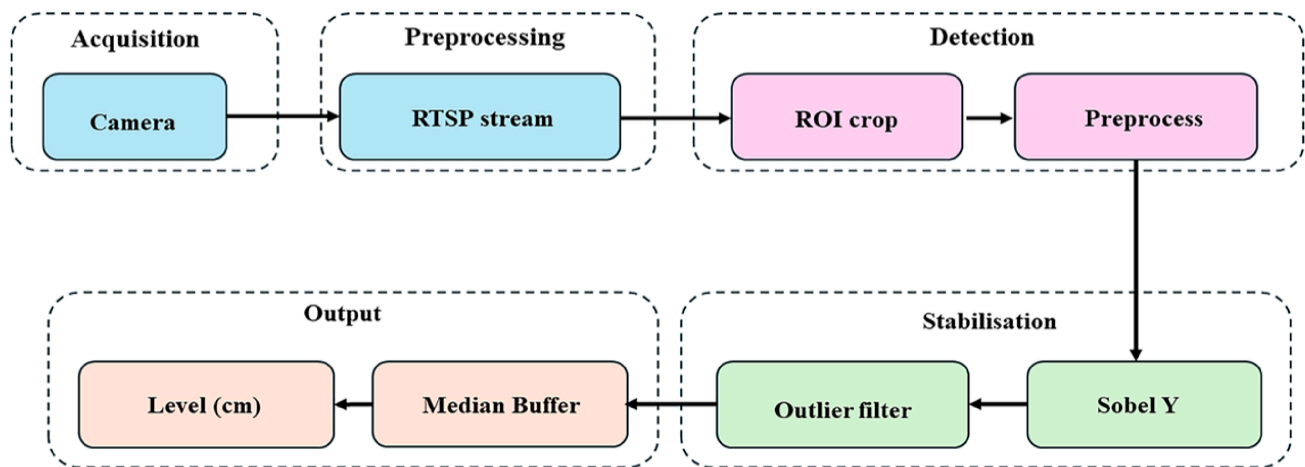


Figure 5. Image processing pipeline for automatic water-level detection.

3.2. Experimental Setup

Figure 6 below illustrates the step-by-step operation of the algorithm, including the initial image of the monitoring section, the water gauge calibration stage, the selection of the region of interest, the detection of the water-level line, and the calculation of the water-level value as the flow rate changes. The presented results demonstrate the algorithm's stable performance under turbulent flow and changing hydraulic conditions. Figure 6a shows an overview of the experimental water-level monitoring site installed on an irrigation canal. A video surveillance camera captures the water flow and the water gauge located at the regulating hydraulic structure. The image also shows the timestamp and the video surveillance system interface. This frame is used as the input image for further processing by computer vision algorithms. The camera is mounted at an angle to the water surface, which allows simultaneous observation of the gauge and the flow surface. This approach enables simultaneous assessment of the water-level and flow characteristics. Figure 6b shows the calibration stage of the water-level measurement system. The upper and lower points of the water-level gauge are manually marked as reference values, TOP = 150 cm and BOTTOM = 0 cm. These reference points are used to convert image pixel coordinates into real-world metric units. Figure 6c shows the interface of the water-level monitoring software module. The top section displays image processing parameters, including Canny Low, Canny High, Min Line Length, ROI height, and Median buffer. These parameters configure the algorithm for detecting edges and the water-level line. The area of the water gauge rod detected by the algorithm is highlighted in red. The blue line indicates the current water-level of 22.6 cm. The calculation result is displayed in centimetres. Figure 6d shows the algorithm's output as water flow increases. An increase in flow level and a change in the water line's position are visible. The algorithm automatically tracks the boundary between the water surface and the gauge, calculating a new level value of 24.7 cm. Figure 6e demonstrates a subsequent increase in the water level to 25.6 cm. It can be seen that the algorithm reliably tracks the water level line even under turbulent flow and changes in the water surface structure. Thus, the system provides stable real-time measurements. Figure 6f shows the final stage of automatic water level measurement. The algorithm detects the water line and calculates a level of 26.4 cm. Despite significant turbulence in the flow, the system correctly determines the water level. The result is displayed directly in the video stream, enabling real-time monitoring.

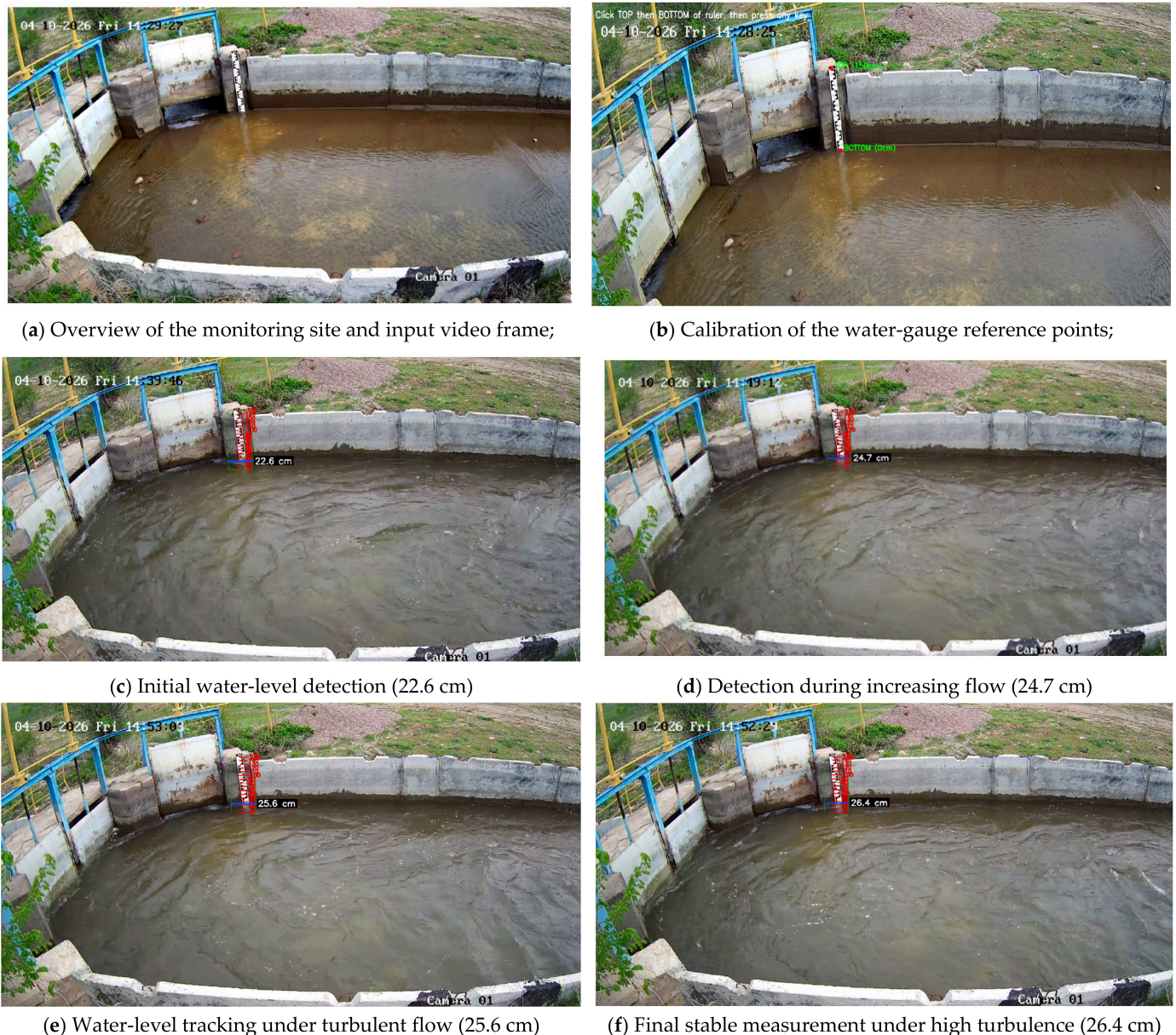


Figure 6. Real-time water-level measurement using computer vision with a calibrated staff gauge.

The results of the experimental evaluation of the sensor node, integrating the ESP8266 microcontroller, temperature and humidity sensors, a solar panel, and a rechargeable battery, are presented in Table 5. The tests were aimed at assessing data collection stability, measurement accuracy, operational stability under reduced supply voltage, power consumption, autonomy, and the system's ability to recover from failure.

The measurement accuracy for temperature and humidity was within 3.2%, significantly below the permissible threshold ($\leq 5\%$), indicating high reliability and credibility of the acquired data. The analysis of node performance under decreasing battery voltage revealed stable operation and maintained communication down to 10.9 V, exceeding the minimum allowable threshold specified in the technical requirements (10.8 V). The energy characteristics of the device also met the prescribed standards: power consumption in active mode was 85 mA (requirement ≤ 100 mA), while in sleep mode it was 12 mA (requirement ≤ 15 mA), confirming the energy efficiency of the implemented hardware–software solutions. Autonomous operation tests demonstrated continuous system functionality for 14 h with the solar panel disconnected and the battery fully charged, exceeding the required

minimum operating time (≥ 12 h). Furthermore, the system exhibited self-recovery capability, following a forced reset, and communication was automatically restored within 6 s.

Table 5. Experimental validations result.

No	Tested Parameter	Test Conditions	Specification	Measured Result
1	Sensor data acquisition	All sensors connected	No read errors	No errors; data stable
2	Measurement accuracy	Reference humidity and temperature measurements performed manually	Deviation $\leq 5\%$	3.2%
3	Node operation under battery voltage drop	Gradual battery discharge down to 11 V	Communication maintained down to 10.8 V	Stable operation down to 10.9 V
4	Power consumption (active mode)	12 V supply; all sensors enabled	≤ 100 mA	85 mA
5	Power consumption (sleep mode)	Battery-powered; data transmission upon wake-up	≤ 15 mA	12 mA
6	Autonomous operation (battery only)	100% battery charge; solar panel disconnected	≥ 12 h	14 h
7	Recovery after failure	Forced reset (reboot)	Automatic reconnection	restored within 6 s

For real-time analysis, we developed a monitoring dashboard as shown in Figure 7.

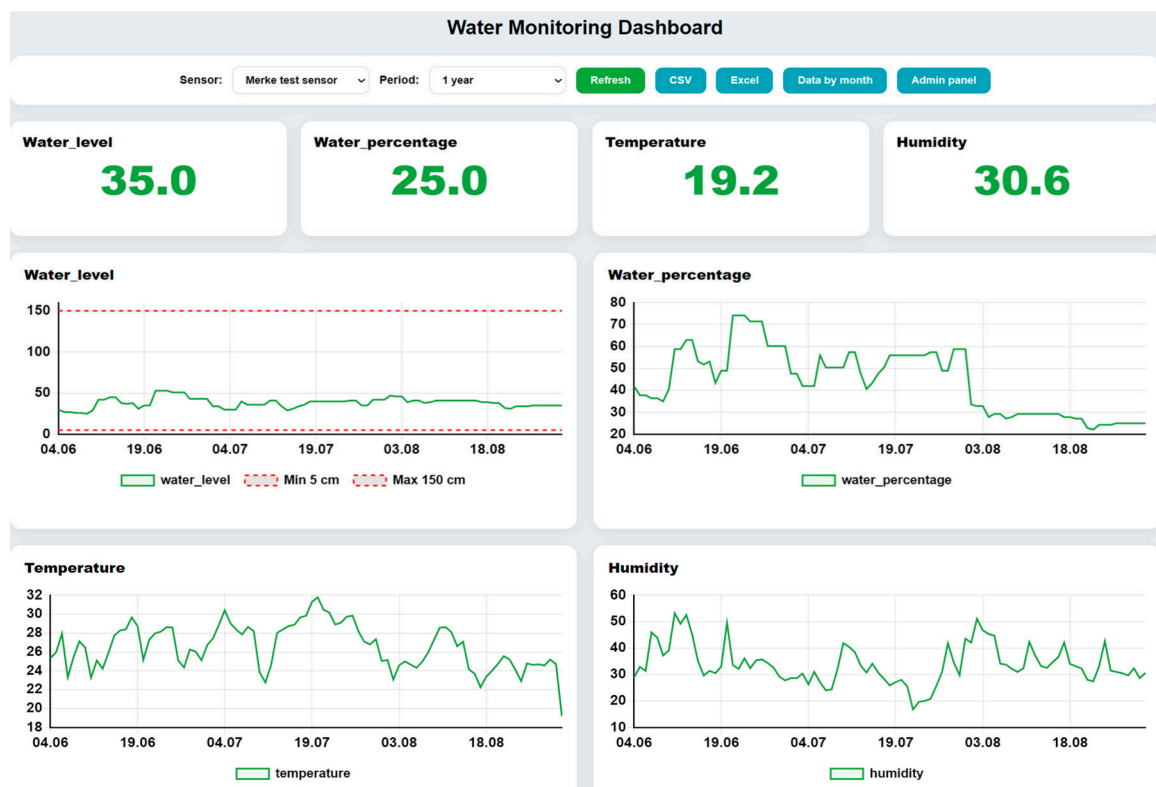


Figure 7. Real-time monitoring dashboard. The dashboard displays time series of water level, air temperature, and humidity received from the sensor node over the wireless channel and stored in the database; values are updated in real time, enabling prompt detection of abnormal readings or non-standard operating modes across multiple sensor nodes.

The figure illustrates the developed monitoring dashboard designed to display and analyse data received from the sensor node in real time. The graphs presented the dynamics of changes in hydrological and meteorological parameters, including water levels,

temperature, and ambient humidity. The graphs are generated automatically based on data received from the sensor node via a wireless communication channel and stored in the database. Data updates are performed in real time, enabling monitoring of ongoing parameter changes and prompt identification of abnormal values or non-standard system operating modes. The monitoring dashboard provides a centralised display of information from multiple sensor nodes, which is especially important for distributed water resource monitoring systems and agricultural infrastructure facilities.

Figure 8 shows the interface of the administrative panel for the developed monitoring system, which provides centralised control and real-time data analysis. The panel displays the total number of districts in the Zhambyl region and the number of sensors installed, along with their current status, including the number of active devices. Additionally, the interface contains information about registered users of the system. A key element is an interactive map that visualises the spatial distribution of sensors across districts, allowing for rapid assessment of the coverage and condition of the monitoring infrastructure. The dashboard also includes an analytics module that displays statistics on detected anomalies and predictive indicators generated by integrating sensor and data. This approach enables a comprehensive analysis of the system's status and supports management decision-making.

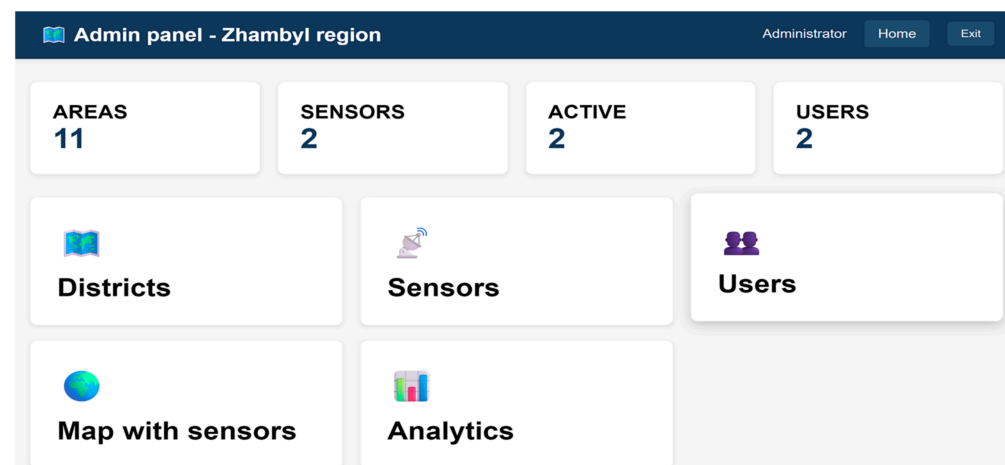


Figure 8. Administrative panel interface.

Figure 9 shows the interface for filtering data by date and water-level values. The system displays key statistical indicators, including the maximum, minimum, and average water-levels for the selected observation period. In addition, these parameters are visualised on a time-series graph, allowing users to track changes in water levels over time. Based on this data representation, users can identify trends, analyse the nature of fluctuations, and generate forecasts of future water-level changes. This tool enhances the monitoring system's informational value and facilitates more informed decision-making.

Figure 10 shows a heatmap of parameter correlations, illustrating the degree of interrelation between key system indicators such as water level, temperature, humidity, and fill percentage. The map's colour scheme allows the direction and strength of the statistical relationship between the analysed parameters to be quickly determined. The Pearson correlation coefficient r , which ranges from -1 to $+1$, is used to measure correlation. Colour interpretation used: dark green—corresponds to a strong positive correlation ($r = 0.70 \dots 1.00$). This means that both parameters change in the same direction, as one parameter increases, the other also increases; light green—corresponds to a moderate positive correlation ($r = 0.30 \dots 0.69$). A partial direct relationship is observed between the parameters; light grey indicates a weak correlation or virtually no relationship.

($r = -0.29$ to 0.29). This means that the parameters change independently of one another. Light red—corresponds to a moderate negative correlation ($r = -0.69 \dots -0.30$). As one parameter increases, the other tends to decrease. Dark red—corresponds to a strong negative correlation ($r = -1.00 \dots -0.70$). This indicates a pronounced inverse relationship between the parameters. The most striking finding in the results is the negative correlation between temperature and relative humidity ($r = -0.69$), shown in red. This indicates that a rise in temperature is accompanied by a decrease in relative humidity. The positive correlation between water level and fill percentage ($r = 0.55$), shown in green, indicates a direct relationship between rising water levels and the degree to which the reservoir is filled. Thus, colour visualisation allows for a quick assessment of the nature of the relationships between monitoring parameters and facilitates data analysis within the analytical water resources management system.

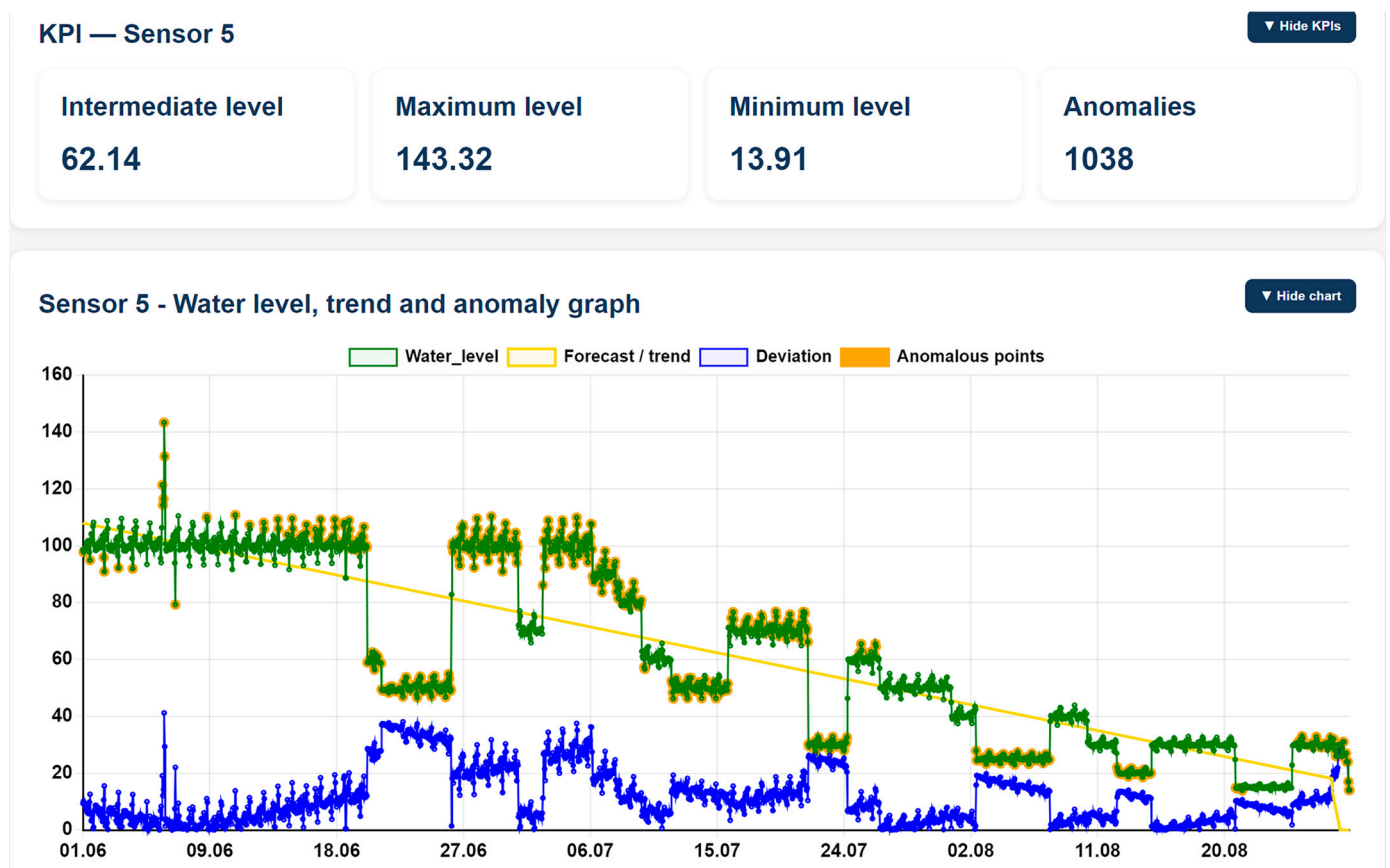


Figure 9. Visualisation of water-level Data. The interface allows filtering of records by date and water-level value and reports the maximum, minimum, and average water level for the selected observation period, visualised on a time-series plot to support trend analysis and forecasting.

During field testing, the hybrid approach demonstrated stability and continuity of monitoring. Even if one channel temporarily loses reliability, the other continues to provide data. The system also enabled calculation of detection quality metrics. Although the sample size is limited, this result demonstrates the potential of hybrid systems to reduce false alarms. To evaluate the performance of the proposed system, it was compared with typical sensor and visual solutions described in the literature. In terms of reliability, the hybrid approach is resistant to weather factors. During testing, the system successfully handled situations in which individual modules (sensors or cameras) failed. The video camera requires periodic cleaning of the lens. The sensor requires checking for fastening and cleanliness. However, the hybrid system can compare discrepancies between readings

and image quality. For example, if the CV module regularly fails to detect the stage gauge, but the sensor shows a stable level, a lens contamination notification is generated. From a practical point of view, the hybrid approach is especially useful where reliability is critical and there is at least minimal communication infrastructure (e.g., 4G or Wi-Fi). In completely isolated locations, LoRaWAN sensor nodes can be used, with hybrid stations serving as reference points. They provide data and serve to validate other sensors. This creates a hierarchical network where a few “Smart” posts calibrate dozens of inexpensive ones. This is particularly relevant to the conditions in the Zhambyl region, as many sunny days provide a stable power supply, and the arid climate reduces issues with condensation and fog, except for dust. Thus, regional characteristics contribute to the successful implementation of hybrid architecture.

Heatmap of parameter correlations - Sensor 5

▼ Hide heatmap

Parameter	Water level	Temperature	Humidity	Filling (%)
Water level	1.00	-0.14	-0.01	0.55
Temperature	-0.14	1.00	-0.69	-0.18
Humidity	-0.01	-0.69	1.00	-0.11
Filling (%)	0.55	-0.18	-0.11	1.00

Interpretation:

0.70 to 1.00 = strong direct relationship

0.30 to 0.69 = moderate direct relationship

-0.29 to 0.29 = weak or no relationship

-0.69 to -0.30 = moderate inverse relationship

-1.00 to -0.70 = strong inverse relationship

Figure 10. Heatmap of parameter correlations.

3.3. Statistical Performance Evaluation

To quantify the agreement between the ultrasonic sensor and the computer vision module, a paired comparison was conducted over a 14-day observation period (1–14 April 2026) at the Merke River monitoring site, as shown in Table 6. Each daily value represents the median of continuous sub-minute readings from both measurement channels, aggregated at 60 s intervals. The following agreement metrics that were computed are Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Bias Error (MBE), maximum absolute error, and the 95% confidence interval of the mean bias. The agreement metrics are calculated as follows:

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |e_i| \quad (13)$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n e_i^2} \quad (14)$$

$$\text{MBE} = \frac{1}{n} \sum_{i=1}^n e_i \quad (15)$$

where s is the standard deviation of the errors and $t_{0.025}$ is Student's t -coefficient for a 95% confidence level with $n - 1 = 13$ degrees of freedom.

Table 6. Paired daily averaged water-level measurements: ultrasonic sensor vs. computer vision system.

Date	Ultrasonic Sensor (cm)	CV System (cm)	Absolute Error	Squared Error
01.04.2026	25.0	24.6	0.4	0.16
02.04.2026	24.0	23.8	0.2	0.04
03.04.2026	24.0	24.1	0.1	0.01
04.04.2026	25.0	24.7	0.3	0.09
05.04.2026	25.0	24.8	0.2	0.04
06.04.2026	24.0	23.9	0.1	0.01
07.04.2026	24.0	24.1	0.1	0.01
08.04.2026	24.0	23.7	0.3	0.09
09.04.2026	26.0	25.6	0.4	0.16
10.04.2026	27.0	26.4	0.6	0.36
11.04.2026	27.0	26.7	0.3	0.09
12.04.2026	26.0	25.8	0.2	0.04
13.04.2026	26.0	25.6	0.4	0.16
14.04.2026	25.0	24.7	0.3	0.09

Based on 14 paired experimental observations, as shown in Table 7, the MAE was 0.279 cm, while RMSE reached 0.311 cm. The MBE was equal to -0.250 cm, indicating a slight systematic underestimation of the water level by the vision-based subsystem relative to the reference ultrasonic sensor measurements. The maximum absolute error observed during the experiments was 0.600 cm. In addition, the 95% confidence interval of the mean bias, calculated using Student's *t*-distribution, was within the range of $[-0.350; -0.150]$ cm, corresponding to $MBE = -0.250 \pm 0.100$ cm. To further evaluate the consistency between the two measurement methods, additional agreement metrics were computed. The Pearson correlation coefficient reached $r = 0.9901$, while the coefficient of determination was $R^2 = 0.9802$, confirming a strong linear relationship between sensor-based and vision-based measurements. Furthermore, the MAPE was only 1.09%, demonstrating the high accuracy and reliability of the proposed monitoring approach under real field conditions.

Table 7. Statistical performance metrics of the proposed hybrid monitoring system.

Metric	Value	Description
Number of paired measurements	14	Daily averaged synchronised ultrasonic–vision pairs (1–14 April 2026)
MAE	0.279 cm	Average absolute difference between h_s ; and h_v
RMSE	0.311 cm	Overall magnitude of deviation
MBE	-0.250 cm	CV system slightly underestimates water level
Maximum absolute error	0.600 cm	Largest recorded difference between the two methods
95% confidence interval of MBE	$[-0.350; -0.150]$ cm	Student's <i>t</i> , <i>df</i> = 13
Pearson correlation coefficient (<i>r</i>)	0.9901	Very strong linear agreement
Coefficient of determination (R^2)	0.9802	98% of variance explained
Mean absolute percentage error	1.09%	Relative measure of accuracy
Waterline detection success rate	96–98%	Field video evaluation
Average processing time	42 ms/frame	Raspberry Pi 5, RTSP 1920 × 1080
Effective frame rate	23 FPS	Near real-time operation

Placing these results in the context of published low-cost monitoring systems reveals both the strengths of the proposed approach and the heterogeneity of current reporting practices. Among the directly comparable works, LevelWAN [12] achieved RMSE = 9.9 mm against a high-precision radar reference over 35,066 paired measurements, a result underpinned by three years of continuous operation and a fully open Bill of Materials (€208.79). Eye of Horus [23] reported water-level RMSE of 15.5–64.7 mm across five storm-event

deployments using a vision-plus-LiDAR framework. The proposed system achieves RMSE = 3.11 mm and MAE = 2.79 mm, the lowest water-level error recorded among directly comparable works. This result is obtained at a station cost of approximately \$800, which is higher than purely sensor-based solutions (\$50–\$212) but reflects the added cost of the integrated vision subsystem and edge-computing hardware.

It must be noted that heterogeneous testing conditions constrain direct system-to-system comparison. The present evaluation was conducted at a single concrete-lined irrigation canal under daytime illumination, whereas [12] operated in a sewer pipe and [23] was deployed along an open creek during storm events. Furthermore, only three of the six reviewed works [12,23] and the present study report water-level RMSE in absolute units. The paper [11] provides segmentation metrics only (F1 = 0.93, precision = 0.97), and [13] reports a relative deviation (0.1%, $R^2 = 0.92$) without an absolute RMSE. The absence of standardised accuracy reporting across the low-cost hydrometric literature is itself a noteworthy finding and limits the feasibility of fully rigorous benchmarking. Notwithstanding these caveats, the quantitative agreement achieved by the proposed system confirms that rule-based sensor–vision fusion can deliver measurement accuracy that is competitive with, and, in the present case, superior to both purely sensor-based and purely vision-based approaches published to date.

3.4. Sensitivity Analysis of Manning-Based Discharge Estimation

Manning’s equation defines discharge Q as a function of three parameters as water level h , roughness coefficient n , and hydraulic slope I . Water level h affects both the wetted cross-sectional area A and the hydraulic radius R , producing a non-linear compound influence on Q . The roughness coefficient n acts as an inverse multiplier, so that higher n values yield lower discharge estimates. The hydraulic slope I enters the equation as $I^{1/2}$, resulting in a sub-linear sensitivity. To quantify these dependencies, a one-at-a-time sensitivity analysis was performed using the baseline parameter values $h = 0.2483$ m, $n = 0.015$, and $I = 0.00724$, corresponding to the mean-observed water level and the calibrated hydraulic parameters of the study reach. The baseline discharge is $Q_{Man} = 3.6377$ m³/s. Each parameter was varied independently while the remaining two were held constant. The results of the sensitivity analysis are summarized in Table 8. The relative change in discharge was computed as:

$$Q = \frac{Q_{new} - Q_{Man}}{Q_{Man}} \times 100\% \quad (16)$$

Table 8. Sensitivity of Manning-based discharge estimation to variations in hydraulic parameters.

Parameter	Relative Change, m	Q_{new} , m ³ /s	Relative Change, Q
h	h − 0.01 m	3.4030	−6.45
h	h + 0.01 m	3.8782	+6.61
n	n + 5%	3.4645	−4.76
n	n − 5%	3.8292	+5.26
I	I + 5%	3.7276	+2.47
I	I − 5%	3.5456	−2.53

The analysis reveals that discharge is most sensitive to water level h . A perturbation of ± 0.01 m produces a discharge variation of -6.45% to $+6.61\%$, reflecting the compound influence of h on both A and R . The roughness coefficient n exhibits the second-highest sensitivity, with a $\pm 5\%$ perturbation yielding discharge changes of -4.76% to $+5.26\%$. The hydraulic slope I has the weakest effect, as expected from its square-root dependence in

Manning's equation, a $\pm 5\%$ change in I results in only approximately $\pm 2.5\%$ variation in discharge.

These results confirm that accurate water-level determination is the dominant source of uncertainty in the proposed discharge estimation model, and consequently that the precision of the computer vision measurement channel demonstrated by an RMSE of 0.311 cm against the ultrasonic reference is critical to the reliability of the final discharge estimate. The comparatively low sensitivity to I suggests that the single back-calculated slope value ($I = 0.00724$) introduces modest uncertainty in the model output, consistent with the quasi-uniform flow conditions observed at the study reach.

4. Discussion

The results of field trials have confirmed that the proposed hybrid architecture combines the advantages of both sensor-based and visual approaches, thereby improving the accuracy and reliability of water resource monitoring. The main advantage is the ability to cross-check measurements. Sensor data serves as the primary source, whilst the CV module allows it to be confirmed or rejected in the event of discrepancies. For example, a spurious level spike caused by ultrasonic interference is discarded if the camera does not detect a corresponding change in the level sensor; conversely, in the event of image loss, the system relies on the sensor. This minimises the likelihood of false alarms and missed events. The interpretation of the quantitative data is presented alongside the corresponding results. The statistical correlation between the two methods is analysed in Section 3.3, whilst the sensitivity of the flow estimate to hydraulic parameters is discussed in Section 3.4, where water level is identified as the primary source of uncertainty, thereby motivating the emphasis on accurate visual estimation of water level. Section 3.3 presents a quantitative comparison with previously published monitoring systems, showing that the proposed system delivers consistent performance metrics on a par with existing sensor-based and visual inspection solutions, and, in some respects, comparable to them, whilst noting inconsistencies in reporting methods in the literature. In addition to numerical results, the visual module provides contextual information unavailable to purely numerical sensors, enabling monitoring of the condition of shorelines, debris, or ice, and allowing events to be interpreted physically rather than solely through numbers. The system's behaviour under failure conditions was tested in field trials (Section 3.2). The hybrid configuration allowed for the failure of individual modules, and the inherent inconsistency between methods was used to generate diagnostic warnings, such as notifications of lens contamination, with automatic recovery within 6 s following a forced reset.

Despite these results, the system has several limitations. First, the validation data set contained only 14 paired observations collected over a 14-day monitoring period, which may not fully reflect the range of conditions encountered during long-term operation. In addition, the computer vision module was not systematically evaluated under varying lighting conditions, poor visibility, or haze, and testing was carried out on a single object within a narrow range of water levels. Although the agreement metrics are reported over 14 daily aggregated pairs, each daily value is itself the median of a large number of continuous sub-minute readings acquired at 60 s intervals over a full 24 h period, so the underlying measurement sample is substantially larger than the number of aggregated points. It should nonetheless be emphasised that this evaluation covers a single 14-day campaign within a narrow water-level range; longer-term, multi-season validation across the full operating range remains necessary to fully establish robustness, as noted in the limitations stated in the Conclusions.

5. Conclusions

This paper presented a hybrid IoT–VIoT architecture for real-time water-level monitoring in irrigation channels, integrating an ultrasonic sensor, a computer vision module with edge processing on Raspberry Pi 5, autonomous solar power, and Manning-based discharge estimation within a single platform. The principal findings are as follows. First, the paired comparison of the ultrasonic sensor and the vision module yielded RMSE = 0.311 cm, MAE = 0.279 cm, and Pearson $r = 0.99$, confirming strong quantitative agreement between the two independent measurement channels. Second, the rule-based cross-validation gate (Algorithm 1) with inverse-error weighting provides a deterministic and interpretable mechanism for detecting single-modality faults before they propagate into discharge calculations. Third, sensitivity analysis demonstrated that water level h is the dominant source of uncertainty in Manning-based discharge estimation ($\pm 0.01 \text{ m} \rightarrow \pm 6.5\% \text{ in } Q$), confirming that the precision of the vision channel is critical to reliable flow estimates.

At the same time, several limitations should be noted. The validation was conducted at a single concrete-lined canal, over a narrow water-level range (22.6–27.0 cm), and under daytime illumination only. The independent discharge validation is based on four measurement points. Future work will focus on multi-site deployment across different channel geometries and climatic zones, long monitoring periods, full-range water-level validation (0–150 cm), systematic evaluation under adverse illumination conditions, integration of machine learning models for predictive analytics and anomaly classification, and expansion of the GIS-based monitoring platform for regional water resource management. The use of energy-efficient AI platforms to accelerate video processing at the network edge will be investigated. A separate area of focus is expanding the functional capabilities of the developed water resource monitoring system. Overall, the integration of IoT and VIoT into a unified architecture represents a good system for digital water resource monitoring. The developed architecture can be adapted for other tasks, from monitoring floods in the mountains to observing urban drainage networks, where smart water vision can improve sustainability and safety.

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Conflicts of Interest: The authors declare no conflicts of interest.

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