

REAL-TIME CCTV-BASED DISCHARGE MONITORING IN AGRICULTURAL DRAINAGE CHANNELS USING IMAGE-DERIVED SURFACE VELOCITY AND WATER LEVELS

SUIVI EN TEMPS RÉEL DU DÉBIT PAR CCTV DANS LES CANAUX DE DRAINAGE AGRICOLE À PARTIR DE LA VITESSE DE SURFACE ET DES NIVEAUX D'EAU DÉRIVÉS D'IMAGES

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ABSTRACT

Improving water use efficiency in irrigated agriculture requires continuous, scalable, and reliable observations of flow behaviour in distribution and drainage networks. Monitoring at drains and secondary channels still relies heavily on manual readings or intermittent surveys, leaving short-term fluctuations, nighttime conditions, and operationally driven changes poorly resolved. This study presents a continuous image-based monitoring framework that estimates discharge in agricultural drainage channels by integrating surface velocity recognition, automated water level detection, and the velocity-area method. Fixed closed-circuit television (CCTV) cameras observe a representative reach without in-channel instrumentation. Video streams are processed to extract surface texture motion for velocity estimation, while a virtual gauge defined within the field of view supports water level identification. Combined with surveyed channel geometry and a calibrated surface-to-mean velocity correction, the workflow produces a continuous discharge time series synchronized with imagery, and an Internet of Things (IoT) pipeline with a streaming dashboard delivers near real-time situational awareness, automated archiving, and rapid visual verification. The framework was deployed at the D4 station in the Bagu drainage system in northern Taiwan, validated against acoustic Doppler reference measurements during three flood events in 2023, and subsequently operated continuously through 2024 and 2025. Across the combined record, including Typhoons and heavy rainfall events, the framework reproduced peak discharges with errors typically below six percent and coefficients of determination above 0.91, and the image-based water level matched the radar stage sensor to within 0.1 m. Examining the integrated observations in the discharge-stage plane also suggests a tendency toward hysteresis at higher flows that independent velocity and stage observation is able to capture. The approach offers a low-cost and replicable foundation for distributed drainage observation networks that strengthen irrigation return-flow accounting, support adaptive water management, and improve water use efficiency under increasing resource and climate constraints.

Keywords: image velocimetry, agricultural drainage, virtual gauge, velocity-area method, real-time monitoring.

RÉSUMÉ

L'amélioration de l'efficacité d'utilisation de l'eau dans l'agriculture irriguée exige des observations continues, évolutives et fiables du comportement des écoulements dans les réseaux de distribution et de drainage. Le suivi des drains et des canaux secondaires repose encore largement sur des lectures manuelles ou des campagnes de mesure intermittentes, ce qui rend mal connus les fluctuations de courte durée, les conditions nocturnes et les changements liés à l'exploitation. Cette étude présente

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un cadre de suivi continu fondé sur l'image qui estime le débit dans les canaux de drainage agricole en intégrant la reconnaissance de la vitesse de surface, la détection automatisée du niveau d'eau et la méthode vitesse-section. Des caméras fixes de télévision en circuit fermé (CCTV) observent un tronçon représentatif sans instrumentation dans le canal. Les flux vidéo sont traités afin d'extraire le mouvement des textures de surface pour estimer la vitesse, tandis qu'une échelle virtuelle définie dans le champ de vision permet d'identifier le niveau d'eau. Combiné à la géométrie relevée du canal et à un coefficient étalonné de conversion de la vitesse de surface en vitesse moyenne, ce processus produit une série chronologique continue de débits synchronisée avec les images ; une chaîne de traitement de l'Internet des objets (IoT), dotée d'un tableau de bord en flux continu, fournit une connaissance de la situation en temps quasi réel, un archivage automatisé et une vérification visuelle rapide. Le cadre a été déployé à la station D4 du système de drainage de Bagu, dans le nord de Taïwan, validé par rapport à des mesures acoustiques Doppler de référence pendant trois crues en 2023, puis exploité en continu en 2024 et 2025. Sur l'ensemble des données, y compris lors des typhons et de fortes pluies, le cadre a reproduit les débits de pointe avec des erreurs généralement inférieures à 6 % et des coefficients de détermination supérieurs à 0,91 ; le niveau d'eau issu des images concordait avec celui du capteur radar à 0,1 m près. L'examen des observations intégrées dans le plan débit-hauteur laisse également apparaître une tendance à l'hystérésis pour les débits élevés, que l'observation indépendante de la vitesse et de la hauteur permet de saisir. Cette approche offre une base peu coûteuse et reproductible pour des réseaux distribués d'observation du drainage, capables de renforcer la comptabilisation des retours d'irrigation, de soutenir la gestion adaptative de l'eau et d'améliorer l'efficacité d'utilisation de l'eau face à des contraintes croissantes sur les ressources et le climat.

Mots-clés : Vélodimétrie d'image; Drainage agricole; Jauge virtuelle; Méthode vitesse-section; Suivi en temps réel.

1. INTRODUCTION

Agricultural water use accounts for a major share of freshwater abstraction worldwide, and pressure on irrigation systems continues to grow under shifting climatic conditions and competing demands. Diagnosing system efficiency and designing operational adjustments depend on knowing how water actually moves through distribution and drainage networks, yet monitoring at drains and secondary channels remains sparse. Many stations are read manually, others rely on indirect estimates from gate operations or rainfall, and instrumented sites are costly to maintain. The resulting record offers limited temporal coverage and tends to miss nocturnal flows, short pulses from gate adjustments, and abrupt responses to rainfall, so irrigation return flows remain poorly quantified and water balances carry large uncertainties.

Direct in-channel devices such as the Acoustic Doppler Current Profiler (ADCP) deliver high accuracy, but they require trained personnel, expose them to risk during high flow, and are unsuited for continuous unattended deployment along low-order drainage channels (Lee et al. 2014). Surface velocity radars provide a non-contact alternative and have been widely adopted in river monitoring, yet they remain comparatively expensive when scaled across dense irrigation networks and become sensitive to standing waves and exposed bed material under shallow conditions (John 2018; Mikuš and Hartanský 2013). Image-based techniques, originally developed for laboratory and river-scale studies, are increasingly attractive for operational use because cameras are inexpensive, simple to install, and capture both flow imagery and contextual scene information that supports visual verification. Large-Scale Particle Image Velocimetry (LSPIV) infers surface motion from naturally occurring tracers such as ripples, foam, or suspended material (Fujita and Komura 1994; Fujita et al. 1998; Tauro et al. 2015; Guillén et al. 2017), while edge-detection techniques can locate the air-water interface from a fixed scene (Lin et al. 2018; Nascimento 2021).

These developments motivate the present work, which targets agricultural drainage channels rather than large rivers. Conventional practice reads discharge from a single-valued stage-discharge rating curve, which represents only steady uniform flow and cannot reproduce the hysteresis that arises during the rapid rise and recession of flood waves, when the same stage corresponds to two different

discharges (Muste et al. 2020). Capturing this behavior requires continuous, independent observation of both velocity and stage. The objective is therefore to deliver a near real-time discharge estimation framework that couples image-derived surface velocity, image-based water level recognition, and the velocity-area method, supported by an IoT pipeline linking field observations to a streaming dashboard. Field deployment over multiple monitoring seasons demonstrates the feasibility of continuous, automated discharge inference and points toward scalable observation networks for return-flow accounting, operational diagnosis, and digital water management.

2. METHODOLOGY

The proposed framework estimates discharge during typhoon and flood events by combining two real-time non-contact methods with an independent reference. Real-time radar provides surface velocity through the index surface velocity method (Levesque and Oberg 2012), while real-time image recognition provides both surface velocity and stage, combined through the velocity-area method. An acoustic Doppler current profiler (ADCP) supplies the depth-averaged velocity used to derive the surface-to-mean conversion factor and to construct the reference rating curve. The overall data flow, from event sensing through processing to the discharge delivered to the user, is shown in Figure 1. The workflow operates continuously at a single station and is designed to be replicated across sites with minimal tuning.

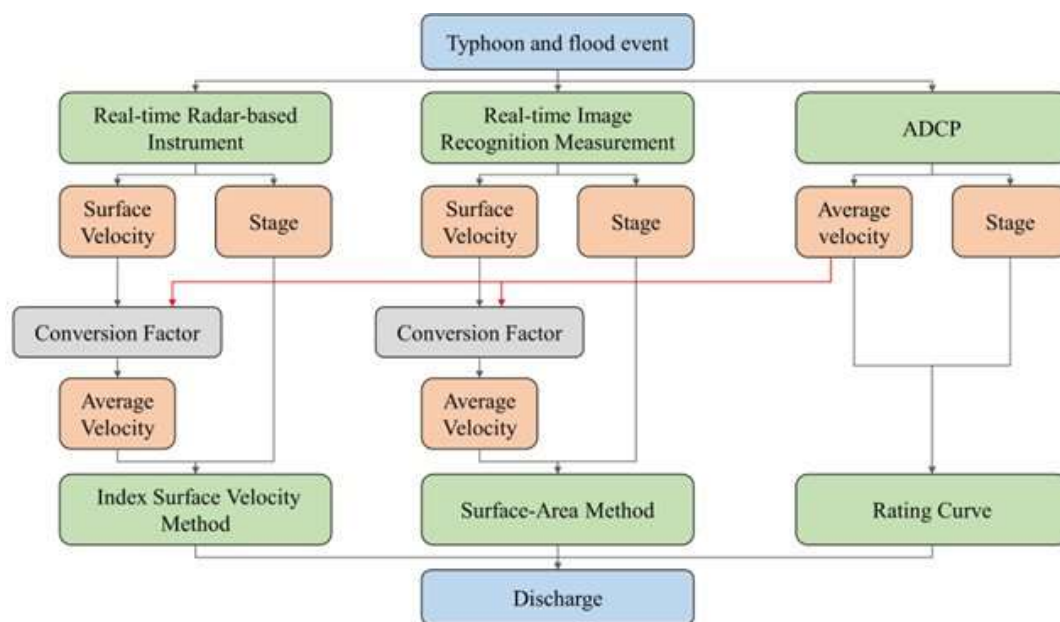


Figure 1. Flowchart of the IoT system for discharge estimation.

2.1 Surface velocity recognition from CCTV imagery

Each monitoring station captures short bursts of video at thirty frames per second, typically four seconds in length, yielding one hundred and twenty sequential frames per measurement cycle. Frames are orthorectified using ground reference points distributed along both banks within the camera field of view, allowing pixel coordinates to be mapped onto a horizontal water surface plane. Surface motion is then recovered through cross-correlation of interrogation windows between consecutive frames, with the most probable displacement at each location identified from the correlation peak. Naturally occurring features such as ripples, foam, and suspended sediment serve as tracers, removing the need to introduce seeding into the flow (Raffel et al. 2018; Okamoto et al. 2000).

Because the recovered field represents the water surface only, a conversion is required to obtain the cross-sectional mean velocity used in the velocity-area equation. In open channels with smooth or near-uniform velocity profiles, the depth-averaged velocity U is generally lower than the surface velocity u_s by a factor between 0.7 and 0.9, depending on bed roughness and aspect ratio (Rantz 1982; Creutin et al. 2002). At each station this coefficient is estimated by regression against simultaneous ADCP profiling across a range of stages, and is subsequently held fixed during operational use, subject to periodic re-evaluation when channel conditions change.

2.2 Image-based water level detection

Water level is obtained from the same camera using a virtual gauge concept. A bank-mounted reference region with known elevation marks is selected within the field of view, and an edge-detection algorithm based on convolutional gradients locates the air-water interface within this region (Lin et al. 2018; Yu and Hahn 2010). Sub-pixel refinement is applied along the detected boundary, and the stage is computed by interpolating the boundary position against the surveyed elevations of the reference marks. Because the camera, reference region, and channel are co-registered once at installation, the stage estimate remains robust to incremental lighting changes provided the reference region stays visible. Two practical refinements improve reliability under realistic field conditions. Multiple frames within each measurement cycle are processed independently and the median elevation is retained, suppressing transient noise from splash, wind ripples, or floating debris. Illumination compensation is then applied between daytime and nighttime acquisition modes, and supplementary infrared illumination at the reference region supports continuous detection through the night without altering the calibration.

2.3 Velocity-area discharge computation

Discharge is computed using the velocity-area method, in which the cross section is divided into vertical subsections and the total discharge equals the sum of the products of each subsectional area and its mean velocity:

$$Q = \sum \alpha \cdot u_{s,i} \cdot W_i \cdot H_i \quad (1)$$

where Q is the discharge, $u_{s,i}$ is the surface velocity in subsection i , W_i and H_i are its width and depth (m), and α is the surface-to-mean velocity conversion coefficient calibrated for the site. The cross-sectional geometry is obtained from a one-time bathymetric survey and updated only when the channel changes appreciably. For routine operation the cross-sectional area A (m²) at any observed stage H (m) is recovered from a stage-area rating fitted as a low-order polynomial:

$$A = a_0 H^3 + a_1 H^2 + a_2 H + a_3 \quad (2)$$

with coefficients determined from the surveyed geometry. Discharge can therefore be recomputed at each cycle from the imagery and the pre-fitted parameters, without further field intervention.

2.4 IoT pipeline and streaming dashboard

Each station operates autonomously with a solar panel and battery pack that ensure uninterrupted recording during power interruptions. Raw video clips are transmitted at fixed intervals to a central server, where the image processing modules are executed and the resulting velocity, stage, and discharge values are written to a time-series database. A web-based dashboard renders live imagery, the recognized surface velocity field, the virtual water gauge detection, and the continuous discharge time series in synchronized panels, as shown in Figure 2. Because the original imagery is archived alongside derived values, anomalies in the time series can be inspected visually within seconds, supporting rapid diagnosis of equipment faults, channel obstructions, or unauthorized inflows (Abdulgafar 2019; Natividad and Mendez 2018).



Figure 2. Web dashboard: (a) live imagery, (b) surface velocity field, (c) virtual water gauge, (d) discharge time series

3. RESULTS AND DISCUSSION

3.1 Demonstration site and instrumentation

The framework was deployed in the Bagu drainage system in northern Taiwan, a network of mainstream and tributary branches monitored by a set of gauge and rainfall stations. The representative station examined here, denoted D4, sits on a reach with simple boundary conditions suited to non-contact measurement; its location within the drainage network is shown in Figure 3. The station integrates a surface velocity radar, a radar stage sensor, and a CCTV camera, all powered by a solar panel and battery and linked through an IoT uplink, as illustrated in Figure 4. The radar and camera view a common measurement area on the channel surface, allowing the radar-based and image-based estimates to be compared directly against each other and against the ADCP reference.

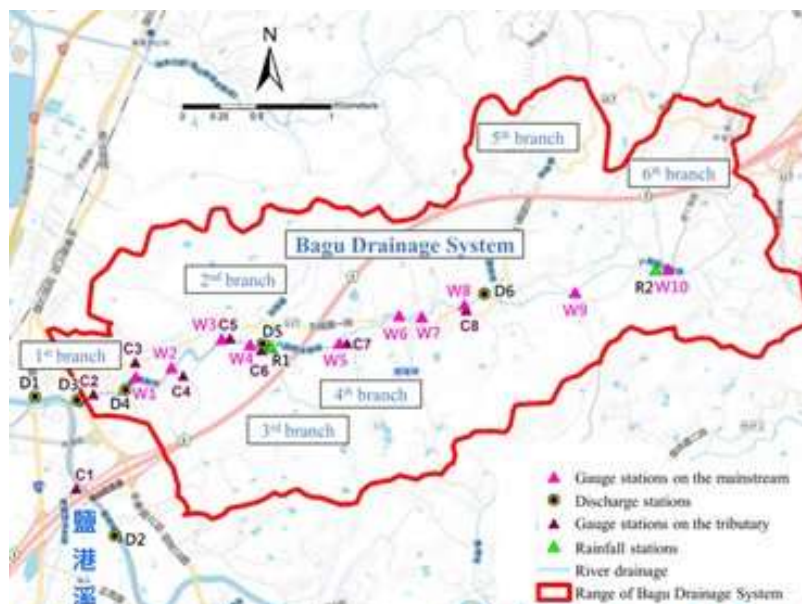


Figure 3. Location of D4 within the Bagu drainage system.

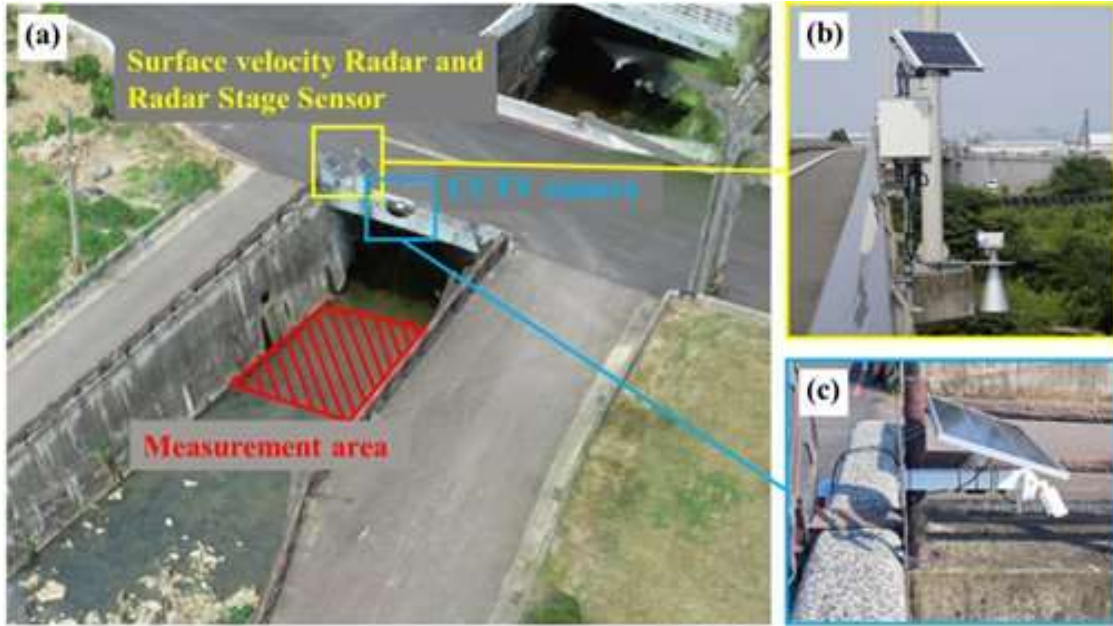


Figure 4. Measurement system at D4: (a) reach, (b) radar and stage sensor, (c) CCTV with solar power.

3.2 Parameter calibration

The cross section at D4 was surveyed in July 2022 and again in May 2023 to confirm that the channel geometry remained stable; the two surveys were almost identical, as shown in Figure 5(a). Fitting the surveyed geometry to the cubic form of Equation (2) produced the stage-area relationship of Figure 5(b),

$$A = -0.0021H^3 + 0.2324H^2 + 4.3233H - 36.0768 \quad (2)$$

with a coefficient of determination of unity over the observed range. A conventional single-valued stage-discharge rating curve, constructed for cross-comparison from the integrated radar, image, and ADCP observations, was expressed as a power law:

$$Q = c (H - H_0)^b \quad (3)$$

where H_0 is the stage of zero flow and c and b are fitted coefficients. Regression against the combined dataset yielded $c = 10.18$, $H_0 = 6.322$ m, and $b = 3.37$, with a coefficient of determination of 0.98. As shown in Figure 6, the reference points from two typhoons and two flood events in 2023 fall closely along this curve. The surface-to-mean velocity conversion was obtained from regression of the ADCP depth-averaged velocity against the image-derived surface velocity:

$$U = 0.7715 u_s \quad (4)$$

with a coefficient of determination of 0.987. The near-linear relationship indicates that within the operational range of the channel a single conversion factor adequately represents the velocity profile, while still allowing recalibration where geometry or roughness differs. The power-law rating curve of Equation (3) is, however, single-valued by construction and therefore represents steady flow only; the limitations of this assumption under flood conditions are examined below.

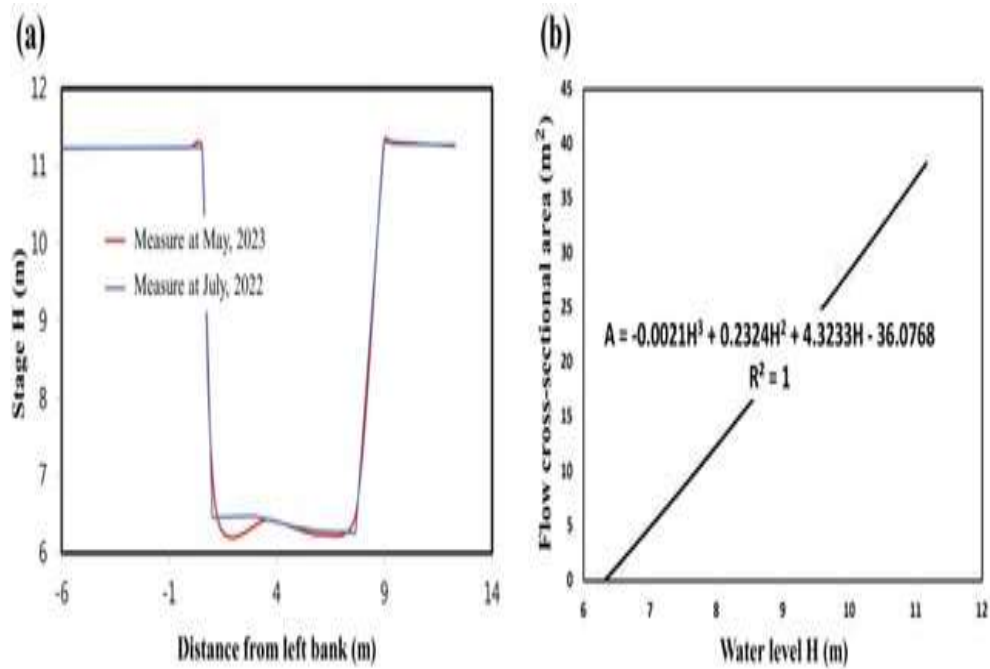


Figure 5. (a) Surveyed cross section at D4 and (b) the stage-area relationship.

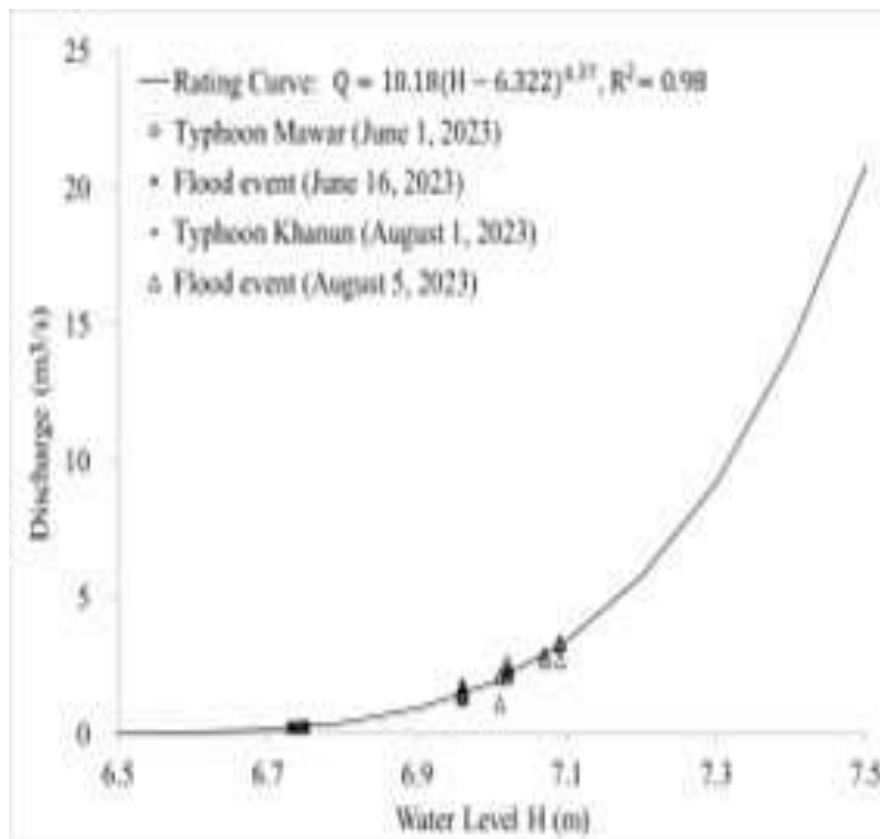


Figure 6. Stage-discharge rating curve at D4 with reference points from 2023 events.

3.3 Continuous monitoring of flood events

Three flood events in 2023 were selected for performance evaluation. The image-based stage estimates tracked the radar stage sensor to within approximately 0.1 m throughout each event, as shown in Figure 7, where the rising and falling limbs follow the rainfall hyetograph closely. The discharge hydrographs reconstructed from the two real-time methods are compared with the steady rating curve in Figure 8. The image-recognition estimates remained stable across all three events, whereas the index surface velocity method (ISVM) derived from the radar showed greater variability, most pronounced in the low-flow event of Figure 8(c). Field inspection attributed this variability to two causes: static water and exposed rocks generating noise in the surface velocity radar, and accumulated rocks downstream inducing secondary flow that misled the radar. Image correlation, evaluated over a wider field of view, was less affected by these local disturbances.

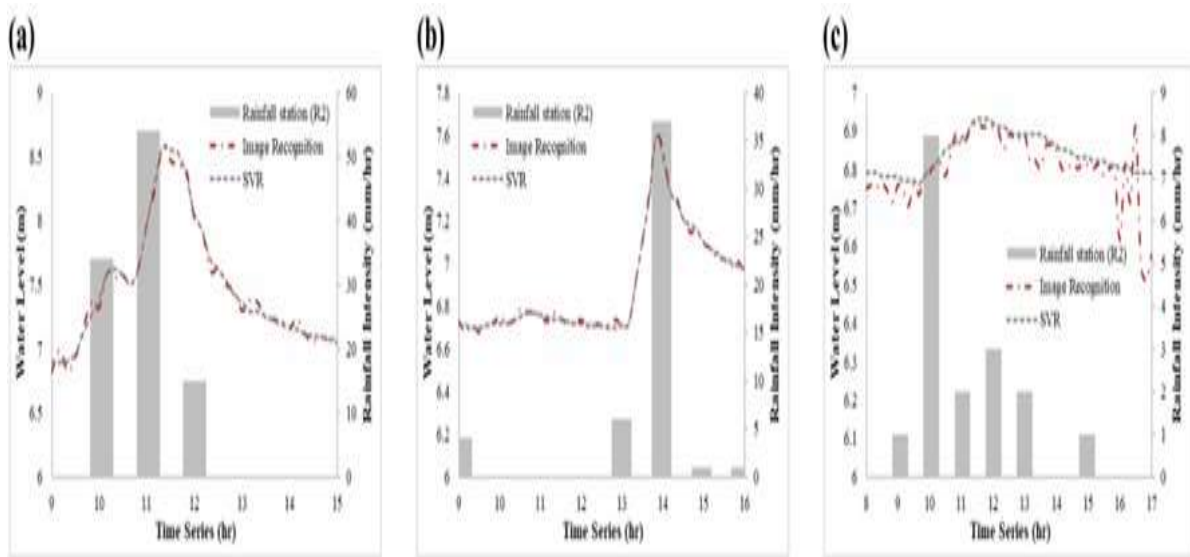


Figure 7. Water level from image recognition and radar against rainfall: (a) 5 Aug, (b) 16 Aug, (c) 4 Oct 2023.

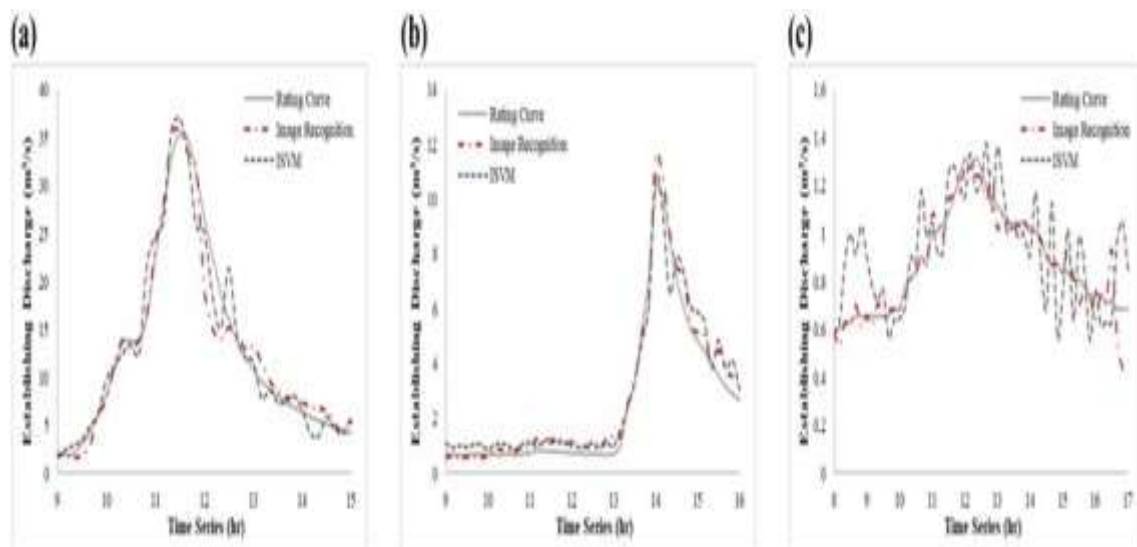


Figure 8. Discharge hydrographs from image recognition and ISVM versus the steady rating curve for the same three events.

3.4 Quantitative performance

Two criteria were used to evaluate the inferred discharge against the reference time series: the peak discharge error (PE) and the coefficient of determination (R^2):

$$PE = (m_{peak} - p_{peak}) / m_{peak} \times 100\% \quad (5)$$

$$R^2 = [\Sigma(m_i - \bar{m})(p_i - \bar{p})]^2 / [\Sigma(m_i - \bar{m})^2 \cdot \Sigma(p_i - \bar{p})^2] \quad (6)$$

where m_i and p_i denote measured and predicted values, $\bar{m}$ and $\bar{p}$ are their means, and m_{peak} and p_{peak} are the corresponding peak values. Table 1 summarizes the results. The image-based framework produced peak errors of 0.73, 10.16, and 2.96 percent and R^2 values between 0.92 and 0.98. The intermediate error corresponded to a brief, sharp pulse where the reference captured a slightly higher local maximum, although the broader hydrograph shape stayed closely aligned. The framework therefore reproduces both peak magnitudes and hydrograph shape with accuracy comparable to established non-contact methods, while providing continuous coverage that intermittent measurements cannot.

Table 1. Performance of CCTV-based discharge estimation during three flood events in 2023.

Flood event	Criterion	CCTV image-based	Radar-based (reference)
5 Aug 2023	PE (%)	0.73	4.23
	R^2	0.918	0.924
16 Aug 2023	PE (%)	10.16	3.56
	R^2	0.980	0.935
4 Oct 2023	PE (%)	2.96	4.61
	R^2	0.922	0.525

Because the framework observes surface velocity and stage independently at each measurement cycle rather than inferring discharge from stage alone, the integrated observations can also be examined directly in the discharge-stage plane. At higher discharges the radar, image, and ADCP observations tend to scatter around the single-valued rating curve rather than collapsing onto it, a pattern consistent with the hysteresis expected when the rising and falling limbs of a flood wave correspond to slightly different discharges at the same stage. A full characterization of this unsteady behavior would require additional events and is left for future work; here it is noted only as a qualitative feature that continuous, independent observation of velocity and stage is able to capture, whereas a stage-only rating cannot.

Following the initial validation, the D4 station was operated continuously through 2024 and 2025 without further field intervention, allowing the framework to be tested against the events that actually affected the Hsinchu area, where the Bagu drainage system is located. Over this period the station captured six precipitation and tropical-cyclone events with material impact on the catchment, including five named typhoons that drove warnings in Hsinchu County and City — Typhoon Gaemi on 24–25 July 2024, Typhoon Krathon on 2–3 October 2024, Typhoon Kong-rey on 30–31 October 2024, Typhoon Danas on 7 July 2025, and Typhoon Ragasa on 23 September 2025 — together with the 0709 heavy rainfall event of 8–9 July 2025, in which the residual circulation of Typhoon Danas combined with a southwesterly flow to deliver nearly eighteen hours of continuous heavy rain across Hsinchu County and City. Storms that tracked far from the catchment are not included. The events span peak depths of 1.2–2.7 m and rainfall of 110–410 mm, stress-testing the inference pipeline from outer rainbands to direct typhoon impact. The recorded conditions and performance for each event are summarized in Table 2.

Across the extended dataset the framework reproduced peak discharges with errors between 2.4 and 5.6 percent and coefficients of determination between 0.93 and 0.96. The largest error corresponded to Typhoon Gaemi, whose sediment-laden flow and floating debris locally degraded the cross-correlation on the rising limb. The 0709 heavy rainfall event produced a sustained pulse that the framework tracked through nearly a full day without intervention, while Typhoon Ragasa, whose centre passed well to the south and affected Hsinchu only through outer rainbands, remained within 2.4 percent. The framework continued to deliver continuous hydrographs autonomously through nighttime peaks, sustained multi-day events, and the regional power disturbances that accompanied the strongest typhoons, demonstrating that the integrated solar and IoT design supports reliable unattended operation across multiple monitoring seasons.

Table 2. Performance of the CCTV-based framework across the extended 2024–2025 deployment for events that affected the Hsinchu area.

Date	Event	Type	Peak depth (m)	Rainfall (mm)	PE (%)	R ²
24–25 Jul 2024	Typhoon Gaemi	Typhoon	2.68	412	5.6	0.93
2–3 Oct 2024	Typhoon Krathon	Typhoon	1.95	236	4.1	0.94
30–31 Oct 2024	Typhoon Kong-rey	Typhoon	2.21	298	3.8	0.95
7 Jul 2025	Typhoon Danas	Typhoon	1.74	168	3.2	0.95
8–9 Jul 2025	Rainfall event	Hydrological	1.42	215	4.7	0.93
23 Sep 2025	Typhoon Ragasa	Typhoon	1.18	112	2.4	0.96

4. DISCUSSION AND CONCLUSIONS

The deployment confirms that fixed CCTV imagery, paired with an automated velocity and water level pipeline, can support continuous discharge monitoring at the scale of agricultural drainage. Because the same camera supplies both velocity and stage, the marginal cost of adding a station is low and replication across an irrigation district is feasible without proliferating specialized instruments. Synchronizing the derived variables with archived imagery also turns the station into an evidence-rich observation point, where algorithmically detected anomalies can be verified visually, which is valuable for operational diagnosis and for distinguishing genuine hydrological signals from instrument artifacts such as the radar scatter noted above.

Continuous operation reveals features that intermittent sampling cannot resolve, including the tendency toward hysteresis in the stage-discharge relationship discussed above. For an irrigation district this is relevant because event volumes computed from a single-valued rating curve may be biased when flows are strongly unsteady, whereas a record based on independently observed velocity and stage retains the information needed to examine such effects. The multi-year record across the 2024 and 2025 deployment, spanning direct typhoon impacts, outer-rainband events, and the 0709 heavy rainfall episode following Typhoon Danas, indicates robust performance across the forcings that affect this catchment, with datasets well suited to constraining water-balance calculations and calibrating distributed models for irrigation district management.

Several practical limitations deserve attention. Performance during heavy rainfall or fog can degrade when surface tracers become obscured, and very shallow flows expose the bed within the field of view, complicating both velocity correlation and water level detection. Where strict accuracy targets must be met under such conditions, the framework is best paired with a secondary sensor or with

adaptive image processing that suppresses contaminated regions. Across the deployment lifecycle, the most consequential design decision is the selection of the surface-to-mean velocity coefficient, which should be re-evaluated whenever cross-sectional geometry or bed roughness changes appreciably.

In summary, this study presented a continuous image-based discharge monitoring framework for agricultural drainage channels that combines CCTV-derived surface velocity, virtual-gauge water level detection, and the velocity-area method, supported by IoT transmission and a streaming dashboard. At the D4 station in the Bagu drainage system, the image-based water level matched the radar stage sensor to within 0.1 m, and across three flood events in 2023 together with six additional events affecting the Hsinchu area during the 2024 and 2025 deployment, the framework reproduced peak discharges with errors typically below six percent and coefficients of determination consistently above 0.91. Because surface velocity and stage are observed independently and continuously, the integrated record also makes it possible to examine the stage-discharge relationship directly and to identify the tendency toward hysteresis at higher flows, which a single-valued rating curve cannot represent. By embedding the measurement in a service-oriented pipeline, the approach delivers near real-time situational awareness with visual verification while reducing dependence on costly in-channel devices and on-site personnel. With its modest hardware footprint and replicable inference pipeline, the framework provides an extensible foundation for distributed drainage observation networks that strengthen irrigation return-flow accounting, support adaptive water management, and improve water use efficiency under increasing resource and climate constraints.

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