INVESTIGATING THE POTENTIAL TO ACCURATELY MEASURE RIVER FLOW DISCHARGE USING REMOTE SENSING TECHNIQUES

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PREFACE

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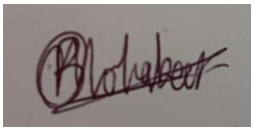
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ABSTRACT

A prevalent decline in the density and operational condition of the South African river flow gauging network is well documented within recent hydrological literature. Although approximately 628 stations are nationally identified as monitoring river streamflow, only 538 are currently classified as capable of providing verified river flows and 30 of those return no data, and the resulting spatial gaps limit the quality of the hydrological record on which national water resource management depends. Non-contact image velocimetry, and specifically Large-Scale Particle Image Velocimetry (LSPIV), has been demonstrated internationally as a low-cost means of extending monitoring coverage into ungauged reaches. However, the published parameter calibrations, velocity index relationships, and accuracy figures have been derived predominantly from stable, perennial river systems in Europe and North America, and their transferability to the highly variable flow regimes, high sediment loads, and rapidly changing channel morphology characteristic of South African rivers remains insufficiently quantified. This research evaluates the technical feasibility, hydrometric accuracy, and operational limitations of virtual gauging within a South African context. Using a pilot monitoring setup in the uMngeni Catchment, KwaZulu-Natal, fixed-camera and smartphone-based image velocimetry systems are benchmarked against synchronous reference gauging data obtained from Department of Water and Sanitation infrastructure and physical hydraulic measurements. The pilot site is established immediately downstream of an actively rated gauging weir, so that a continuous and independently rated reference discharge is available at the measurement section across the full monitoring period. Uncertainty is propagated from surface velocity measurement, through the velocity index relationship and cross-sectional geometry, to final discharge. The research is intended to establish whether image velocimetry can produce accurate, reproducible, and uncertainty-characterised discharge measurements suitable for operational integration as a supplement to the existing national gauging network.

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1. INTRODUCTION

River flow measurement is used as a primary parameter for understanding the dynamic characteristics of river systems (Bashit *et al.*, 2025). Therefore, adequate quantification of river discharge is the basis for effective water resource management, soil and water conservation, terrestrial hydrological cycle monitoring, and flood disaster mitigation (Long *et al.*, 2025). An understanding of the flow velocities over large areas directly contributes to the understanding of natural river phenomena and influences better decision making (Trieu *et al.*, 2021). Traditionally, velocity is measured via the use of mechanical or electromagnetic current meters (Herschy, 1995). However, traditional monitoring methods involving the use of physical gauging stations face limiting factors relating to sparse spatial coverage, data sharing restrictions, in-field deployment, and infrastructure degradation (King *et al.*, 2018; Sheffield *et al.*, 2018). Thus, alternative methods of flow monitoring are needed to supplement existing flow gauging networks (Long *et al.*, 2025). Within a South African context, Johnson *et al.* (2021) stated that the decline in flow gauging infrastructure has been evident since the 1980s by referring to work done by Pitman (2011).

Advancements in technologies such as Acoustic Doppler Current Profilers (ADCPs) have allowed for velocity field derivation across river cross-sections (Shekhar *et al.*, 2021). ADCPs offer high accuracy under favourable conditions (Løken *et al.*, 2024), but are subject to physically disrupting materials (Sočuvka *et al.*, 2024), and are still reliant on physical contact with the river system (Jolley *et al.*, 2021). Technological advancements in Particle Image Velocimetry (PIV) have given rise to non-contact alternatives in flow discharge quantification (Kim *et al.*, 2008; Tauro *et al.*, 2014; Pearce *et al.*, 2020). Large-scale PIV has emerged as a favourable method in open-channel flow measurement (Tarya and Aqdam Prasetyo, 2024), with Space-Time Image Velocimetry (STIV) also being prominent (Watanabe *et al.*, 2021). Both ADCP and LSPIV reduce physical intrusion and offer significant scalable advantages but are subject to limiting factors relating to accuracy (Jolley *et al.*, 2021), sensitivity to environmental conditions (Muste *et al.*, 2004; Jolley *et al.*, 2021; Le Coz *et al.*, 2021; Sočuvka *et al.*, 2024), and processing complexity (Lin *et al.*, 2024).

This study aims to evaluate the potential for image-based discharge estimation to supplement the South African river gauging network, thereby improving the national gauging density.

This document is structured as follows. Chapter 2 reviews the literature on traditional gauging structures, Acoustic Doppler Current Profilers and image velocimetry, comparing their accuracy, cost and operational requirements, and concludes by identifying the research gaps and the main research question arising from them. Chapter 3 sets out the project proposal, comprising the aims, objectives and hypotheses, the methodology by which the research question will be answered, the work plan and deliverables, the resources required, and the intellectual property considerations of the study.

2. LITERATURE REVIEW

Traditional gauging structures, Acoustic Doppler Current Profilers (ADCPs), and Particle Image Velocimetry (PIV) represent distinct paradigms in open-channel discharge measurement, each defined by inherent trade-offs across financial, operational, and hydraulic dimensions. This review evaluates these three methodologies against four primary criteria: hydraulic measurement accuracy, capital and recurring maintenance expenditure, environmental and in-situ footprint, and operational flexibility under transient flow conditions. Each technology is discussed against these criteria, before a direct comparative synthesis is presented in Section 2.3.

2.1 Analysis of the Current South African River Gauging Regime

Globally, there has been a tangible decline in flow gauging structures over recent years (Long *et al.*, 2025). This decline can be observed since around the 1980s in South Africa (Johnson *et al.*, 2021). South Africa faces increasing data sparsity because of the decline in its traditional river flow gauging network. Datasets from the Department of Water and Sanitation (DWS) (DWS, 2026) demonstrate the sparsity of open river gauges within the South African river system and depicts the state of the river gauging network, with 59% of all gauges being closed. A figure representing all active and inactive DWS river gauges can be seen in Figure 2.1.

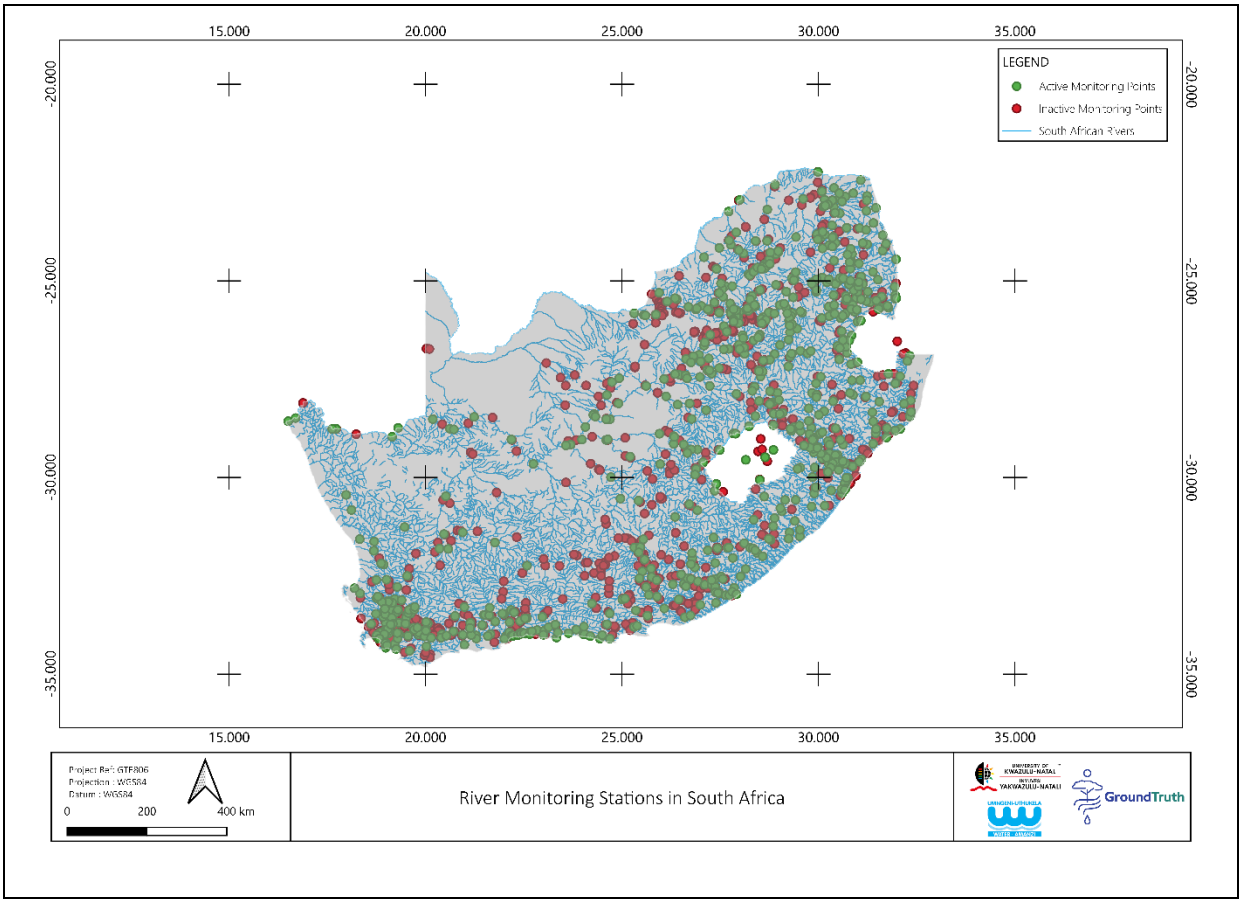


Figure 2.1 A map of South African river gauging network showing all open and closed river gauges. Created using datasets obtained from DWS (2026)

Published counts of the national network differ according to what is counted, since the surface water monitoring network includes canals, pipelines, reservoirs, and estuaries alongside river gauging sites. The National State of Water Report identifies approximately 628 stations nationally as monitoring river streamflow (DWS, 2024). Interrogation of the DWS hydrological services dataset undertaken for this review returns 538 stations currently classified as capable of providing verified river flows, of which 30 return no flow data, giving an effective count of 508 (DWS, 2026). The distinction between the nominal and the effective network is material, because a station that remains on the national register does not necessarily deliver the quality-coded record on which water resource management depends. Apart from the declining number of operational gauging weirs in South Africa, there also exists large portions of the South African river network that remain ungauged as can be seen in Figure 2.2.

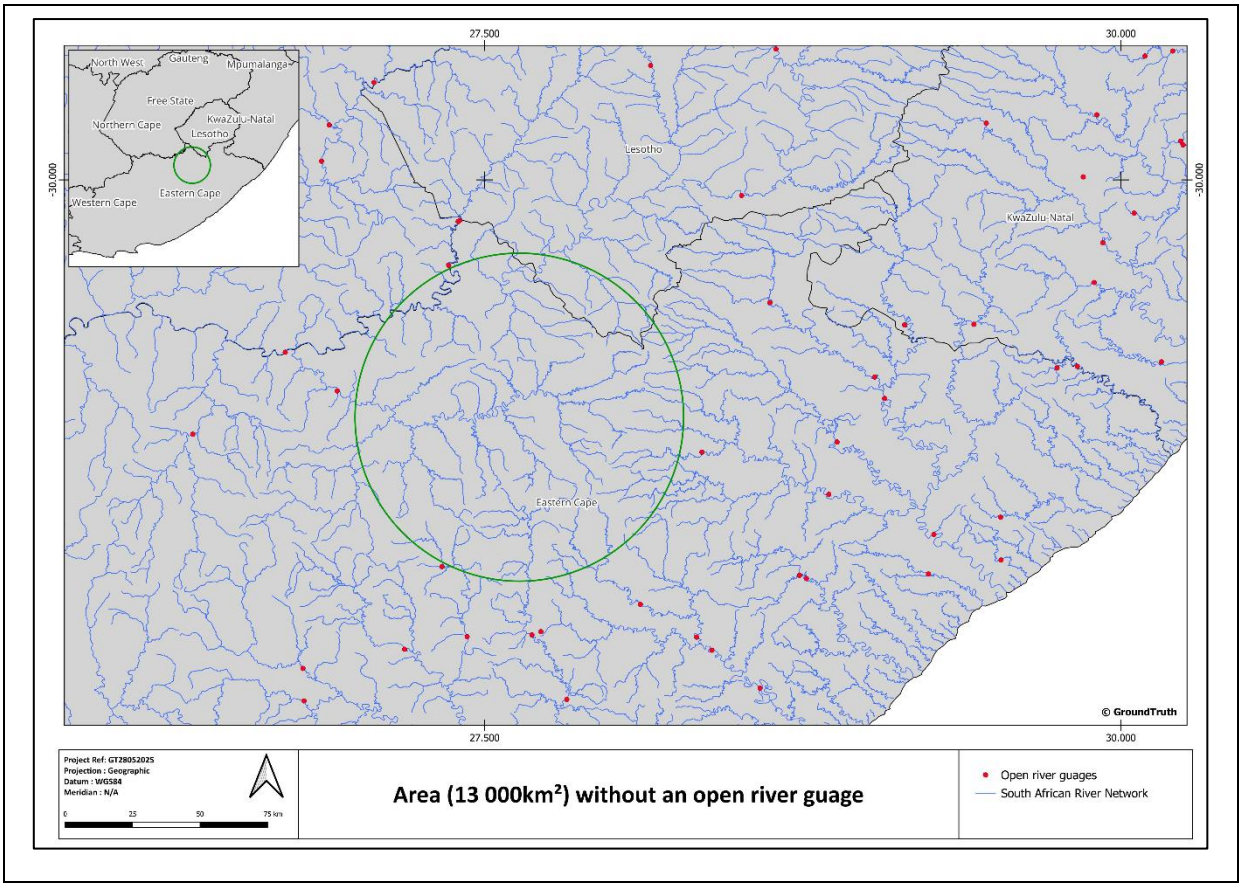


Figure 2.2 An example of a large area (13 000 km^2) without an open river gauge. Created using datasets obtained from (DWS, 2026)

These figures demonstrate that the South African river flow gauging regime is spatially and temporally constrained. While South Africa does maintain an operationally active national gauging network, the regime functions under reduced monitoring density and record continuity when compared to its historical capacity (Johnson *et al.*, 2021).

2.2 Existing Range of Technologies for Channel Flow Measurement

River flow discharge measurement is a primary contributor of effective water resource management, soil and water conservation, terrestrial hydrological cycle monitoring, and flood disaster mitigation (Long *et al.*, 2025). The globally increasing scarcity of traditional gauging stations has given rise to challenges in securing continuous and valid river flow discharge data (Long *et al.*, 2025). Thus, there has been an increasing demand for low-cost, low-maintenance, and preferably ex-situ methods of obtaining river discharge data (Manfreda *et al.*, 2024; Tsubaki *et al.*, 2025).

2.2.1 Traditional gauging structures

The established methodology for open-channel river flow measurement in South Africa is the use of physical gauging structures such as weirs and flumes (Wessels and Rooseboom, 2009). The fundamental science behind these hydrometric structures is the use of the relationship between upstream water level and flow rate (stage-discharge relationship), allowing for accurate discharge measurements (Badhe *et al.*, 2015; Kadlec, 2017).

2.2.1.1 Principles of weir hydraulics

Weirs are engineered in-situ structures designed to be placed in a channel and measure flow by guiding water to pass over a defined crest (Badhe *et al.*, 2015). The potential energy (upstream head) is converted to kinetic energy (flowing water), allowing for a quantifiable relationship between head and discharge to be created. Typically, weirs are subcategorised into sharp-crested weirs, such as rectangular and V-notch weirs, and broad-crested weirs (Vatankhah and Khamisabadi, 2019; Salmasi *et al.*, 2023). Different weir types inherently have varying proportional relationships between discharge (Q) and head (H) due to the difference in geometric shape and area. Flumes, such as Parshall, Trapezoidal, H-flumes, and Cutthroat, are used to achieve critical flow within a contracted section of a river and use a stage-discharge relationship to measure open-channel flow (Sibale *et al.*, 2023).

2.2.1.2 Advantages of traditional river gauging structures

Traditional weirs and flumes can attribute their longevity as a viable method of measuring river flow discharge to a few key strengths, particularly in the accuracy of results produced when used appropriately (Adeogun and Mohammed, 2019).

Accuracy: Weirs have an inherent capability to ensure high accuracy in discharge measurements, with an error margin typically ranging between 2 to 5% as per Computational Fluid Dynamics (CFD) compared against empirical hydraulic data (Kusher, 2020). However, the uncertainty can be materially larger due to rating extrapolation, sedimentation, drift, and stage-sensor error. When properly designed, installed, and maintained, these structures accurately utilise the head-discharge relationship, which they were designed to uphold (Gang *et al.*, 2023).

2.2.1.3 Disadvantages and challenges of traditional gauging structures

There are a variety of economic, environmental, and social challenges associated with the use of traditional gauging structures within a river system. These relate to their inherent design limitations (Clemmens *et al.*, 2001), maintenance (Ogden *et al.*, 2017), cost implications (DWS, 2017), and environmental impact (Munzhelele *et al.*, 2024; Mulligan *et al.*, 2025).

Design limitations: Weirs were designed to be operational in low-flow to mid-flow conditions (Clemmens *et al.*, 2001). The quantification of applicable flows differs between different weir types. For all weirs, the minimum head on the weir should be approximately 0.2 ft (0.06 m) (Dodge, 2001). For rectangular weirs, the ratio of head to height of crest above approach invert should always be less than 2.4 (Dodge, 2001). For this specific V-notch geometry, the applicable flow range is approximately 0.05 to 4.25 ft^3/s (approx. 0.0014 to 0.12 m^3/s) (Dodge, 2001). Data inaccuracies are caused by weir submersion during high-flow events (Chanson, 2004). When weirs are submerged during high-flow events, the standard head-discharge equations become invalid, and without the use of complex correction factors, the data is inadmissible (Chanson, 2004). Flood events often result in water levels exceeding the design capacity of weirs, necessitating the correctional factors for the stage-discharge rating curves to compensate flows above the structural limit (Gericke and Williams, 2023). Unsteady flow conditions as a result of rainfall and runoff variability, can introduce significant errors when utilising traditional stage-discharge measurements (Baiamonte, 2021).

Sedimentation and debris accumulation: Weirs and flumes are susceptible to debris accumulation, which can alter their hydraulic characteristics and lead to inaccuracies with the data produced (Ogden *et al.*, 2017). This is particularly significant within South African rivers that experience seasonal sediment loading (Grenfell and Ellery, 2009). The removal of debris and sediments is often impractical and economically unfeasible (Ogden *et al.*, 2017).

Economic viability: Planning, construction, and installation of these structures are costly, often millions of Rands (R) per unit as shown in the cost breakdown conducted by DWS (2017). Additionally, maintenance and recalibration are represent recurring operational costs (DWS, 2017). The cost analysis breakdown can be seen within Section 2.3.2.

Environmental impact: Weirs are an in-situ (intrusive) method of river gauging. Inherently, weirs disrupt river flow regimes, impose differing physical conditions, and cause alterations to the biological composition of the river (Munzhelele *et al.*, 2024). These alterations pose threats

to river functionality, integrity, and sustainability. These structures also act as barriers to fish migration, causing a hindrance to the natural health and survival of many fish populations (Mulligan *et al.*, 2025).

2.2.2 Acoustic Doppler Current Profilers (ADCPs)

Acoustic Doppler Current Profilers (ADCPs) have become prominent tools for river discharge estimation (Klema *et al.*, 2020), as they offer the ability to provide detailed velocity profiles and comprehensive bathymetric data (Shekhar *et al.*, 2021).

2.2.2.1 Principles of ADCPs functionality

ADCPs are based on the scientific foundation of the Doppler effect (Meselhe *et al.*, 2004). The Doppler effect is based on the principle that the frequency of a sound wave changes with the relative motion between the source and the scatterer; in a river ADCP the transducer is normally stationary and it is the suspended scatterers that move (Pinkel, 1980). Within hydrometry, an ADCP emits acoustic pulses onto water columns (Fleit *et al.*, 2025). The pulses emitted encounter particles within the water which act as acoustic scatters (Gasparato *et al.*, 2022). These particles move along with the water, and as they move, they backscatter (reflect) the ADCPs emitted soundwaves. The backscattered soundwaves undergo a frequency shift which is proportional to the velocity of the water along the acoustic beam's axis (Yang and Fang, 2021). Figure 2.3 shows an illustrated demonstration of the acoustic beams emitted by an ADCP (Bailey, 2022)

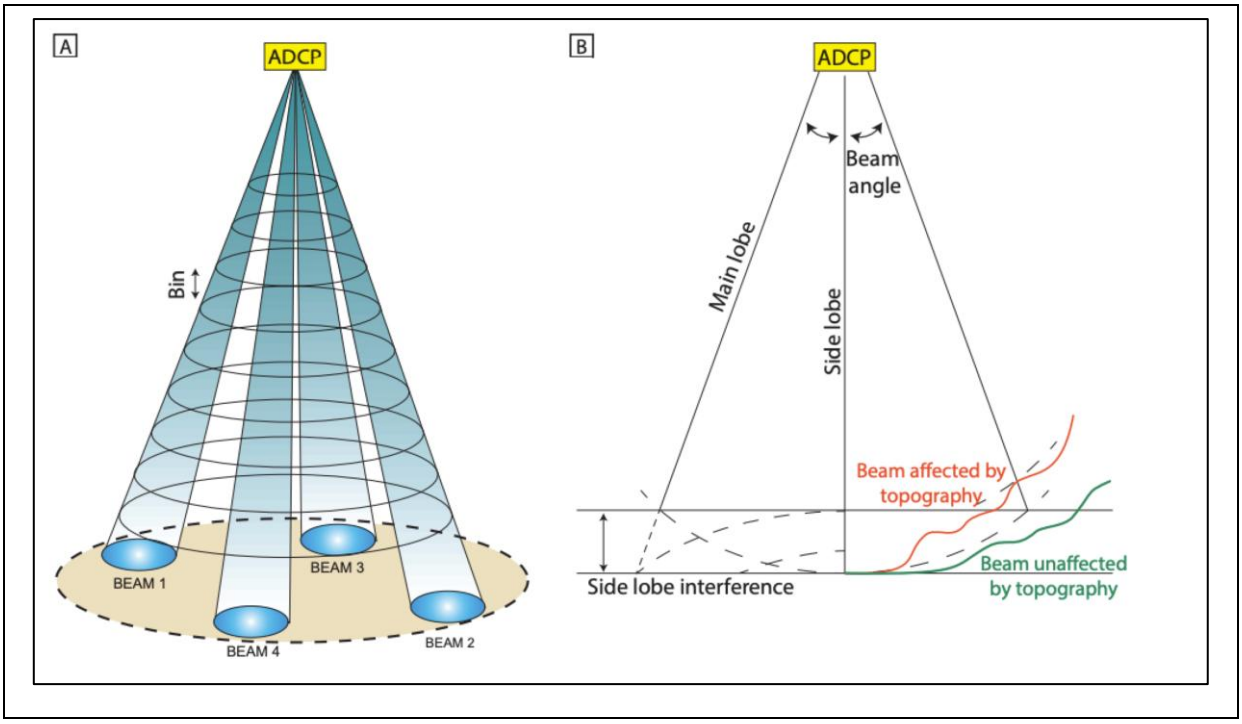


Figure 2.3 Illustrated demonstration of acoustic beams emitted by an ADCP (Bailey, 2022).

Through use of multiple acoustic beams orientated at varying angles relative to the instrument, the ADCP has the capability to resolve the three-dimensional velocity components of flow along the water column (Figuérez *et al.*, 2021), creating a comprehensive velocity profile (Lake *et al.*, 2024). The vertical spatial resolution improves with higher acoustic frequency and shorter pulse length, at the cost of profiling range (Yang and Fang, 2021). Higher frequencies are more suitable for shallower water and offer better resolution, whilst lower frequencies can obtain more depth but with a coarser resolution (Rahul *et al.*, 2020).

2.2.2.2 Advantages of ADCPs

The advantages of ADCPs relate to detailed creation of velocity profiles (Figuérez *et al.*, 2021), safety and efficiency (Iozzi Sperandelli and Zenker Gireli, 2023), versatility (Boon *et al.*, 2023), and labour intensity (Chen *et al.*, 2022).

Spatial resolution: ADCPs have the ability of providing detailed velocity profiles, capturing complex flow, and profile temporal variability, which point-measurement methods often lack (Figuérez *et al.*, 2021; Fleit *et al.*, 2025). ADCPs are valuable in dynamic environments, and are useful for quantifying turbulence (Løken *et al.*, 2024).

Safety and efficiency: Measurements can be taken by the user remotely controlling the ADCP device from an ex-situ position, which mitigates the safety concerns over personnel entering the river system when utilising the ex-situ method of ADCP (Iozzi Sperandelli and Zenker Gireli, 2023). ADCPs are efficient, as a single transect can rapidly provide comprehensive hydrometry datasets (Shekhar *et al.*, 2021). An ADCP transect can be completed substantially faster than a manual staff survey and is less prone to human error.

Versatility: ADCPs are able to function under a variety of flow conditions (Klema *et al.*, 2020).

Data acquisition and labour intensity: ADCPs can provide real-time hydrometry data (Yang and Fang, 2021), whilst being minimally labour intensive (Chen *et al.*, 2022).

2.2.2.3 Disadvantages and challenges of ADCPs

The disadvantages of ADCPs relate to its sensitivity to physical signal disrupting materials (Sočuvka *et al.*, 2024), its relatively expensive equipment, and its reliance on physical contact with the river system (Jolley *et al.*, 2021).

Sensitivity to physical signal disrupting materials: ADCPs are capable of adequate functionality in varying environmental conditions, however, the presence of suspended debris can severely hinder the performance of ADCPs due to acoustic signal attenuation (Sočuvka *et al.*, 2024). Similarly, dense aquatic vegetation can distort data accuracy (Sočuvka *et al.*, 2024).

Cost and expertise: Instrumentation pivotal to ADCPs functionality are generally expensive relative to alternative methods of obtaining flow data. Additionally, specialised training is required to adequately operate the equipment and interpret the results. This can be a deterrent to adoption in some smaller projects, particularly in developing countries. The cost analysis breakdown can be seen within Section 2.3.2.

Physical contact reliance: Whilst ADCPs offer some advantages over traditional gauging structures, a critical limitation which they fail to completely overcome is their reliance on physical contact with the water body (Jolley *et al.*, 2021). This may render the method unsuitable during high-flow event when physical access to the channel is not possible (Jolley *et al.*, 2021)

Inherent limitations: ADCPs estimate velocity fields through acoustic backscatter and Doppler frequency shift (Muste *et al.*, 2004). Although highly accurate in lab based settings

and ideal field conditions, the sensitivity of ADCP to moving-bed conditions, side-lobe interference, shallow depths, signal disruption, and obstructing sedimentation, hinders its real-world performance (Rennie and Villard, 2004).

2.2.3 Particle image velocimetry (PIV)

Particle Image Velocimetry (PIV) is an ex-situ, optical measurement technique used to quantitatively map instantaneous velocity fields (Rohacs *et al.*, 2023).

2.2.3.1 PIV variations for river discharge estimation

Currently the two prominent methods of PIV for open channel velocity measurement are LSPIV as stated by Bashit *et al.* (2025), and space-time image velocimetry (STIV) (Watanabe *et al.*, 2021).

Large-Scale PIV (LSPIV): LSPIV uses planar PIV to interpret a velocity field. LSPIV is a non-intrusive technique used mainly in the quantification of surface flow velocities over large open channels (Tarya and Aqdam Prasetyo, 2024). LSPIV is the variation of PIV most utilised within open channel hydrometry. This is in part due to its adaptation to the conventional PIV to allow for broader measurement areas with the use of inexpensive video equipment (Meselhe *et al.*, 2004). The core methodology of LSPIV has been described in Section 2.2.3.2.

Space-Time Image Velocimetry (STIV): Amongst the image-based methods of flow determination, space-time image velocimetry (STIV) is regarded as a powerful tool for flow measurement due to its high measurement accuracy and robustness (Watanabe *et al.*, 2021). STIV works by initially setting a search line of arbitrary length in the mainstream direction of the image and thereafter calculating flow velocity from the gradient of the striped pattern that appears in space-time image (STI), which is generated from the stacking of image information in the time direction (Watanabe *et al.*, 2021). Figure 2.4 (Fujita *et al.*, 2019) illustrates how videos taken obliquely in Figure 2.4(a) is converted to the orthorectified image in Figure 2.4(b) using search lines parallel to the flow (red lines) with a constant physical length.

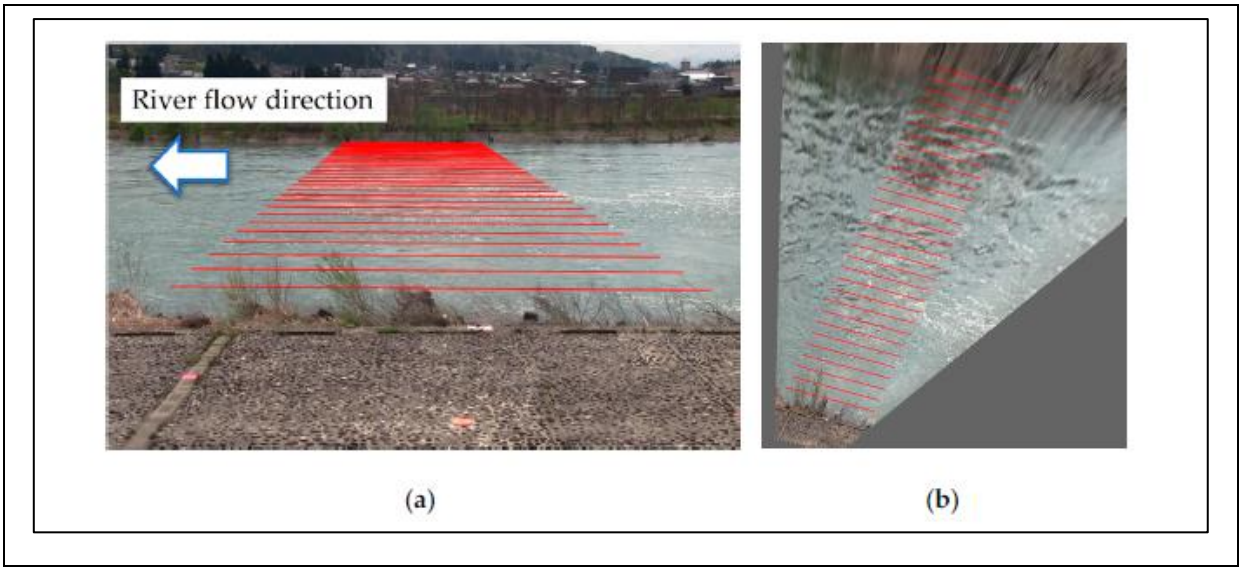


Figure 2.4 Images with search lines (Fujita *et al.*, 2019). (a) Original image, (b) Orthorectified image

Figure 2.5 (Watanabe *et al.*, 2021) illustrates how original STI in Figure 2.5(a) is converted via the Fourier transform in Figure 2.5(b) which creates a striped pattern on the STI which represents the trajectory of the ripples from which velocity can be calculated through use of correctional coefficient accounting for the conversion between pixels and real scale. The resulting STI contains textures generated by the ripples advected with surface flow velocity with vectors distinguishing between positive and negative directions (Watanabe *et al.*, 2021).

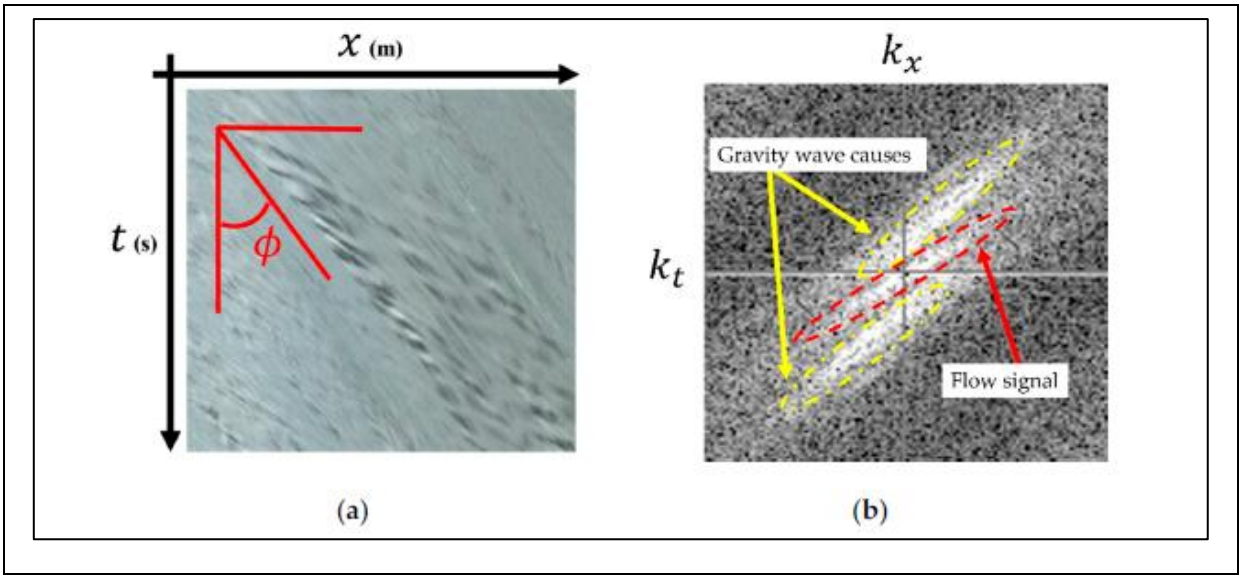


Figure 2.5 Space-time Image (STI) (Watanabe *et al.*, 2021). (a) Original Image, (b) Fourier transform image

Alternatively, the conventional STIV method involves calculating the gradient tensor of an STI and performing a pattern angle estimation (Fujita *et al.*, 2007). (Watanabe *et al.*, 2021) illustrate the calculation of pattern angles for overlapping blocks in Figure 2.6(a). These patterns are subsequently enhanced to higher pattern clarity in Figure 2.6(b) via empirical equations, and finally a histogram of pattern angles in Figure 2.6(c) is derived from further empirical equations. This is an automatic estimation method developed in STIV, and can accurately estimate the pattern angle under good video conditions (Watanabe *et al.*, 2021). Under less-than-ideal video conditions, minor adjustments of the window size, window width, coherency threshold, and histogram range will need to be undertaken for reasonable analysis (Watanabe *et al.*, 2021). Watanabe et al. (2021) also tested the applicability of deep learning models to automate this process further and eliminate the need for parameter adjustments.

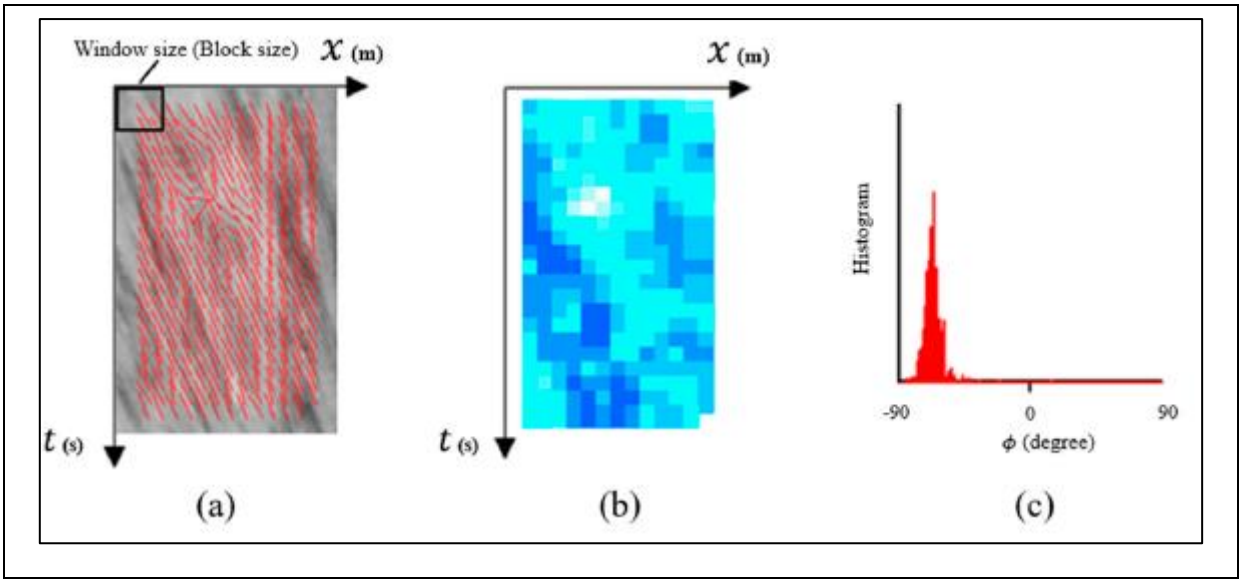


Figure 2.6 The gradient tensor method (Watanabe *et al.*, 2021). (a) Pattern calculated with each block, (b) Calculated coherency with each block, (c) Histogram of pattern angles

Post-processing algorithms are applied to the space-time image produced to create surface flow velocity data (Fujita *et al.*, 2007).

2.2.3.2 Principles of Large-Scale Particle Image Velocimetry (LSPIV)

LSPIV is an advanced ex-situ method of open-channel surface velocity measurement and functions by calculating the displacement of patterns and particles between successive digital frames or video footage (Jolley *et al.*, 2021). Fundamentally, LSPIV involves the tracing of visible, buoyant particles along the flow surface for a known time interval (Thomas Jr *et al.*, 2011). Images or video footage capture the distribution of the visible particles across multiple time stamps. The displacement of the particles can then be determined through cross-correlation algorithms (Zhong *et al.*, 2017). A velocity vector is used to generate an instantaneous velocity field (Ben-Gida *et al.*, 2020). Figure 2.7 illustrates the concept of tracking visible particles of low density (left), medium density (middle), and the correlating interrogation windows (right) (Scharnowski and Kähler, 2020). The bottom row shows the vector displacement fields correlating to the top row's particle image distribution.

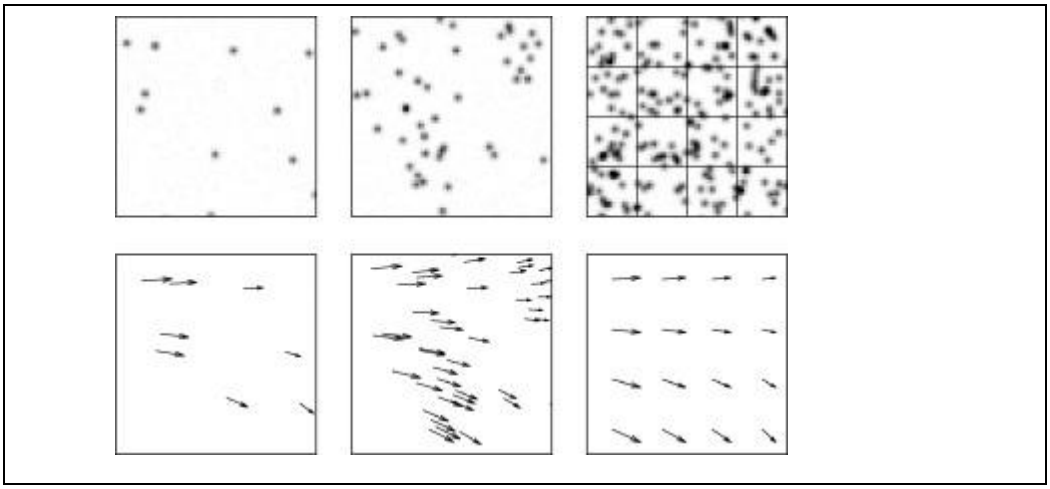


Figure 2.7 Concept of tracking individual particle images and correlating interrogation windows to create displacement fields (Scharnowski and Kähler, 2020)

As one of the most widely implemented optical velocity measurement techniques (Muste *et al.*, 2008), its accuracy depends on optimizing the image sampling frequency relative to spatial resolution. Specifically, the frame interval (Δt, the inverse of frames per second) must be calibrated in conjunction with the ground sampling distance to ensure that inter-frame tracer displacement remains within approximately one-quarter of the interrogation window dimension (Muste *et al.*, 2008; Thielicke and Stamhuis, 2014). Sub-pixel displacements below this threshold are susceptible to image noise, whereas excessive displacements cause tracer particles to exit the interrogation window between consecutive frames, resulting in cross-correlation failure (Muste *et al.*, 2008; Thielicke and Stamhuis, 2014). Methodologically, the LSPIV workflow comprises four sequential phases: (i) image acquisition, (ii) seeding material identification or introduction, (iii) orthorectification, spatial calibration, and pre-processing, and (iv) velocity field calculation (Muste *et al.*, 2008).

Image acquisition: Images are typically obtained in the form of digital video camera footage from either standard smartphone cameras, dual-cameras, high-resolution cameras, Unmanned Aerial Vehicles (UAVs), or from satellites (Kim *et al.*, 2008; Tauro *et al.*, 2014; Pearce *et al.*, 2020).

Tracing and seeding: Particle Image Velocimetry (PIV) relies on observable surface features, typically utilising natural tracers such as foam, organic debris, or surface ripples to track movement across consecutive frames (Muste *et al.*, 2008). When natural tracers are insufficient, artificial seeding can be introduced by deploying visible, biodegradable materials into the flow path to improve image cross-correlation (Tauro *et al.*, 2014; Alongi *et al.*, 2023).

To circumvent reliance on visible surface features, thermal infrared imaging has been explored as a non-contact alternative (Legleiter *et al.*, 2017). Legleiter *et al.* (2017) demonstrated that mid-wave infrared cameras (3–5 μm) can track micro-scale thermal patterns on the water surface independently of ambient illumination, enabling diurnal operation. However, thermal PIV remains heavily constrained by high instrumentation costs, lower spatial resolutions relative to optical sensors, and intensive pre-processing and orthorectification requirements (Legleiter *et al.*, 2017).

Orthorectification, calibration, and image processing: Images and footage acquired from field cameras frequently exhibit geometric perspective distortions and camera lens aberrations (Tauro *et al.*, 2014). To correct for these spatial distortions, orthorectification transforms oblique raw image pixels into a planar, georeferenced coordinate view (Toth *et al.*, 2018; Sharif, 2022). This operation relies on Ground Control Points (GCPs) of known spatial positions to map 2D image coordinates to real-world ground coordinates, establishing a metric grid essential for accurate displacement measurement (Muste *et al.*, 2008).

Following spatial orthorectification, velocity vectors are calculated via cross-correlation across sub-image sections termed Interrogation Areas (IAs) (Bashit *et al.*, 2025). The dimensions of the IA establish a fundamental trade-off between spatial resolution and cross-correlation robustness: an overly large IA averages localised velocity gradients, whereas an IA that is too small contains insufficient tracer features, reducing the signal-to-noise ratio (Muste *et al.*, 2008; Thielicke and Sonntag, 2021).

To enhance visual contrast between surface tracers and the background water surface prior to cross-correlation, digital image pre-processing is typically required (Muste *et al.*, 2008). A widely utilised open-source suite for PIV pre-processing and cross-correlation is *PIVlab*, developed within MATLAB (Thielicke and Stamhuis, 2014; Thielicke and Sonntag, 2021). Legleiter *et al.* (2017) evaluated PIVlab alongside the commercial platform *PIVview*, reporting comparable qualitative performance across both tools.

Within PIVlab, three primary pre-processing algorithms are implemented (Thielicke and Sonntag, 2021): (i) Contrast Limited Adaptive Histogram Equalisation (CLAHE): Enhances local contrast across independent sub-tiles of an image (Bashit *et al.*, 2025), making it effective under heterogeneous lighting conditions (Sharif, 2022). For LSPIV deployments, CLAHE is widely cited as the preferred pre-processing technique. (ii) High-Pass Filtering: Eliminates

low-frequency background lighting variations and static environmental features while retaining high-frequency tracer signals (Bashit *et al.*, 2025). This technique is particularly effective in channels bounded by rocks, sand, or static vegetation (Strelnikova *et al.*, 2020). (iii) Intensity Capping: Limits extreme brightness values, preventing overexposed regions or reflections from dominating the cross-correlation matrix (Bashit *et al.*, 2025). While specific filtering guidelines exist, pre-processing selection remains site-specific, requiring empirical optimisation based on illumination, water clarity, and tracer density.

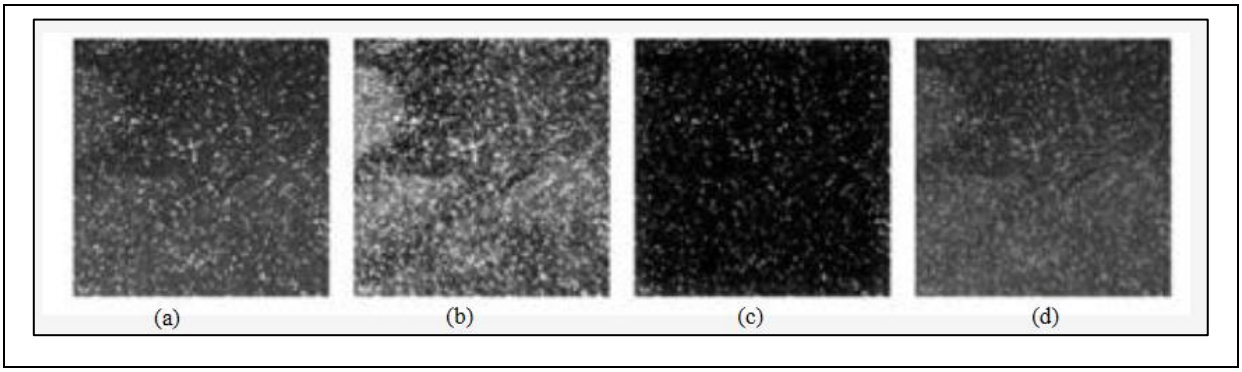


Figure 2.8 The resulting images from the different PIVlab image enhancement techniques. (a) Original, (b) CLAHE, (c) high-pass, (d) intensity capping

Post-processing techniques are available on PIVlab. The post-processing techniques available are (i) vector correction, (ii) outlier removal, and (iii) interpolation. These data correction processes are illustrated in Figure 2.9 (Muste *et al.*, 2008).

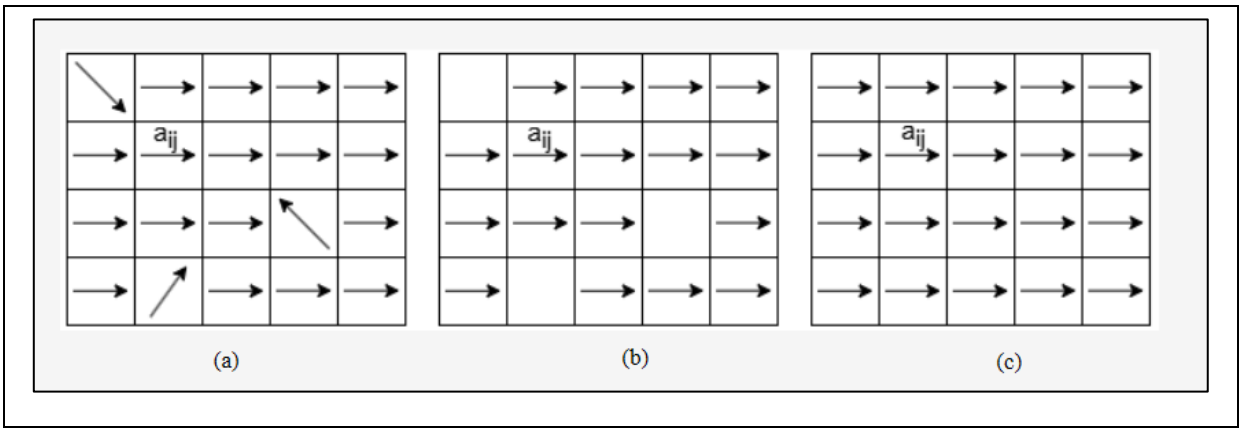


Figure 2.9 Post-processing LSPIV data correction process (Muste *et al.*, 2008). (a) before vector correction, (b) after vector correction and outlier removal, (c) after interpolation

Typically, Ground Control Points (GCPs) are necessary for orthorectification, however, there are systems being developed that are attempting to phase out PIV's reliance on them (Zhang *et*

al., 2024). GCPs are essentially control point data with known coordinates which are used for orthorectification processing and Independent Check Points (ICPs) for data quality testing of orthorectified points (Bashit *et al.*, 2025). A minimum of four GCPs, two along each side of the river, is required by LSPIV (Jolley *et al.*, 2021). The establishment of GCPs, especially during floods, poses a significant safety risk to researchers (Genç *et al.*, 2015). Additionally, submerged GCPs may become invalidated (Zhang *et al.*, 2024). The accuracy of the traditional GCP and ICP methods heavily rely on quantity and coverage range of control points, which necessitates their widespread distribution around the river study area (Zhang *et al.*, 2024). Zhang *et al*. (2024) further states that this becomes burdensome in real-world applications, and oftentimes, unfeasible. Thus, the research done by Zhang *et al*. (2024), aimed to surmount the limitations of conventional camera calibration through the introduction of an innovative near-field remote-sensing measurement system. Zhang *et al*. (2024) concluded that using a triaxial accelerometer, a GCP-free method of LSPIV is possible, resulting in higher efficiency and reliability, though at higher financial costs.

Velocity Calculations: Cross correlation techniques are applied to orthorectified successive image pairs, to identify interrogation zones and to determine the displacement of particles (Patalano *et al.*, 2017; Fakhri *et al.*, 2020). Displacement vectors are automatically analysed against a known time window to yield a field of surface velocity vectors (Pearce *et al.*, 2020; Strelnikova *et al.*, 2020).

2.2.3.3 Successful implementation of Large-Scale Particle Image Velocimetry for real-world applications

There have been multiple documented cases of successful implementation of LSPIV for real-world applications.

Naka River, Japan. Lin *et al.* (2024) employed LSPIV in a mountainous river system in the Naka River basin. The use of LSPIV was explored as traditional current meters which are generally used for similar applications, were deemed impractical due to shallow depths, high velocities, and hazardous access. Lin *et al*. (2024) deployed the PIV system downstream of a dam during sediment replenishment operations. The objective was to measure surface flow velocities and monitor sediment transport dynamics. The operation was successful, with the spatial evolution of flow acceleration and deceleration zones near the replenishment site being successfully captured. Additionally, the system was able to provide near real-time feedback. A

key takeaway from the study was that LSPIV is efficient in capturing transient flow features during intervention implementation. However, Lin *et al*. (2024) does take note of the systems dependency on adequate natural seeding such as floating debris, which may not always be naturally present in a river system. The equipment utilised in this case study was a Pan-Tilt-Zoom (PTZ) camera with a refresh rate of 15 FPS. The system's power source was a solar panel which powered the camera and a Raspberry Pi system. Lin *et al*. (2024) opted to use 'Fudaa LSPIV' (Le Coz *et al.*, 2014), which is an open source software used to extract frames. The entire system was placed on a nearby bridge, the Kohama bridge, and was 45m above the channel. The camera was placed at an oblique angle of 20º to the surface of the water. The study team also opted for the use of STIV to verify the results against LSPIV results. Both methods were assessed against reliable, gauged data. The team concluded that LSPIV is preferable for measuring high-flow areas and for the creation of a flow map. However, STIV is more efficient at static locations such as near the riverbank. Figure 2.10 (Lin *et al.*, 2024) illustrates the surface flow maps created by LSPIV for four different upstream conditions. Figure 2.11 (Lin *et al.*, 2024) illustrates the results obtained from use of STIV under the same conditions as those obtained by LSPIV in Figure 2.10 Distribution of surface flow derived from the use of LSPIV under four different upstream conditions (Lin *et al.*, 2024).

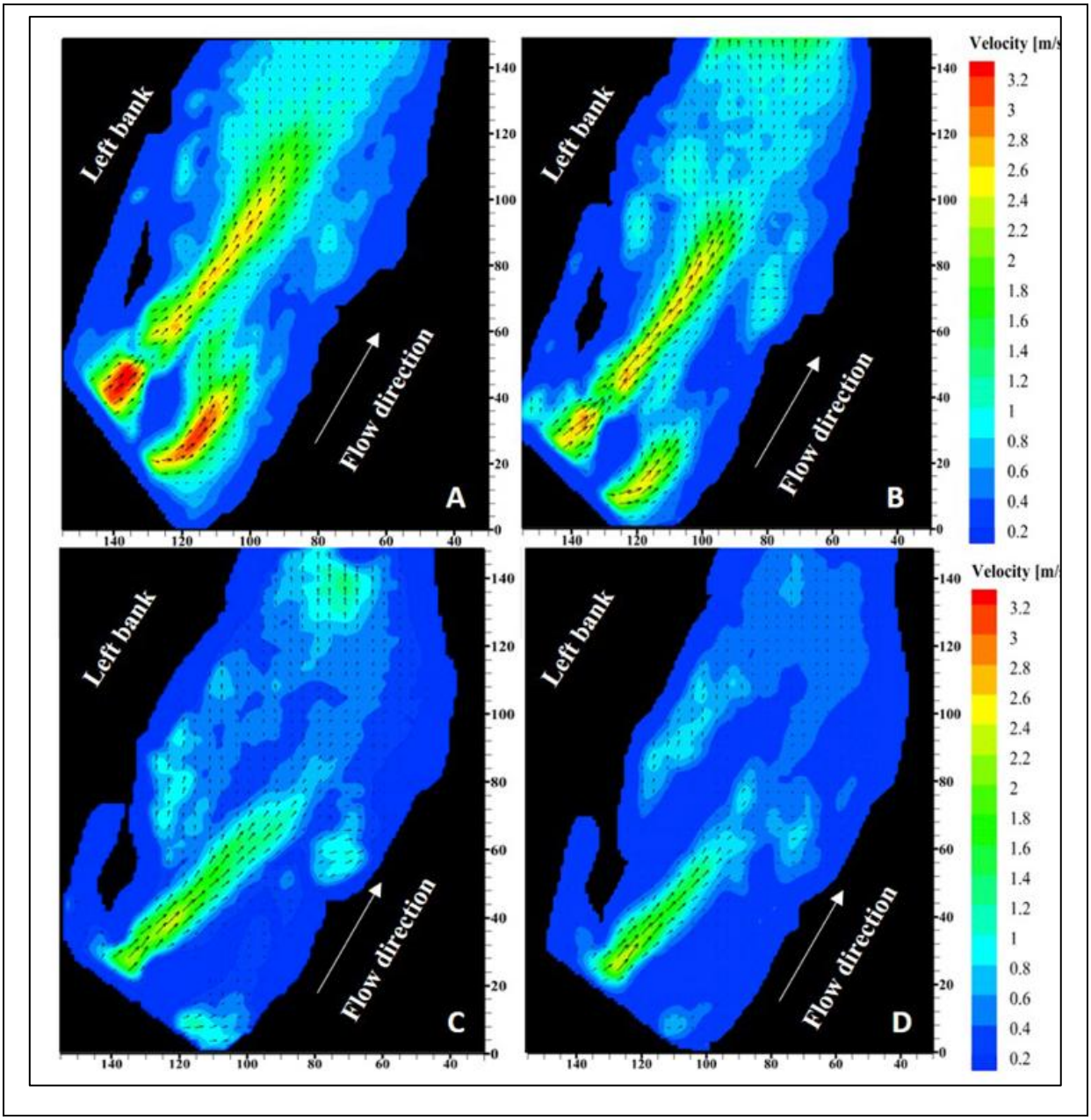


Figure 2.10 Distribution of surface flow derived from the use of LSPIV under four different upstream conditions (Lin *et al.*, 2024). (A) 900m^3/s, (B) 700m^3/s, (C) 500m^3/s, (D) 300m^3/s

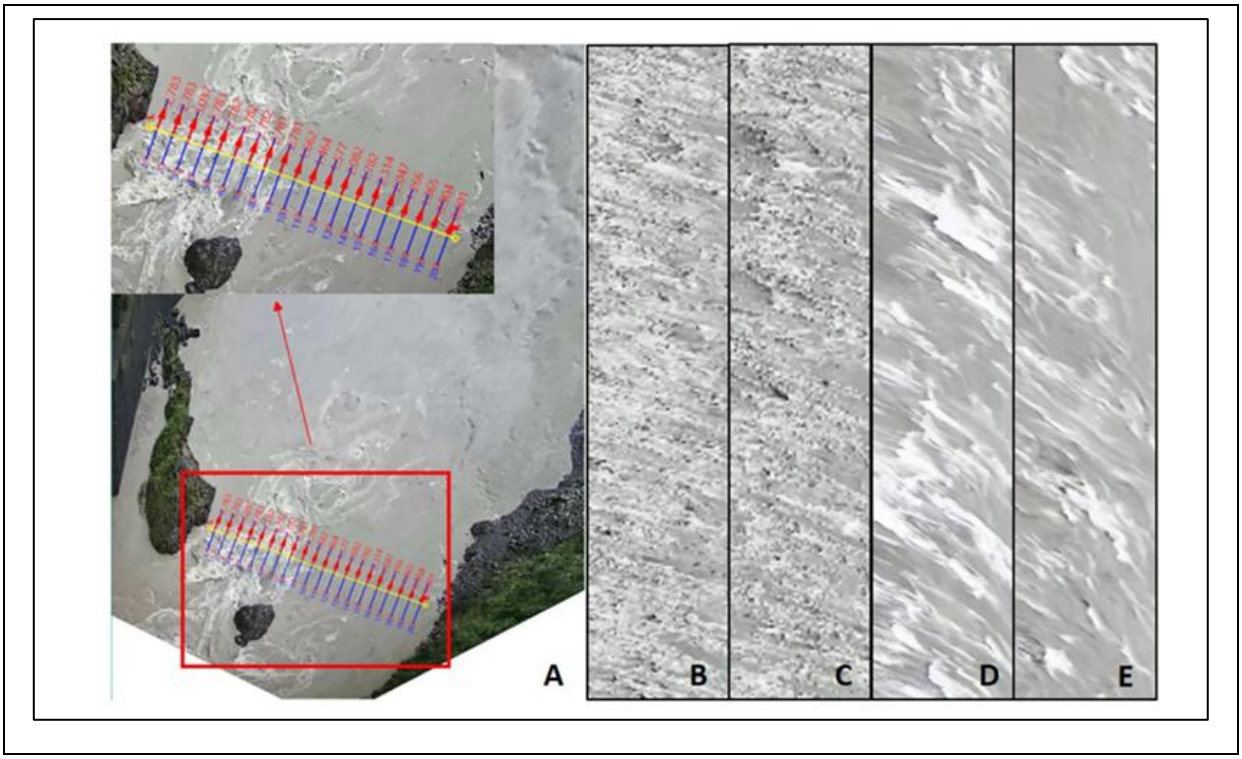


Figure 2.11 Calculated results from STIV (Lin *et al.*, 2024). (A) results obtained from Hydro-STIV, (B) 900m^3/s, (C) 700m^3/s, (D) 500m^3/s, (E) 300m^3/s

Ender Estuary, Cirebon. Tarya and Aqdam Prasetyo (2024) utilised a UAV to identify surface velocity through the use of LSPIV in both flood and ebb tides. The LSPIV-derived velocities showed a strong correlation to in-situ measurements, which validated the method's applicability for measurement of dynamic, bi-directional flows. A significant takeaway from the study was that drone altitude significantly influenced measurement uncertainty. Lower altitudes improve spatial resolution but reduce coverage, whilst higher altitudes increase perspective distortion. Figure 2.12, Tarya and Aqdam Prasetyo (2024) illustrates the surface pattern of the current as obtained by LSPIV for flood tides (bottom) and ebb tides (top).

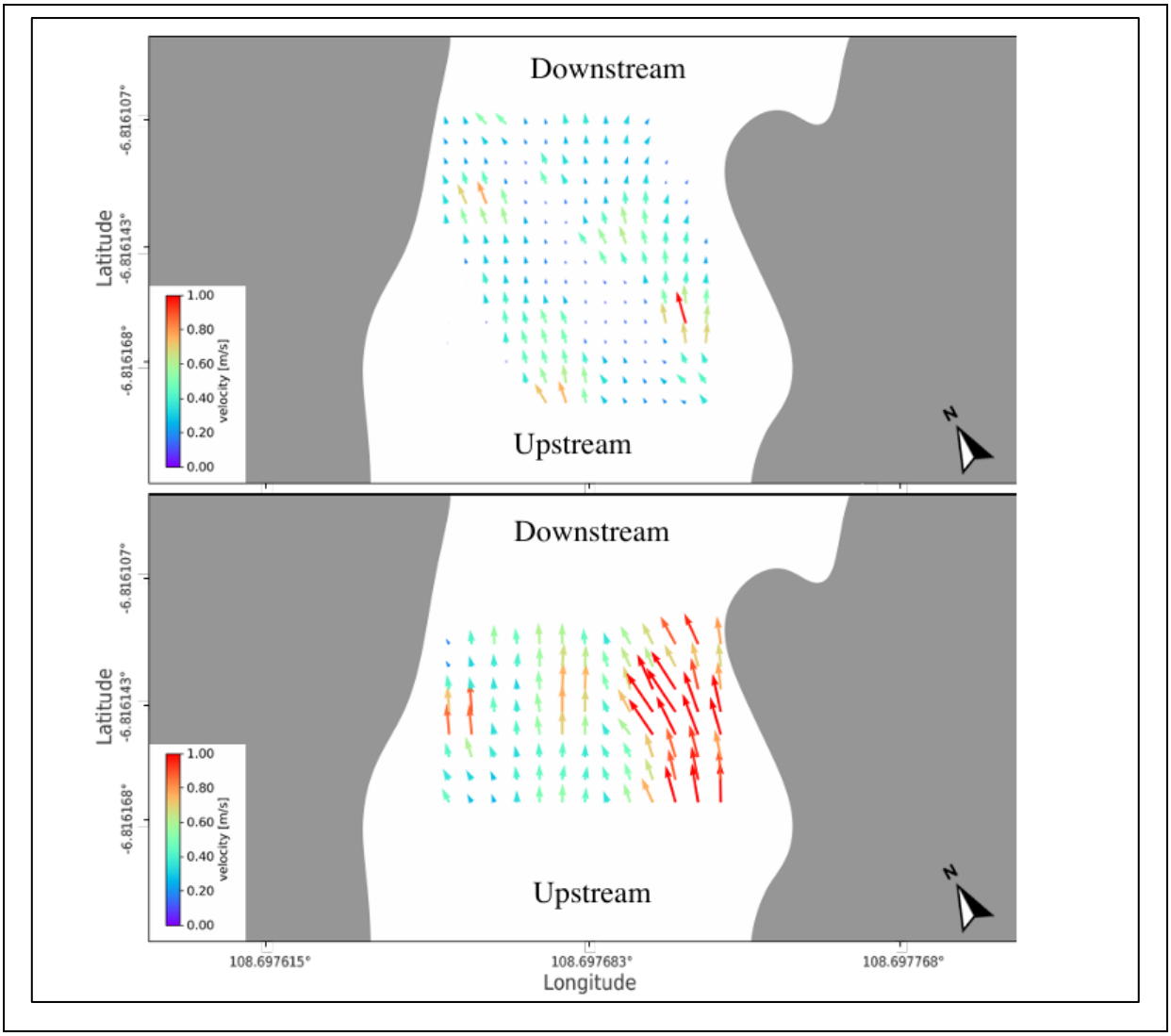


Figure 2.12 Surface current pattern obtained by LSPIV during flood tides (bottom) and ebb tides (top) (Tarya and Aqdam Prasetyo, 2024)

Shimen Reservoir, Taiwan. Huang *et al.* (2018) employed PIV for extreme events such as flash flooding. A dual-camera LSPIV was installed at multiple gauging stations to operate continuously during typhoon-induced floods. A method used by study team was to employ near-field and far-field imagery to mitigate resolution loss at distance and provide reliable discharge estimates even under the strains of an extreme event. This study used an LSPIV system which was adapted to detect large, heterogeneous surface particles, i.e. debris, which contrasts with the finer tracers used in clear-water PIV. This study confirms two important operational parameters of LSPIV: (i) LSPIV is effective under low-flows (Tarya and Aqdam Prasetyo, 2024), medium-flows (Lin *et al.*, 2024), high-flows (Tarya and Aqdam Prasetyo, 2024), and extreme-flows (Huang *et al.*, 2018) as demonstrated in Figure 2.13 Photos obtained from the dual-cameras for normal flow (a,b) and typhoon-induced flows (c,d) (Huang *et al.*,

2018), and (ii) LSPIV can be modified to detect a variety of seeding conditions with the algorithm being adjustable to handle sparse-seeding, irregular-seeding, and dense-seeding alike.

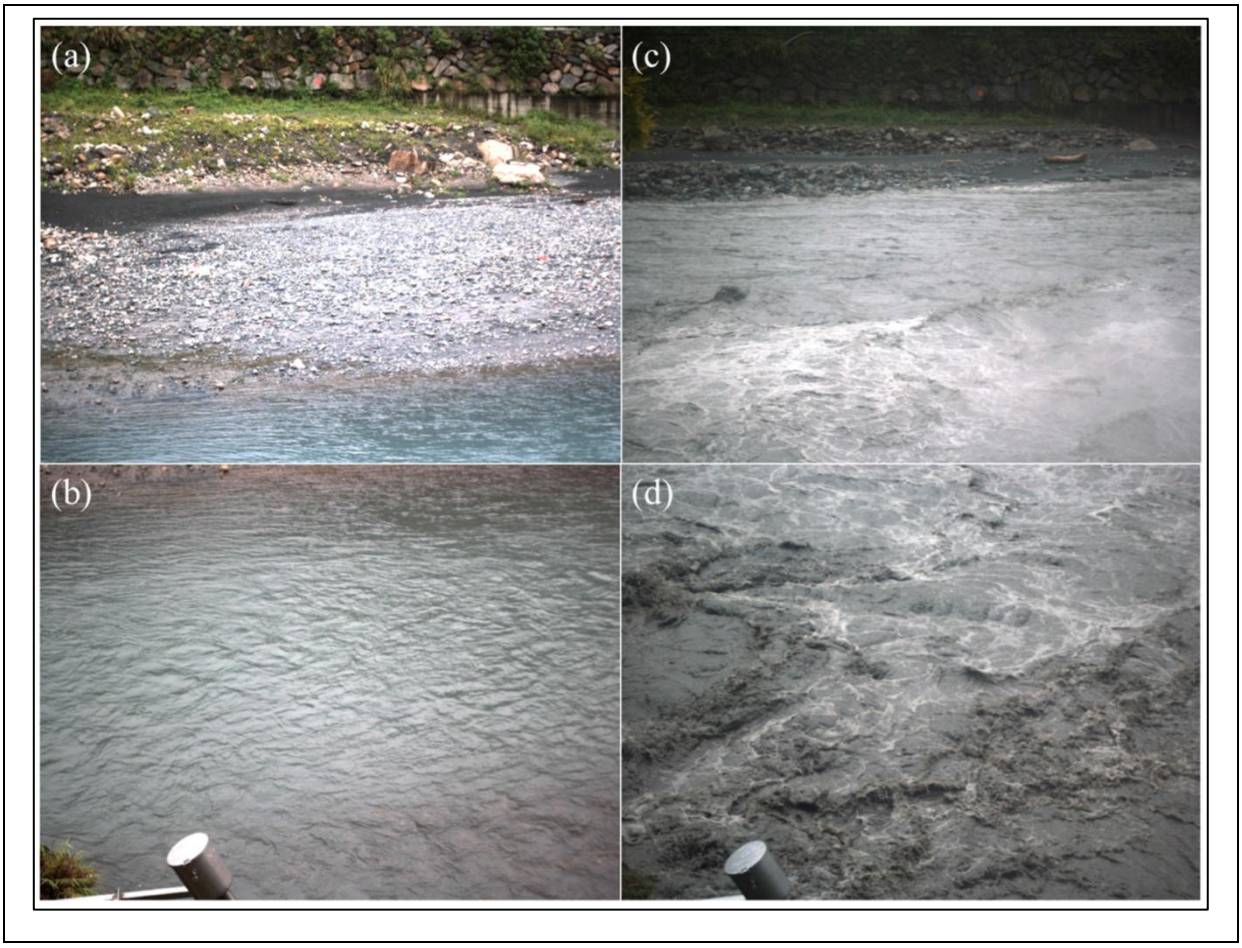


Figure 2.13 Photos obtained from the dual-cameras for normal flow (a,b) and typhoon-induced flows (c,d) (Huang *et al.*, 2018)

Additional case studies: Additional case studies have been conducted using LSPIV in the Houlong River, Taiwan (Liu *et al.*, 2021), a fish passage at a hydropower dam in Austria, using a consumer drone with artificially seeded flow (Strelnikova *et al.*, 2020), East Central Illinois River, USA (Lewis *et al.*, 2018), Murg River, Switzerland (Detert *et al.*, 2017), amongst others (Ran *et al.*, 2016; Huang *et al.*, 2018; Gonzalez *et al.*, 2022; Tesch *et al.*, 2022; Eder *et al.*, 2023; Lin *et al.*, 2024; Zhang *et al.*, 2024; Bashit *et al.*, 2025).

Table 2.1 Summary of reviewed real-life PIV application in open channel discharge measurements

Study	Location & System Setting	Channel Width (m)	Flow Regime / Discharge Range (m^3/s)	Platform & Sensor Setup	Image Acquisition Parameters	Seeding Method	Processing Software	Reference / Validation Method	Reported Accuracy / Error
Lin et al. (2024)	Naka River, Japan (Mountainous river downstream of dam)	~45	High flow & transient releases (300−900)	Fixed (Bridge mount, 45 m elevation, 20∘ oblique)	PTZ Camera @ 15 FPS; Solar & Raspberry Pi	Natural (floating debris, foam)	Fudaa-LSPIV	Gauged data & Hydro-STIV	High correlation; captured spatial acceleration/deceleration zones
Tarya & Aqdam Prasetyo (2024)	Ender Estuary, Cirebon, Indonesia	~30 – 80	Tidal (Flood & ebb regimes)	Unmanned Aerial Vehicle (UAV)	Optical camera @ 30 FPS	Natural (turbidity, surface features)	Custom / OpenCV PIV	In-situ current meters	Strong correlation; accuracy sensitive to flight altitude
Huang et al. (2018)	Shimen Reservoir, Taiwan	~100	Extreme typhoon flood events	Fixed (Dual-camera setup: near & far field)	Dual Optical Cameras @ 30 FPS	Natural (large heterogeneous debris)	Custom LSPIV	Gauged rating curve	Reliable discharge estimation under extreme sediment and flow loads
Liu et al. (2021)	Houlong River, Taiwan	~60	Medium to high flood flows	Fixed infrastructure	Optical camera @ 30 FPS	Natural	Custom LSPIV	Stream gauging station	Relative error <8% against rating curve
Lewis et al. (2018)	East Central Illinois River, USA	~25	Low to medium flow	Fixed & temporary mast	High-resolution DSLR @ 24 FPS	Artificial & natural	Fudaa-LSPIV	ADCP transects	Mean velocity deviation within 5−10%
Detert et al. (2017)	Murg River, Switzerland	~15	Low-flow regime	UAV (Low-altitude hover)	4K Action Camera @ 30 FPS	Natural ripples & tracer foam	Mobile-LSPIV / Dischargeapp	Handheld flow meter	Velocity error <6%
Strelnikova et al. (2020)	Hydropower Fish Pass, Austria	~3 – 5	Controlled low flow	Consumer UAV	HD Video @ 60 FPS	Artificial (spruce wood shavings)	PIVlab (MATLAB)	ADV point measurements	Sub-pixel accuracy (<3−5% error)

The empirical studies synthesised in Table 2.1 confirm that LSPIV is a versatile non-contact gauging technique capable of operating across low, medium, high, and extreme flow regimes (Huang *et al.*, 2018; Lin *et al.*, 2024; Tarya and Aqdam Prasetyo, 2024). Furthermore, algorithm parameters can be tuned to process diverse seeding conditions, ranging from fine artificial particles to coarse, highly heterogeneous flood debris (Huang *et al.*, 2018).

2.2.3.4 Transferability to South African conditions

Direct transferability of these global findings to sub-Saharan river systems, such as those in KwaZulu-Natal, cannot be assumed. The international literature predominantly reports on controlled laboratory flumes, managed European channels, or regulated dam releases with relatively stable bed boundaries and predictable tracer densities (Detert *et al.*, 2017; Strelnikova *et al.*, 2020; Lin *et al.*, 2024). By contrast, South African catchments present distinct operational challenges that remain largely unquantified in the context of continuous, autonomous LSPIV deployments: Rather than establishing immediate transferability, the existing literature highlights a clear research gap: the operational reliability, continuous power autonomy, and measurement accuracy of fixed-station LSPIV remain untested under the seasonal sediment, illumination, and flow dynamics typical of South African river systems. This study directly addresses this gap by designing, deploying, and evaluating a pilot virtual weir monitoring system at a dedicated field site within the uMngeni catchment in KwaZulu-Natal.

2.2.3.5 Advantages of Particle Image Velocimetry

The core advantages of PIV are related to its non-intrusion (Bashit *et al.*, 2025), full-field instantaneous measurement (Atkins, 2016), cost, versatility (Lagemann *et al.*, 2021), and safety and accessibility.

Minimal disruption of the river system due to non-intrusion: Overcoming a significant shortfall of traditional gauging structures, PIV is a completely non-intrusive method of discharge measurement (Bashit *et al.*, 2025). It does not obstruct the flow being measured, nor does it alter the river's physical or chemical properties (Muste *et al.*, 2008).

Full-field measurement: The creation of a vector field, rather than the conventional point measurement, provides instantaneous velocity vectors across an entire plane which results in comprehensive spatial information (Atkins, 2016). Atkins (2016) further explains that a

practical advantage of PIV is that it is a quantitative full-field measurement technique capable of providing physical insight into the overall flow behaviour and characteristics of the analysed channel.

Cost comparison: PIV systems generally have lower initial and maintenance costs when compared to traditional weirs and ADCPs. The cost analysis breakdown can be seen within Section 2.3.2.

Versatility: PIV can be utilised under a variety of flow conditions (Lagemann *et al.*, 2021). PIV also has versatility in its requirements, such as being able to analyse footage from specialised UAV lenses and standard smartphone cameras alike (Kim *et al.*, 2008; Tauro *et al.*, 2014; Pearce *et al.*, 2020). The method of flow monitoring via PIV is highly scalable, being viable across varying sizes of rivers, differing flow regimes, and different geographic locations as explained in Section 2.2.3.3. PIV can measure a range of flows from close to $0 m.s^{-1}$, as seen in Figure 2.10, to flows in flash floods as explored by (Huang *et al.*, 2018).

Safety and accessibility: The increased safety of the system is rooted in the use of fixed cameras and remote sensing for high-flow and potentially dangerous extreme events as demonstrated by Huang *et al.* (2018). PIV systems also allow for flow determination in otherwise inaccessible sites (Lin *et al.*, 2024). However, it is important to observe adequate safety protocols when using smartphone-based PIV.

2.2.3.6 Challenges and limitations of Particle Image Velocimetry

In the current state of PIV, there exist sources of accuracy limitations, processing complexity, and environmental hindrance.

Accuracy limitations:

a) Extent of camera visibility: Should the camera have a limited field of view, particles moving outside of this field of view can weaken the cross-correlation between frames and potentially lead to inaccurate velocity estimates (Jolley *et al.*, 2021).
b) Signal-to-Noise Ratio (SNR): Accuracy of PIV systems generally depend on strong cross-correlation SNR. Excessive noise can lead to errors in particle pattern displacement (Xue *et al.*, 2014).

c) Resolution: Lower resolution cameras can lead to inadequate capturing of tracer particles, leading to a reduced number of interrogation zones (Pearce *et al.*, 2020) across the river. This can lead to a sparse velocity field and potentially lead to non-capturing of zones of flow deceleration and acceleration (Pearce *et al.*, 2020).
d) Sensitivity to lighting and seeding: Environmental factors such as direct sunlight and shadows can affect the performance of PIV (Le Coz *et al.*, 2021). Direct sunlight may cause a glare on the water surface. The reflections saturate pixels, causing the cross-correlation algorithm to track the high-intensity reflections rather than the tracer particles (Le Coz *et al.*, 2021). This causes inaccuracies in flow measurement. Moving shadows can also be misinterpreted as tracers (Watanabe *et al.*, 2021), leading to similar distortions. However, post-processing algorithms such as intensity capping can be used to mitigate the effects of excessively imposing shadows or light sources.

Processing Complexity: PIV algorithms, particularly volumetric PIV (2D3C or 3D3C), can be computationally intensive (Pimienta and Aider, 2024). LSPIV (2D2C) may not be as computationally demanding but will require a certain level of computational competence. Typically the minimum system requirements are a power source, a single-board computer (such as Raspberry Pi), image processing software, and computational software as used by (Lin *et al.*, 2024).

2.2.3.7 Particle Image Velocimetry Processing Software

There are a few commercially available PIV processing software available. Some of these are native for use in LSPIV or STIV, whilst others are capable of being used interchangeably within both image velocimetry methods. Table 2.2 provides a summary of the PIV software utilised in real-world applications.

Software selection is not a neutral implementation detail, since the same footage processed through different packages does not yield the same velocity field. Tauro *et al.* (2017) compared LSPIV against particle tracking velocimetry and found that the two do not degrade identically as tracer density falls, with the better performing method depending on site conditions rather than being fixed. Alongi *et al.* (2026) report a sensitivity analysis across many velocity fields benchmarked against acoustic reference data, finding that one package was more robust in visually complex scenes while another was more accurate in turbid conditions.

Software availability also bears on the choice of technique. Public-domain implementations of STIV exist, including the STIV module distributed with the RIVeR package, alongside proprietary implementations such as Hydro-STIV. This matters for the present study because it means STIV can be evaluated as a secondary comparison without additional instrumentation, using the same footage captured for LSPIV.

2.2.3.8 Quantifying seeding conditions

Tracer availability governs LSPIV performance more strongly than any other environmental variable. Recent work has moved from describing seeding qualitatively towards quantifying it. Pizarro *et al.* (2020) introduced the dimensionless seeding distribution index, which combines tracer density with spatial distribution and demonstrates that clustering matters independently of density: a given percentage of surface coverage produces materially different results depending on whether tracers are evenly spread or concentrated in part of the section. Dal Sasso *et al.* (2020) extended the index to identify the optimal frame window within a video, reporting substantial reductions in discharge error relative to processing all available frames.

The practical significance for the present study is twofold. First, it establishes that an aerial coverage threshold is an insufficient criterion on its own, which has direct implications for how seeding adequacy is screened in this study, as set out in Section 3.3.5. Second, it provides a published, dimensionless basis for deciding in the field whether a capture is adequately seeded, in place of a subjective judgement, which is a precondition for the automated screening required by a continuously operating installation.

Table 2.2 Summary of commercially available PIV software

Name	PIV Method	Utilised by	Paid / Open Source	Platform / Language	Processing Mode
Fudaa-LSPIV	LSPIV	(Le Coz *et al.*, 2014)	Open Source	Java (Windows/Linux)	Post-processing
HydroSTIV	STIV	(Fujita *et al.*, 2019; Biggs *et al.*, 2022)	Paid (Commercial)	Cloud / Windows	Real-time & Post
PIVlab	LSPIV	(Stamhuis and Thielicke, 2014;	Open Source	MATLAB App	Post-processing

Name	PIV Method	Utilised by	Paid / Open Source	Platform / Language	Processing Mode
		Bashit *et al.*, 2025)			
KU-STIV	STIV	(Fujita *et al.*, 2007; Kim *et al.*, 2008; Fujita *et al.*, 2019)	Academic	Windows Executable	Real-time focus
OpenPIV	LSPIV	(Ben-Gida *et al.*, 2020; Liberzon *et al.*, 2021)	Open Source	Python / C++	Post-processing
RIVeR	LSPIV/STIV	(Patalano *et al.*, 2017; Jolley *et al.*, 2021)	Open Source	MATLAB / Python	Post-processing
OpenRiverCam	LSPIV/STIV	(Le Coz *et al.*, 2021)	Open Source	MATLAB/ Python	Post-processing

2.2.3.9 Virtual weirs

A comprehensive image-based virtual gauge, termed ‘virtual weir’, is a digital integration of surface velocity, channel geometry and channel hydraulics (Tauro *et al.*, 2016). A virtual weir makes use of mathematic transformations through the use of a correctional factor to convert surface flow patterns into volumetric flow rates (Manfreda *et al.*, 2024).

Effective operation of virtual weirs relies on three critical components: (i) kinetic measurement, (ii) velocity coefficient, and (iii) static bathymetry (Jolley *et al.*, 2021; Chen *et al.*, 2022; Tsubaki *et al.*, 2025):

a) Kinetic Measurement: The use of LSPIV allows for effective generation of a 2D velocity field by tracking the movement of tracer particles along the surface of the water over time (Jolley *et al.*, 2021).
b) Velocity Coefficient: A depth-averaged velocity coefficient is needed to convert surface flow velocity (2D) obtained by LSPIV into discharge flow rates (3D) along the

water column (Tsubaki *et al.*, 2025). This coefficient is based on factors such as bed roughness and channel morphology (Tsubaki *et al.*, 2025). Factors such as riverbed structure, river profile, current aspect ratio, and Reynolds number will contribute to the conversion of surface velocity to depth velocity (Bandini *et al.*, 2021). The depth average velocity is the product of surface average velocity and a velocity index (Zhang *et al.*, 2024). The magnitude of this coefficient is not a universal constant and must be either assumed from published ranges or empirically derived for the specific site. ISO 748:2021 (fifth edition), the current international standard for velocity-area gauging, which explicitly covers surface-velocity systems and includes an uncertainty annex (Annex D), indicates that the ratio of depth-averaged to surface velocity typically ranges between 0.84 and 0.90, with the upper end of this range associated with smoother beds and the lower end with coarser, rougher beds such as those composed of rock or gravel (ISO, 2021). This range is consistent with the classical multi-point velocity-profile method of Rantz (1982), in which the mean column velocity is derived from a weighted combination of velocities measured at fixed fractions of total depth: the 0.2 and 0.8 depths for the standard two-point method, or the 0.6 depth alone for the one-point method (surface readings belong instead to the six-point method). This has a direct implication for PIV-based virtual gauging stations, which measure only the surface velocity component: unless the velocity index is empirically calibrated on site or dynamically estimated, a fixed coefficient risks introducing systematic bias into the derived discharge, particularly during unsteady or flood flows when the vertical velocity profile deviates most strongly from its low-flow shape.

c) Static Bathymetry: Chen *et al*. (2022) states that for surface flow velocity to effectively be used to calculate discharge, a river cross-sectional area (A) must be mapped. So long as this cross section remains unchanged, the area will remain a known variable.

2.3 Comparative Analysis of the River Flow Gauging Methods

For an accurate comparative analysis between the different methods (traditional gauging stations, ADCPs, LSPIV) of river flow gauging, key factors such as accuracy, cost, environmental impact, and related disadvantages will need to be comprehensively accounted for.

2.3.1 Accuracy analysis

The accuracy attainable by each gauging technique is compared in Table 2.3 which reports the quantity measured directly, the uncertainty achieved under ideal conditions, the uncertainty observed under disturbed or extreme conditions, and the reference benchmark against which each figure was established. Traditional gauging structures and Acoustic Doppler Current Profilers occupy a comparable position under ideal conditions, both returning discharge to within approximately 2 to 5%, although the two degrade for different reasons: the structure degrades as its approach channel silts, its crest erodes, or its downstream control drowns out, whereas the profiler degrades as suspended sediment attenuates the acoustic signal or a mobile bed corrupts the bottom-tracking reference (Morlock, 1996; Kusher, 2020; ISO, 2021). Image velocimetry must be assessed separately for the quantity it measures directly and the quantity ultimately required, since surface velocity is recovered to within approximately 5 to 10% under favourable illumination and seeding, which is comparable to the contact methods, whereas integrated discharge derived from that velocity field carries approximately 10 to 15% uncertainty under ideal conditions and between 25 and 40% under disturbed conditions (Muste *et al.*, 2008; Le Coz *et al.*, 2021; Torres *et al.*, 2024). The additional uncertainty arises after the velocity measurement, in the conversion of surface velocity to volumetric flow, where the velocity index adopted and the currency of the surveyed cross-section both govern the result. Consequently, Table 2.3 does not rank the three techniques on a single accuracy scale. It establishes that the dominant contribution to image velocimetry discharge uncertainty lies in a conversion step that requires local quantification before the method can be relied upon in a South African river.

Table 2.3

Summarised comparative accuracy analysis of the different flow gauging techniques

Gauging Technique	Measured Quantity	Typical Uncertainty (Ideal Conditions)	Uncertainty Under Disturbed / Extreme Conditions	Reference Benchmark / Standard	Primary Sources of Measurement Error	References
Traditional Gauging Structures (Weirs & Flumes)	Stage (h) -> Discharge (Q)	±2% - 5%	±10% - 20%	ISO 1438 (Thin-plate weirs); Hydraulic laboratory flume calibration	Siltation / sedimentation in weir pool, downstream submergence, crest erosion, dynamic bed scour	(Kusher, 2020; ISO, 2021)
Acoustic Doppler Current Profilers (ADCP)	3D Velocity Profile & Integrated Discharge (Q)	±2% - 5%	±15% - 25%	ISO 748; Price AA current meter transects	High suspended sediment loads (acoustic attenuation), moving bed conditions, near-surface/near-bed blind zones	(Morlock, 1996; Oberg and Mueller, 2007)
LSPIV (Velocity Only)	2D Surface Velocity Vector (V_surf)	±5% - 10%	±15% - 25%	Point ADV / Micro-propeller flow meters; PIVlab / Laboratory PIV	Surface illumination / glare, low tracer seeding density, wind shear, orthorectification errors	(Torres *et al.*, 2024)
LSPIV (Integrated Virtual Weir)	Total Volumetric Discharge (Q)	±10% - 15%	±25% - 40%	Synoptic ADCP transects; Rated physical gauging stations	Compounded error from V_surf, uncertain/variable velocity index (alpha), unmapped bathymetric scour during high flow	(Muste *et al.*, 2008; Le Coz *et al.*, 2014)

2.3.2 Cost estimate analysis

A major constraint to the development and sustainability of national flow gauging networks is the high cost associated with the different primary and supplementary flow gauging techniques (Tauro *et al.*, 2016). The three techniques differ less in total expenditure than in where that expenditure falls. Traditional gauging structures commit the greatest proportion of cost before any record is produced, since the civil works, the environmental authorisation, and the recurring operation and maintenance obligation are all incurred at a single fixed cross-section (Adeogun and Mohammed, 2019). Acoustic Doppler Current Profilers remove the civil works but concentrate cost in a transportable instrument requiring trained operation, so that recurring cost scales with the number of site visits rather than with the number of sites instrumented (Oberg and Mueller, 2007). Image velocimetry displaces majority of the cost from infrastructure towards calibration and processing effort, since acquisition hardware may be drawn from general-purpose consumer components, whereas the velocity index determination and the cross-sectional survey on which discharge depends must still be established and maintained at every site (Tauro *et al.*, 2017).

2.3.3 Analytical overview

The analysis of the three systems reveals a broadly inverse relationship between measurement certainty and deployment flexibility. Traditional gauging structures offer the lowest error margins but the least spatial and hydraulic flexibility, being fixed, capital-intensive, and often unsuitable for high-flow conditions. ADCPs narrow this gap, achieving comparable accuracy while removing the need for a permanent structure, but they retain a dependency on physical river access and remain vulnerable to the same high-flow conditions that require reliable discharge data. PIV-based methods relax both constraints simultaneously, requiring no in-channel infrastructure and remaining operable across a wide range of flow conditions, but at the cost of a wider and less predictable accuracy envelope, with documented degradation from glare, shadow, and cross-sectional uncertainty. None of the three technologies is therefore unconditionally superior; each occupies a different point on the trade-off between data quality, deployment cost, and operational resilience. This suggests that the most effective strategy for a data-sparse, resource-constrained context such as South Africa is not wholesale replacement of the existing gauging network, but a tiered approach in which PIV-based virtual gauges extend spatial and temporal coverage into currently ungauged reaches.

2.4 Discussion and Conclusion

The declining state of traditional flow gauges (Johnson *et al.*, 2021; Long *et al.*, 2025) necessitates the paradigm shift of river discharge measurement techniques away from expensive (DWS, 2017) and ecologically disruptive structures, toward innovative ex-situ methods. The cost barriers of expensive gauging structures limit its usage, resulting in poor spatial coverage of spatial data. While traditional weirs provide theoretically grounded stage-discharge relationships (Bos, 1976; Badhe *et al.*, 2015), they depend on continually sustained maintenance and structural integrity to preserve output data quality. Additionally, the poor performance of gauging structures in high-flow conditions (Clemmens *et al.*, 2001; Chanson, 2004), results in an absence of critical quantification of flood data. ADCPs offer detailed velocity field mapping (Figuérez *et al.*, 2021) but remain sensitive to hydraulic complexity and operational constraints (Sočuvka *et al.*, 2024). Optical methods, such as LSPIV, embody a paradigm shift toward a fully ex-situ (Bashit *et al.*, 2025) measurement method capable of enhancing scalability and reducing infrastructure dependency in hydrometry, or supplementing existing gauging infrastructure.

This evolution, however, does not represent a linear improvement in accuracy. Rather it shifts the uncertainty from structural uncertainty in physical gauging stations (Clemmens *et al.*, 2001), to performance uncertainty of ADCP and PIV equipment functionality under non-ideal field conditions (Muste *et al.*, 2004; Jolley *et al.*, 2021; Le Coz *et al.*, 2021; Sočuvka *et al.*, 2024). The introduction of LSPIV into the river flow gauging regime provides a platform for citizen science integration by way of smartphone-based PIV. This represents a shift from in-situ citizen science methods such as use of a Transparent Velocity Head Rod (TVHR).

In a current regime defined by declining gauging infrastructure, limited maintenance, and hydrological variability, the ideal measurement system will need to primarily display scalability, resilience, and precision. The ideal system will also be one that can operate under financial, technical, and geographical restrictions i.e. low cost, easy to use and understand, and ability to operate in river systems with poor accessibility. The identified research gaps highlight the urgent need for a comprehensive assessment of remote-sensing based methods in a South African context. The subsequent research seeks to critically evaluate the potential of remote sensing techniques to accurately determine discharge flow measurements and contribute to the national river flow gauging regime. A crucial faculty of the study will be on improving the

sustainability of the current river gauging techniques in terms of cost, location, accessibility, and technical requirements.

Three gaps follow from this review. First, the parameter calibrations that govern image velocimetry accuracy, principally the velocity index, have been derived almost entirely in stable, perennial channels, and their transferability to the variable flows, high sediment loads and shifting bed morphology of South African rivers has not been established. Second, the comparative economics of gauging structures, ADCPs and image velocimetry have not been assessed under South African market conditions, despite cost being the decisive constraint on a contracting national network. Third, there is no operational guidance on how image-derived measurements would meet the data quality and traceability requirements of the national hydrometric record, without which technical accuracy alone does not translate into adoption.

These gaps converge on a single question: can image velocimetry produce discharge measurements of known and acceptable uncertainty under South African river conditions? Answering it requires the accuracy of the surface velocity measurement and the uncertainty introduced by its conversion to discharge to be established together rather than separately, since a method of unquantified uncertainty extends the monitoring record in neither reach nor confidence. The project proposal that follows addresses this question through a single-site pilot in the uMngeni Catchment, in which fixed-camera, mobile, and potentially UAV footage derived velocimetry are benchmarked against a rated reference across a full annual cycle.

3. PROJECT PROPOSAL

3.1 Background and Research Gap

A prevalent decline in the river flow gauging network within South Africa is well documented in recent hydrological literature (Johnson *et al.,* 2021; Long *et al.,* 2025). The comparative review presented in Chapter 2 establishes that image velocimetry offers a non-contact alternative to traditional gauging structures and Acoustic Doppler Current Profilers, and that it occupies a distinctly different position on the trade-off between measurement certainty, capital cost, and operational resilience. That review further establishes that the parameters governing image velocimetry accuracy, in particular the velocity index and the seeding conditions required for reliable tracking, have been derived almost entirely in perennial channels outside southern Africa. Consequently, the conditions under which the method can be relied upon within a South African river regime remain insufficiently quantified.

Although international research demonstrates the successful application of image velocimetry across river systems in Europe, Asia, and North America, the direct transfer of these approaches to the South African hydrometric context remains constrained by distinct environmental and operational conditions. South African rivers are frequently characterised by highly variable flow regimes, substantial sediment transport, seasonal vegetation encroachment, and complex and rapidly changing channel morphology. A critical synthesis of the literature reviewed identifies four principal knowledge gaps that currently limit the broader adoption and operationalisation of image-based discharge measurement within South Africa.

First, there remains a significant gap in empirical validation and parameter calibration under South African river conditions. As discussed in Section 2.2.3, the majority of published LSPIV surface velocity models and velocity index calibrations, including the alpha values used to relate surface velocity to mean cross-sectional velocity, have been developed and validated predominantly in stable, perennial, and relatively low-gradient river systems in Europe and North America. Consequently, there is limited empirical, field-based evidence regarding how conventional optical processing parameters perform under South African conditions. In particular, the effects of cross-correlation search window dimensions, surface tracer availability and tracking efficiency, image quality, and orthorectification accuracy under high turbidity, flash flood prone, and morphologically variable conditions remain insufficiently quantified. It therefore remains uncertain whether parameterisations established in

comparatively stable international environments can be transferred directly to South African rivers without site-specific calibration.

A second gap concerns the rigorous assessment of measurement accuracy and the propagation of uncertainty through the complete discharge estimation process. As demonstrated in the accuracy synthesis presented in Section 2.3.1 and Table 2.3, uncertainty in optical surface velocity estimation does not translate directly into an equivalent uncertainty in discharge. Instead, total discharge uncertainty may arise from the cumulative effects of surface velocity measurement error, uncertainty in the velocity index relationship, channel geometry, and temporal changes in the cross-sectional profile. Comprehensive end-to-end uncertainty assessments under South African field conditions remain limited, particularly where measurements are affected by severe solar glare, insufficient natural surface tracers, wind-induced surface disturbances, rapidly changing flow conditions, and scour or deposition that alters channel geometry. There is consequently a need for systematic benchmarking of optical discharge estimates against synchronous, high-confidence reference measurements, such as ADCP transects, established gauging structures, or controlled laboratory flume measurements. Such comparisons would allow the individual sources of uncertainty to be quantified and their cumulative effect on final discharge estimates to be established.

A further knowledge gap relates to the operational standardisation of mobile and citizen science approaches to image velocimetry. Mobile and smartphone-based image velocimetry provides a potentially scalable means of supplementing conventional monitoring networks, particularly at ungauged or intermittently monitored sites. However, handheld image acquisition introduces additional sources of variability that are largely absent from fixed camera installations, including uncontrolled camera orientation, camera movement, variable frame rates, inconsistent imaging geometry, and differences in operator competency. There is currently insufficient quantitative evidence regarding the magnitude and relative contribution of these factors to measurement uncertainty. Limited research has established standardised acquisition procedures or quantified error budgets that distinguish between measurements collected by trained and untrained operators. Establishing such protocols is therefore necessary if mobile image velocimetry is to provide reproducible measurements suitable for operational hydrometric applications rather than remaining primarily a research-oriented technique.

Finally, an important institutional gap exists concerning the standardisation and integration of image-derived measurements within national hydrometric data systems. South African water

resource management depends on validated and quality-controlled hydrometric observations, including datasets managed through the Department of Water and Sanitation (DWS). The operational adoption of alternative measurement technologies therefore requires not only demonstrated technical accuracy but also data quality, traceability, and compatibility with established hydrometric systems. At present, no clearly established framework has been demonstrated for the systematic ingestion, quality assurance, validation, and archival of non-traditional velocity measurements, including image-derived and potentially citizen science observations, within national hydrometric databases. This limitation is partly attributable to the relatively limited availability of systematic side-by-side validation against established DWS gauging infrastructure across both low and high flow conditions. Consequently, the institutional pathway through which image-derived measurements could be assessed, quality controlled, assigned confidence levels, and incorporated into existing hydrometric data management systems remains insufficiently defined.

Collectively, these gaps indicate that the principal research challenge is no longer simply to demonstrate that image velocimetry can measure surface velocity. Rather, the critical requirement is to establish whether the technique can produce accurate, reproducible, uncertainty-characterised, and operationally transferable discharge measurements under the specific environmental and institutional conditions encountered in South Africa. Addressing these gaps would provide the empirical basis necessary to progress image velocimetry from an internationally demonstrated measurement technique towards a validated and operationally viable component of South Africa's broader hydrometric monitoring framework.

3.2 Project Aim

The aim of this research is to determine whether image velocimetry can produce river discharge estimates of known and acceptable uncertainty under South African river conditions.

3.2.1 Sub-objectives

This aim is addressed through four sub-objectives:

I. To quantify the sensitivity of LSPIV surface velocity accuracy to environmental factors, surface tracer density, and channel geometry at a pilot site.

II. To derive a stage-dependent velocity index relating mean cross-sectional velocity to surface velocity at that site, and to report the scatter of that relationship across the observed flow range.

III. To quantify the total uncertainty of LSPIV-derived discharge relative to synchronous reference gauging, propagated from surface velocity measurement error, the velocity index, and the surveyed cross-sectional geometry.

IV. To compare the discharge accuracy and operational reliability of a fixed-camera installation against handheld smartphone acquisition at the same site and over the same flow range.

3.2.2 Research Hypotheses

I. Surface tracer availability, rather than solar illumination glare, is the dominant control on LSPIV surface velocity error at the pilot site.

II. The velocity index at the pilot site varies with stage rather than remaining constant across the observed flow range.

III. Surveyed cross-sectional geometry contributes a greater share of total discharge uncertainty than surface velocity measurement error.

IV. Handheld smartphone LSPIV exhibits a greater variance in discharge error than the fixed-camera installation at the same site and over the same flow range.

3.3 Methodology

This section provides an overview of the practical, field-based methodology to investigate the feasibility and effectiveness of deploying low-cost, image-based virtual gauges for river flow monitoring.

3.3.1 Site selection

A pilot site will be selected through a structured screening process applied to the active gauging stations of the uMngeni Catchment. Candidate sites will be assessed against three sets of criteria covering weir geography and reliability, hydraulic suitability, and logistical accessibility. Stations with a history of exceedance will be excluded, since exceedance

invalidates the stage-discharge relationship and would compromise the reference measurement. Remaining candidates will be ranked using the published DWS data-quality codes, and the highest-ranked candidate will be verified in the field before installation.

The measurement section will be established on a straight, uniform reach a short distance downstream of the retained gauging weir, positioned so that no tributary inflow occurs between the two. Discharge continuity then holds, and the weir provides a continuous, independently rated reference discharge at the measurement section for the full monitoring period. This removes the principal weakness of validating an image-based method at an ungauged reach, where the reference is available only when an operator is present.

3.3.2 Monitoring period and sampling regime

Monitoring will run continuously across a full annual cycle so that all flow regimes encountered at the site are represented. The controlling requirement is coverage of the flow range rather than elapsed time, and monitoring will be extended if any part of the range remains unrepresented. This is expected to span to capture the full seasonal range of the catchment, comprising dry-season low flows and wet-season high flows. A single fixed installation at a single site is used, and the study is therefore explicitly a single-site pilot rather than a multi-catchment validation. Smartphone footage and, if sufficient budget is available, UAV footage will be taken congruently and processed. The results will be compared against the fixed-camera system benchmark.

Two candidate regimes are under consideration: three captures per day scheduled in the morning, around midday and in the late afternoon; or captures that align directly with the DWS recording interval, giving roughly eight captures per day and permitting timestamp-matched comparison without interpolation. The DWS aligned regime is preferred on measurement grounds and will be adopted provided the energy budget supports it under winter and multi-day overcast conditions; the reduced regime is retained as the fallback. The regime adopted, and the energy analysis supporting it, will be stated before monitoring begins. Event-triggered capture at higher frequency during rising stage will be considered in addition to the routine schedule, since the routine interval alone is unlikely to resolve flash events adequately. Each capture will be paired with the reference discharge derived from the weir rating curve at the corresponding timestamp. It is important to distinguish this figure from the effective sample size for the accuracy analysis. Successive captures taken hours apart under near-identical flow

conditions are strongly autocorrelated and do not constitute independent observations, so the number of captures will not be used as the sample size in any inferential statistic. Independence will instead be established by stratifying the record into low, medium and high flow bands defined from the observed stage record, and by treating independent reference gauging as the unit of analysis. Additionally, independent velocity-area gauging using a handheld flow meter will be undertaken at approximately monthly intervals and opportunistically during rainfall-driven high-flow events to be used as a supplementary reference.

3.3.3 Reference measurement and its stated uncertainty

Two reference measurements are used. The primary continuous reference is the discharge derived from the established rating curve at the nearby gauging weir, which is available at every LSPIV capture time. The secondary and independent reference is a set of velocity-area gauging undertaken with a handheld flow meter at a rated cross-section, following the procedures set out in ISO 748:2021. Reported uncertainty for well-maintained rating curves is typically in the order of 5 to 10 per cent, and for velocity-area gauging conducted under favourable conditions in the order of 5 to 7 per cent at the 95 per cent confidence level. These figures will be recorded alongside each comparison so that LSPIV error is never reported against a reference treated as exact.

3.3.4 Determination of the velocity index

The velocity index relating mean cross-sectional velocity to surface velocity is identified as the dominant systematic error in image-based discharge estimation and is therefore determined empirically at the site rather than adopted from published ranges. Vertical velocity profiles will be measured at multiple depths across the rated cross-section using a handheld flow meter, following United States Geological Survey guidance (Rantz, 1982). Mean column velocity will be derived using the six-point method at surface, 0.2, 0.4, 0.6, 0.8 of the total depth and bottom. Where this is impractical due to shallow water, the standard two-point method of 0.2 and 0.8 depth will be taken. The velocity index is then computed as the ratio of mean column velocity to the concurrently measured surface velocity. A separate velocity index will be derived for each surveyed flow condition rather than a single site-wide constant.

3.3.5 Illumination, glare and operating window

Unprocessed captures will be systematically screened against defined rejection criteria covering saturated pixel fraction within the interrogation area, shadow encroachment across the measurement section, and visible surface disturbance from wind. Rejected captures will be logged with the reason for rejection, and the rejection rate will be reported as a result, since the proportion of captures usable under operational conditions is directly relevant to the feasibility claim being tested. Night-time and low-light operation will not be attempted, and the resulting loss of temporal coverage is stated as a limitation of the study.

3.3.6 Image acquisition system specification

The fixed installation is specified by capability rather than by product, so that the requirement remains valid if a particular model becomes unavailable. The camera shall be an outdoor-rated fixed unit with an ingress protection rating of at least IP66. Minimum capture resolution is 1920 by 1080 pixels at a sustained frame rate of at least 25 frames per second, with manual control of exposure, gain and focus, since automatic exposure adjustment between frames introduces apparent motion that corrupts cross-correlation. Lens focal length shall be selected so that the measurement section spans the majority of the frame width at the intended standoff distance, and a circular polarising filter shall be fitted to reduce specular reflection from the water surface.

The governing acquisition constraint is that inter-frame tracer displacement must fall within approximately one quarter of the interrogation window. Ground sampling distance, camera depression angle and mounting height will therefore be determined together from the expected surface velocity range at the site rather than selected independently, and the resulting displacement verified against this criterion before the installation is finalised. Mounting height and depression angle will additionally be constrained so that the full measurement section remains within the field of view at the highest stage of interest, and so that at least four ground control points of known position remain visible and above water across the full stage range.

3.3.7 Cross-section re-survey and morphological change

A baseline cross-section survey will be undertaken at installation, and the section will be re-surveyed under each distinct flow condition encountered across the monitoring period rather than on a fixed calendar interval. Surveying by flow condition serves two purposes: it detects

scour and deposition, which are most likely to occur during and after high flows, and it provides the concurrent geometry required for the flow-specific velocity index described above. Each survey will be paired with the stage and velocity index determination made at the same time, so that geometry, index and discharge estimate share a common flow condition. Survey dates and the corresponding stage will be recorded against every discharge estimate so that geometric provenance is traceable.

3.3.8 Contingency for absent surface seeding

Insufficient natural surface tracer is identified as the principal operational weakness of LSPIV and is anticipated to be a live constraint at any clear-water site during sustained low flows. Where a capture fails the seeding-density screening criterion, artificial seeding will be introduced upstream of the measurement section using an inert biodegradable tracer distributed across the channel width. Where artificial seeding is not practical, the capture will be excluded and recorded as a seeding failure, and the frequency of such failures across the flow range will be reported.

3.3.9 Data analysis

Acceptance criteria for the comparison are defined in advance. Fixed-camera LSPIV discharge estimates will be regarded as fit for operational supplementary use where the mean absolute percentage error relative to the reference does not exceed 15 per cent across the observed flow range, with no systematic bias exceeding 10 per cent within any individual flow band, and where the Nash-Sutcliffe efficiency of the derived time series exceeds 0.75. Handheld smartphone estimates will be assessed against the same criteria. These thresholds are stated as pre-registered targets against which performance will be judged, not as expected outcomes, and failure to meet them constitutes a reportable result rather than a failed study.

Uncertainty will be propagated from surface velocity measurement error, through the velocity index relationship and the surveyed cross-sectional geometry, to final discharge, following the framework of JCGM 100:2008 and the guidance in ISO 748:2021 Annex D. The contribution of each component to the combined standard uncertainty will be reported separately.

A detailed analysis and investigation of the data obtained from both the fixed-camera and smartphone image velocimetry systems will be conducted with a key focus on their technical quality of results and their suitability for utilisation within a South African water resource

management context. Fixed-camera and smartphone discharge estimates will each be compared against the synchronous reference gauging record using: linear regression with 95% confidence intervals; root-mean-square error (RMSE) and mean bias; the Nash-Sutcliffe efficiency (NSE) and percent bias (PBIAS) for the continuous time series; and a Bland-Altman agreement analysis. Uncertainty will be propagated from surface velocity measurement error, through the velocity index relationship, to cross-sectional area and final discharge following the ISO 748:2021 Annex D. Handheld captures will be corrected for platform motion by post-processing frame stabilisation and dynamic ground control point mapping before discharge is derived, so that the comparison isolates residual motion error rather than uncorrected camera movement.

3.4 Work Plan and Deliverables

The study is scheduled over 24 months from registration. Phase 1 (months 1 to 4) covers the literature review, site screening and project proposal. Phase 2 (months 5 to 7) covers installation of the fixed camera system, the baseline cross-section survey, establishment of ground control and commissioning of the stage determination method. Phase 3 (months 8 to 19) is the monitoring period, running across a full annual cycle so that dry-season low flows, wet-season high flows and the transitions between them are represented, with periodic reference gauging, flow-condition re-surveys and velocity index determinations undertaken throughout. Phase 4 (months 20 to 22) covers data processing, uncertainty analysis and the accuracy comparison. Phase 5 (months 23 to 24) covers dissertation writing and submission. The controlling constraint is Phase 3, since coverage of the upper flow range depends on rainfall and cannot be compressed.

The deliverables of the study are: (a) a commissioned image velocimetry monitoring installation at the pilot site; (b) a stage-dependent velocity index relationship for the site, with its scatter reported; (c) a paired dataset of image-derived and reference discharge estimates spanning the observed flow range; (d) an end-to-end uncertainty budget attributing error to surface velocity, velocity index and cross-sectional geometry; (e) a comparative cost analysis under South African market conditions; (f) the dissertation; and (g) at least one paper submitted to a peer-reviewed journal.

3.5 Equipment and Resources

The fixed installation requires an outdoor-rated camera meeting the specification in Section 3.3.6, a circular polarising filter, a weatherproof enclosure, a pole or bracket mount, a solar panel with charge controller and battery, a single-board computer for on-site processing, and a cellular modem for data transmission. Field measurement requires a dumpy level and staff, a handheld electromagnetic or mechanical flow meter, a transparent velocity head rod, a survey tape, and rods or visible markers. Ground control points require durable markers and fixings. Consumables include inert biodegradable tracer for artificial seeding. Software requirements are met by open-source tools, comprising an image velocimetry processing package and a space-time image velocimetry implementation, together with a statistical environment for the uncertainty analysis.

- Hazardous materials clearance (Y/N): N
- Ethical clearance required (Y/N): N
- Confidentiality agreement required (Y/N): Y

3.6 Contribution to Knowledge

The international literature has established that image velocimetry can measure surface velocity accurately under favourable conditions, and has quantified the principal error sources, notably the velocity index, seeding distribution (Pizarro *et al.*, 2020) and operator effect (Bodart *et al.*, 2024). What that literature has not established is how those findings translate to the seasonal dynamism of South African rivers. This study is positioned in that gap and makes two major contributions.

First, it produces a stage-dependent velocity index for a South African river site under high sediment load and variable flow, in place of the single site constant assumed in most published applications. The index is derived across the observed flow range rather than at one condition, so its variability with stage becomes a measured quantity rather than an assumption. Second, it reports an end-to-end uncertainty classification in which the contribution of surface velocity, velocity index and cross-sectional geometry are separated, so that the dominant error term is identified rather than inferred. Torres *et al.* (2024) demonstrated that discharge error in image velocimetry is driven principally by cross-sectional geometry rather than by the velocimetry itself, and this study tests that finding under South African conditions.

The intended outcome is not a claim that image velocimetry should replace the existing gauging network, but a defensible statement of the conditions under which it can extend that network, and of the uncertainty that extension carries.

Intellectual property arising from the study is governed by the University of KwaZulu-Natal intellectual property policy, and by the terms of the support provided by GroundTruth and uMngeni-uThukela Water. The processing software used is open-source and no proprietary algorithm is developed, so the intellectual property arising is confined to the derived datasets, the velocity index relationship, and the written outputs. Data collected under this study will be made available in a form consistent with any conditions attached by the supporting organisations.

3.6.1 Implications for current practices

The framework developed in this project can facilitate a substantial increase in the density of river flow gauging stations, resulting in a more comprehensive understanding of water resources across different catchments. The inclusion of smartphone-based methods introduces the possibility for nation-wide utilisation of citizen science to vastly improve flow data and encourage community engagement.

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