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Comparative Assessment of Image-Based Velocimetry Techniques for River Flow Monitoring: Accuracy, Efficiency, and Practical Implication

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Abstract. Accurate river flow monitoring is critical for water resource management, yet traditional methods face limitations in cost, spatial coverage, and real-time applicability. This study evaluates two open-source image-based velocimetry techniques, Large Scale Particle Image Velocimetry (LSPIV) from openrivercam and Particle Tracking Velocimetry (PTV) from tractrac, using field observation data from the Wesenitz and Freiberger Mulde rivers in Germany. Orthorectified video footage was processed to estimate surface velocities, validated against Acoustic Doppler Current Profiler (ADCP) measurements. Results demonstrate that openrivercam (LSPIV) achieved higher accuracy (R^2 = 0.57—0.62, RMSE = 0.11—0.23 m/s) for large-scale flow patterns, while tractrac (PTV) offered finer spatial resolution but was sensitive to noise. Computational efficiency favored tractrac with processing times 50-70% faster than another velocimetry tool. A sensitivity analysis revealed that time resolution and transect placement significantly influenced accuracy, whereas spatial resolution had a nuanced impact. These findings provide actionable insights for selecting velocimetry tools based on monitoring objectives, advancing non-invasive river flow monitoring.

Keywords: image velocimetry, surface flow velocity, OpenRiverCam, Tractrac, LSPIV, PTV, in-situ measurement, ADCP validation

1. Introduction

Data availability remains a critical challenge for hydrological research in many developing countries, where limitations arise due to high equipment costs, insufficient technological infrastructure, and bureaucratic restrictions on access to government-held datasets (Heppner & Loague, 2008). In regions such as Indonesia, for instance, restricted access to daily precipitation datasets, despite being fee-based, often results in incomplete or missing data from numerous observation stations, ultimately hindering the effectiveness of hydrological (Rakhmalia, Soleh, Sartono, & Applications, 2020). Whereas, the needs to contribute on conserving water resources for sustainable development in SDGs and climate resilience actions are relied on information and research of river flow conditions (Bianucci, Sordo-Ward, Lama-Pedrosa, & Garrote, 2024).

Additionally, traditional observational techniques, such as stream gauges and current meters, are often impractical in river systems characterized by complex cross-sections and variable water levels (Lee, Kim, Son, Min, & Choi, 2022). These challenges are further compounded by the geographical and financial constraints that result in sparsely distributed monitoring stations, limiting the spatial and temporal resolution of hydrological observations. High-resolution data on river surface velocities are essential for accurately characterizing hydrological processes, improving water resource management, and mitigating natural hazards (Mirus, Loague, Cristea, Burges, & Kampf, 2011). However, conventional measurement tools face limitations in data precision and deployment flexibility, while remote sensing techniques are often con-strained in spatial coverage, particularly in narrow or cluttered observation environments (Hannah et al., 2011). Another approach from UAVs provided promising surface velocity estimation with more detailed and accurate data collection (Tauro, Porfiri, & Grimaldi, 2016) of remote landscapes and covered difficult-to-access areas (Eltner, Baumgart, Maas, Faust, & Landforms, 2015). The paper of (Jyoti, Medeiros, Sebo, McDonald, & Instrumentation, 2023) comparing aircraft technique with direct measurement hand-held velocimeter in point locations, also mentioned another benefit, that the measurement doesn't require external seeding as tracers for the rivers.

In recent years, image-based surface velocimetry has emerged as a promising, low-cost alternative for flow monitoring. Image-based approaches utilize inexpensive off-the-shelf cameras, employing various algorithms to estimate stream surface velocity (Meselhe, Peeva, & Muste, 2004). In general, the procedure of image-based analysis is as follows: data acquisition, pre-processing, image evaluation, and post-processing phase (Fujita, Muste, & Kruger, 1998). Common techniques include analyzing digital images with large-scale particle image velocimetry (LSPIV) (Le Coz, Hauet, Pierrefeu, Dramais, & Camenen, 2010) and particle tracking velocimetry (PTV) (Aleixo, Soares-Frazão, & Zech, 2011). Other approaches like space-time image velocimetry and dimensionality-reduction algorithms have also been employed to extract flow regime details from images (Tauro, Grimaldi, & Porfiri, 2014). These methods use recorded videos or images to estimate flow velocities, offering scalability and adaptability with minimal hardware requirements. Prior studies have evaluated LSPIV and PTV in controlled settings, but field-based comparisons are scarce. These two applications represent state-of-the-art open-source tools, yet their trade-offs in accuracy, efficiency, and sensitivity to environmental conditions are underexplored.

This overall aim for this study is to addresses the gap by comprehensive comparison of two open-source tools performance, openrivercam (for LSPIV) (Winsemius et al., 2023) and tractrac (for PTV) (Heyman & Geosciences, 2019), for river surface velocity estimation. The research focuses on assessing their accuracy against ADCP measurement, sensitivity to spatial and temporal resolution, and its efficiency through computational latency and scalability.

The novelty of this research lies in the advanced approach of hydrological monitoring by providing the first comprehensive comparison of well-known image-based velocimetry tools under real-world river conditions, addressing critical gap in prior lab-focused evaluation. This paper evidence-based guidelines for selecting velocimetry techniques tailored to specific monitoring needs. The findings directly address practical challenges in water resource management with providing low-cost, non-invasive flow measurement in data scarce region in particularly developing countries. The research also can bring support for real-time flood monitoring through rapid processing and high accuracy assessment, as well as enhancing sustainability of water management by improving accessibility of reliable file data for stakeholder and policymakers

2. Materials and Methods

2.1. Project overview

This proposed study addresses the critical need for accessible, non-invasive river flow monitoring by conducting a comprehensive field-based evaluation of two opensource image-based velocimetry techniques: Large-Scale Particle Image Velocimetry (LSPIV) implemented in openrivercam (Winsemius et al., 2023) and Particle Tracking Velocimetry (PTV) via tractrac (Heyman & Geosciences, 2019). The research leverages field data from the Wesenitz and Freiberger Mulde rivers in Germany to assess the accuracy, computational efficiency, and environmental adaptability of these methods under real-world conditions. Orthorectified video footage, captured using terrestrial cameras (Canon EOS 500D/1200D and Casio EX-F1), was processed to estimate surface velocities, validated against reference Acoustic Doppler Current Profiler (ADCP) measurements from (Eltner, Sardemann, Grundmann, & Sciences, 2020). The methodology included rigorous orthorectification using ground control points (GCPs), and gray-scale normalization to enhance tracer visibility. To comprehend its ability under several conditions and changes, sensitivity and flexibility test is computed for the prospected model with various schemes, evaluating the impact of temporal/spatial resolution and cross-section placement. By quantifying performance through coefficient of determination (R^2) and root mean square error (RMSE), this work bridges a gap in hydrological monitoring literature, providing actionable insights for selecting context-appropriate tools in data-scarce regions. The workflow of this research is shown in the **Figure 1** below.

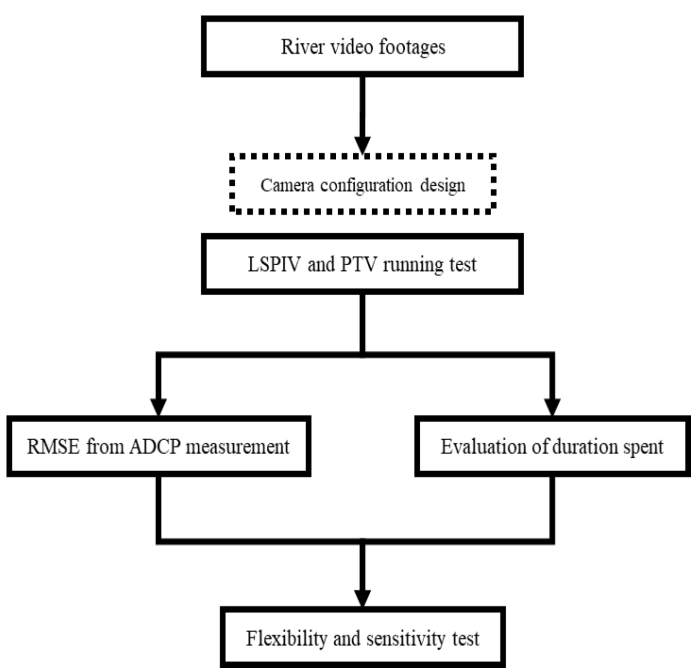


Figure 1 Flowchart of project overview

2.2. Study areas and data acquisition

Field campaigns were conducted at two contrasting river systems in Germany, the Wesenitz River (51.027249°N, 13.990514°E) and the Freiberger Mulde River (51.065340°N, 13.265547°E), presented in **Figure 2**. These sites were strategically selected to evaluate image-based velocimetry techniques under diverse hydrological and geomorphic conditions. The Wesenitz River, monitored on 31 March and 4 April 2017, features a semi-engineered channel with a paved riverbed and localized sandbanks, creating dynamic flow patterns at a discharge of 2.7 m^3/s and water depths of 51 cm. In contrast, the Freiberger Mulde River, surveyed on 26 October 2016, represents a natural, meandering reach with non-uniform flow regimes, characterized by a discharge of 5.7 m^3/s and water depths of 68 cm. These disparities in river morphology, ranging from modified to natural banks, enabled a robust assessment of velocimetry performance across variable turbulence, sediment loads, and illumination conditions.

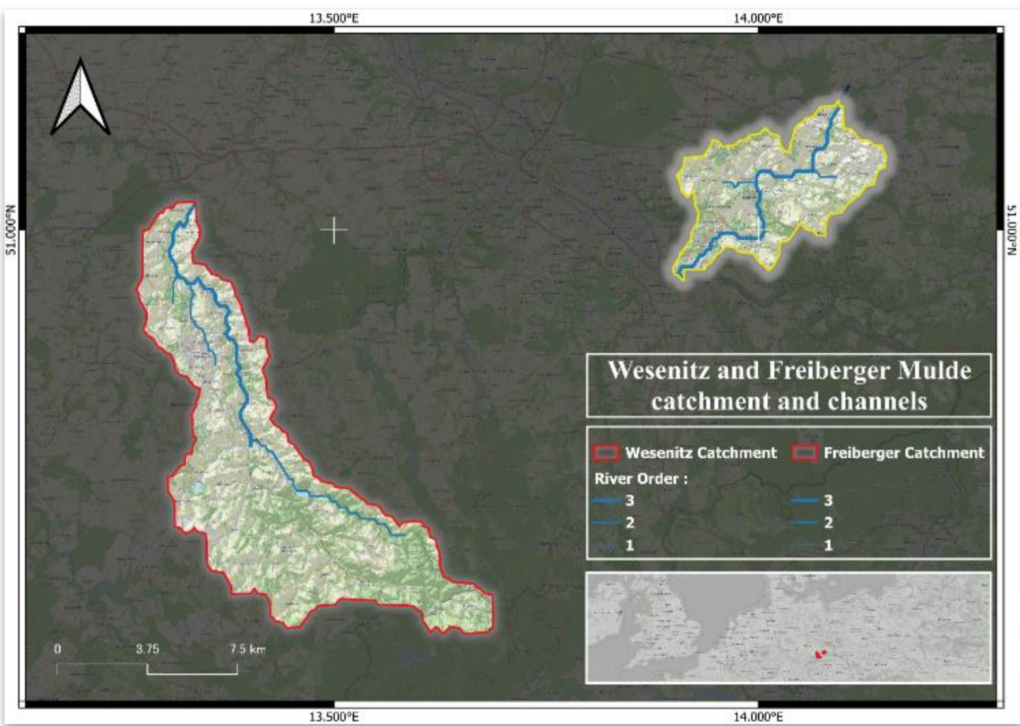


Figure 2 Map showing the Wesenitz and Freiberger Mulde River catchments

Video footage was captured using terrestrial cameras installed on bridges across the rivers. At the Wesenitz River, three cameras were used: a Canon EOS 500D (1280 x 720 pixels, 30 fps), a Canon EOS 1200D1 (1920 x 1080 pixels, 25 fps), and a Canon EOS 1200D2 (1920 x 1080 pixels, 25 fps). At the Freiberger Mulde River, a Casio EX-F1 camera (640 x 480 pixels, 30 fps) was used. The videos were recorded for durations ranging from 6 to 8 seconds, providing sufficient temporal resolution for velocimetry analysis. Ground control points (GCPs) were marked on the riverbanks and surfaces to facilitate orthorectification and normalization of the images.

As illustrated by Figure 3 below, the placement of devices is varied in several positions. In Wesenitz River, two cameras, Canon EOS 500D and Canon EOS 1200D2 share the same point of view. Installed on top of the bridge in the middle of the river site, these instruments captured the equal dimension on the left and right banks. A difference between these recorded videos can be seen, the first camera captured a wider dimension of the picture than the second-mentioned device, meaning there was a different configuration on the zoom settings of the camera. Another device, Canon EOS 1200D1 was placed on the left side of the river, recording a slightly bigger portion on the right side of the river, but was still able to reach the upstream part of the site. On another observation site, Casio EX-F1 was positioned on the right side of the stream. This camera covered more frames of the left side of the river.

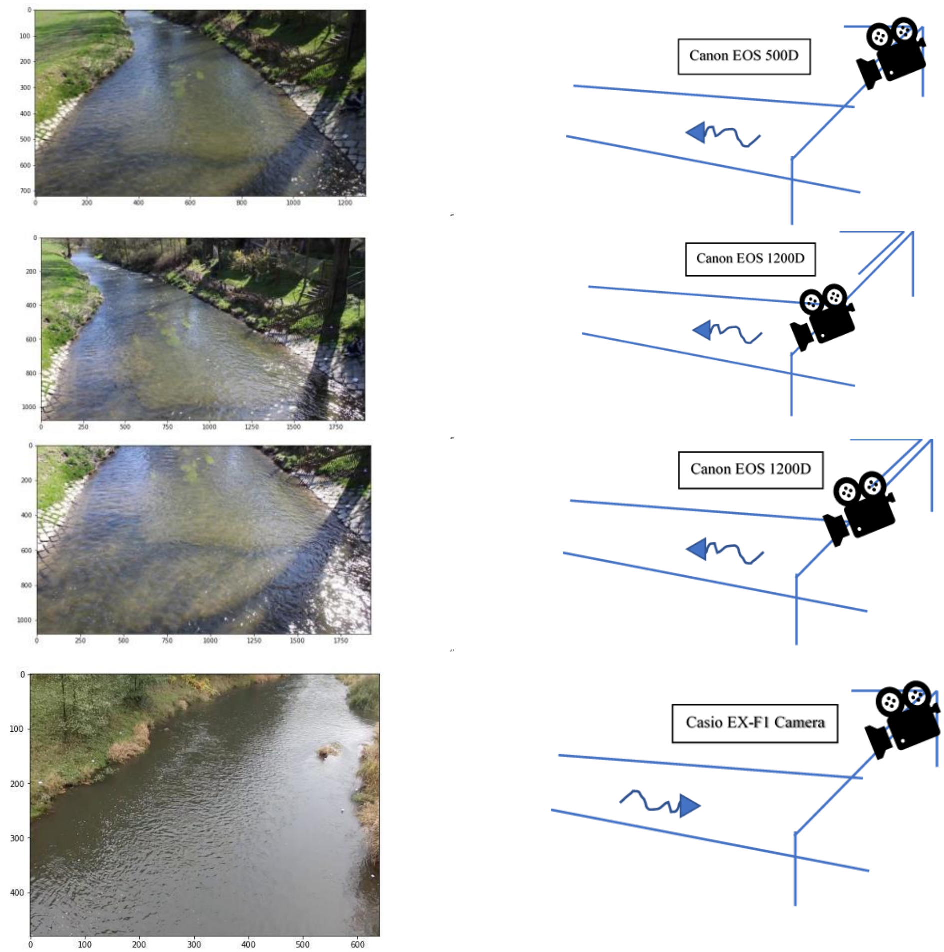


Figure 3 Captured frame and illustration of camera orientation in Wesenitz and Freiberger Mulde River catchments

As the evaluation dataset, the research of (Eltner et al., 2020) in Germany's rivers, Wesenitz and Freiberger Mulde rivers, operating a moving boat approach for the ADCP measurement (**Table 1**), with the StreamPro program from RDI is applied. The profiles of water velocity were calculated with a blanking range of 14 cm near the water surface, and the datasets were computed using German Federal Institute of Hydrology software. Then, the cross-sectional areas were referenced from the boat track before the flow surface velocities could be extrapolated as base data for a comparison to the image-based process. All the ADCP measurements from the profile were considered to extrapolate surface velocities.

Table 1 River velocity measured with ADCP on the observation sites

	Mean surface velocity (m/s)	Water depth (m)	Cross-section area (m²)	Transect points
Freiberger Mulde	0.60	0.68	11.75	153
	0.70	0.68	10.45	
	0.76	0.68	10.30	
Wesenitz	0.70	0.51	4.63	94

2.3. Orthorectification, normalization, and velocimetry analysis

To ensure accurate spatial measurements, the video frames were orthorectified and normalized. Orthorectification involved transforming the video frames to a nadir view (90-degree angle to the river surface) using GCPs. According to (Muste, Fujita, & Hauet, 2008), the 3D-transformation of transformation coefficient from a hilly field of project with high elevation differences demands at least six GCPs coordinates. However, in a gentle landscape where devices are installed at the same level as the water surface (2D transformation), the need for GCP's quantity in the project location may be less. In this study, four GCPs were used for each site, with their real-world coordinates mapped to the pixel coordinates in the video frames. This step corrected for perspective distortions caused by the camera angle. Normalization involved converting the images to grayscale and enhancing the contrast between the water surface and tracer particles to improve the accuracy of velocimetry analysis. Two image-based velocimetry techniques were employed: Large-Scale Particle Image Velocimetry (LSPIV) using openrivercam and Particle Tracking Velocimetry (PTV) using tractrac.

As both LSPIV and PTV procedures work on the similarities between pairs of images and yield stream surface velocity distribution over the two-dimensional domain (Willert, Wereley, & Kompenhans, 2007), the LSPIV algorithm estimates stream velocity at the image subregion with its semi-Eulerian approach, while PTV prefers to observe the trajectory of individual tracer transiting in on the measured river with the Lagrangian methodology (Tauro, Piscopia, & Grimaldi, 2017). For openrivercam (LSPIV), the workflow (**Figure 4**a) began with camera configuration, where a JSON file was created to define camera parameters, including lens type, field of view, and GCP coordinates. The orthorectified video was then processed to generate a 2D velocity field using the LSPIV algorithm. The algorithm divided the image into interrogation areas (25 x 25 pixels) and calculated the dis-placement of tracer particles between consecutive frames using cross-correlation. The output was a NetCDF file containing the 2D velocity field, which was then converted to a spatial transect for comparison with ADCP measurements.

For tractrac (PTV), the workflow (**Figure 4**b) involved object detection using a median background subtraction method to identify moving particles in the video frames. The trajectories of individual particles were tracked across frames using a nearest-neighbor search, and velocity vectors were calculated based on the displacement of particles over time. Outliers were filtered out using statistical criteria, and the final velocity field was generated as a 32-bit TIFF image.

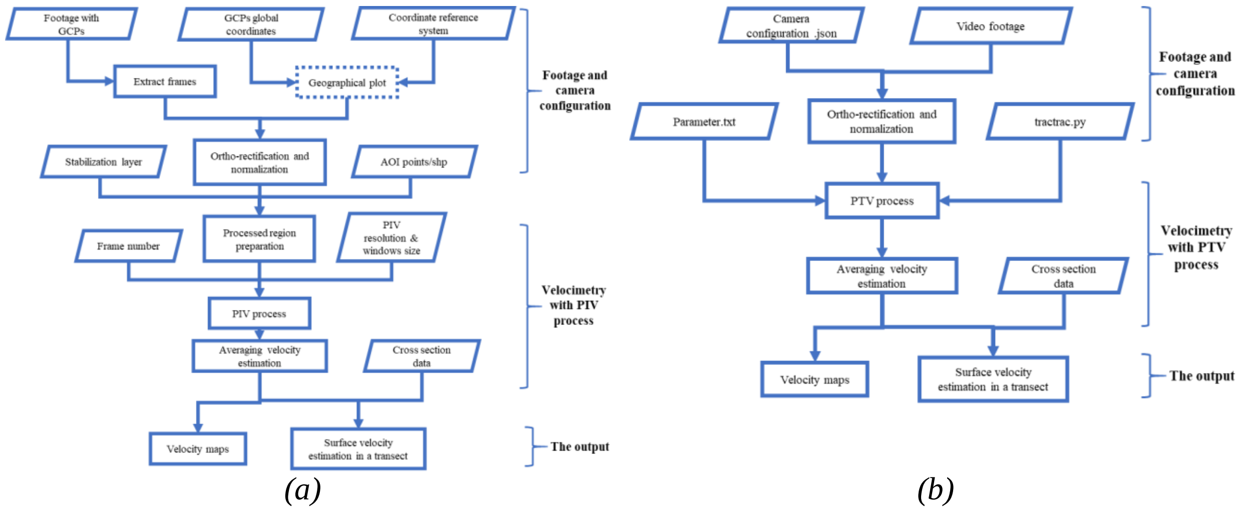


Figure 4 Workflow of the openrivercam process (a) and tractrac process (b)

2.4. Reference measurement and evaluation

The accuracy of the image-based velocimetry techniques was evaluated using reference measurements obtained from an Acoustic Doppler Current Profiler (ADCP). The ADCP measurements provided cross-sectional velocity profiles, which were used as the ground truth for comparison with the image-based results. At the Wesenitz River, a single cross-section with 94 observation points was measured, while at the Freiberger Mulde River, three cross-sections with 153 observation points were measured. The performance of the velocimetry techniques was evaluated based on accuracy and latency. Accuracy was assessed using the coefficient of determination (R^2) and root mean square error (RMSE) to compare the image-based velocity estimates with the ADCP measurements. Several previous studies related with the implementation of these error methods to compare fluid flow estimation can be seen in these papers (Legleiter & Kinzel, 2020).

The formula of R^2 can be written as (Zhang, 2017):

$$R^2 = 1 - \frac{SSres}{SStot} = 1 - \frac{\sum(v_i^o - v_i^p)^2}{\sum(v_i^o - v^a)^2}$$

The RMSE can be expressed as (Legleiter & Kinzel, 2020):

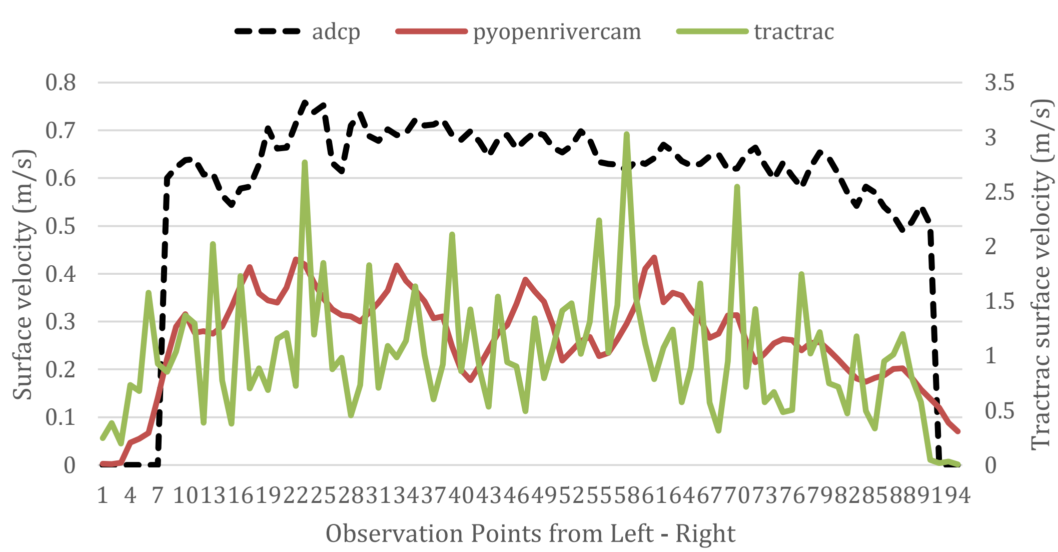
$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(V_i^o - V_i^p)^2}$$

Latency was measured by recording the time required to process the video footage for each technique, providing insights into computational efficiency. Additionally, a sensitivity analysis was conducted to evaluate the impact of varying parameters on the accuracy of the velocimetry techniques. The parameters tested included time resolution (number of frames used in the analysis: 100, 200, and 290 frames), spatial resolution (size of the interrogation area: 12 cm², 25 cm², and 50 cm²), and transect location (position of the cross-section line used for velocity extraction).

3. Results

3.1. Accuracy of Velocity Estimation

The performance of image-based algorithms in this study represented by openrivercam and tractrac is compared with the ADCP, being an established tool, as the reference data for analysing surface velocity estimation in the Wesenitz river. ADCP observation from Wesenitz River (**Figure 5**a) visualizes that, over the 94 observation points from left to right of the bank, the actual ADCP measurement shows a rapid increase of surface velocity near the riverbanks, with an average velocity around 0.5 to 0.7 m/s in the middle part of the river, before declining sharply towards the opposite side of the river. This sharp fluctuation on the side of the river were influenced by the no-stream-condition or dry bed on the bank where ADCP took measurements at the first and last observation points. Openrivercam as an LSPIV software estimates a slightly lower value, ranging from 0.3 to 0.5 m/s, but still follows the overall trend of the ADCP measurement. While it still underestimates the surface current observation, it shows a smoother which indicates the model's ability to filter out noise or fluctuations. On the other hand, tractrac delivers higher discrepancies, with frequent spikes and dips, mostly overestimating value retrieved by ADCP measurement with the highest velocity data reaching above 3.0 m/s, as can be referenced on the x-axis on the right side of the graph below. In capturing the general velocity trend, the noise in this program dataset suggests high instability in the estimation process.



(a)

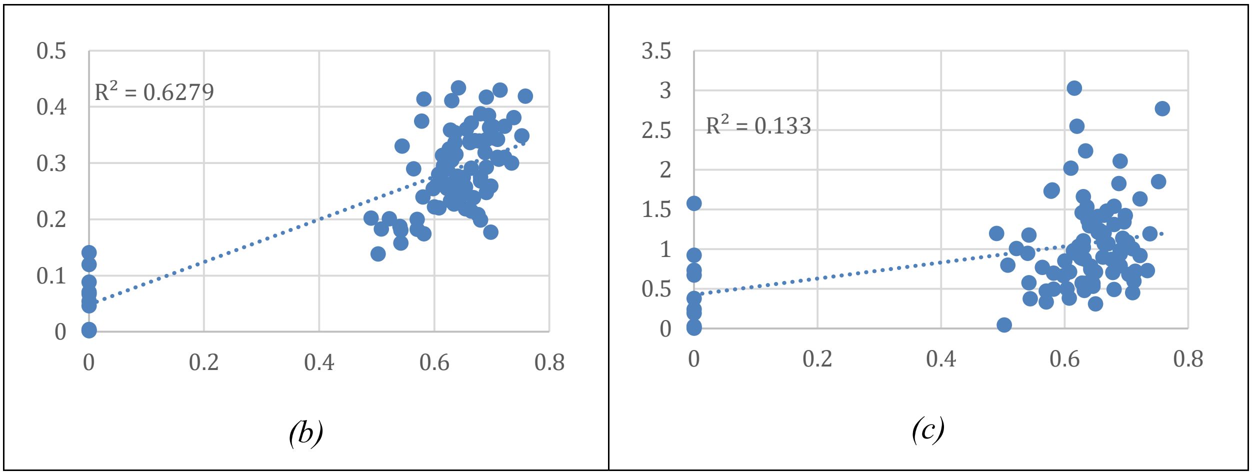


Figure 5 Field measurement (ADCP) values and surface velocimetry model (openrivercam and tractrac) comparison at the Wesenitz River with the Canon 500 Camera (a) with coefficient of determination between ADCP with openrivercam model (b) and tractrac model (c)

The relationship between two model predictions with the actual surface velocity is provided with two scatter plots containing the coefficient determination to indicate the strength of each correlation. A moderate to strong positive correlation between the openrivercam estimation with measurements taken by ADCP can be seen in **Figure 5**b, with the data points clustered around the trendline. Although it still predicts lower values from ADCP, it still computes the main trend of the velocity information. A much weaker fit with the ADCP data with 0.133 as its R^2 is shown from the correlation between the measurement data with the estimation velocity values from tractrac. Significant variability in its prediction with numerous over across the range of velocities is proven by dispersed scatter points from the trendline. This indicates that this approach does not accurately predict the ADCP velocity patterns with too much noisier and variabilities.

From another device at the same site, Canon 1200D1 provides an interesting output after the video footage is carefully computed with both programs in **Figure 6**a. Identical measurement values are provided from ADCP measurement drawing rapid fluctuation of surface velocity on the left and right banks with a gentle movement on the middle part of the river. Openrivercam estimation still follows overall trends which obtain an increase-decrease of the surface velocity. While in several points the model does not predict accurate oscillations, the difference of value between the image-based computation with the measurement record is declined, even from observation points 55 to 62, estimation values reach the level of ADCP measurement, resulting in a closer model projection. As for tractrac calculation, much noise recorded gives a wider variability of velocity instability. A high over-estimation from this model with velocity value scoping from 1.0 to more than 4.0 m/s against 0 to 0.8 m/s from ADCP assessment proves that many evaluations should be considered to use the tractrac program at this river.

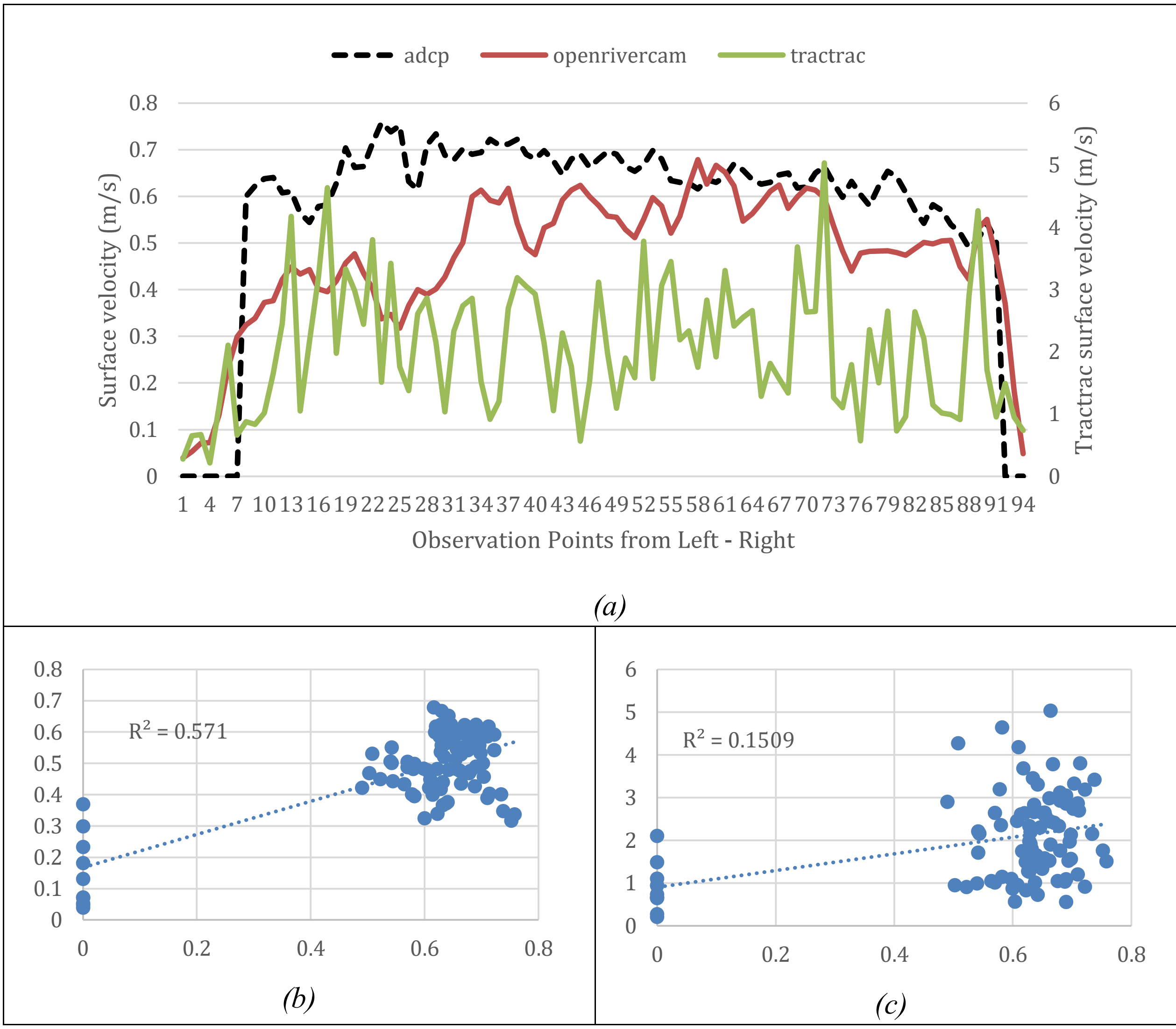


Figure 6 Field measurement (ADCP) values and surface velocimetry model (openrivercam and tractrac) comparison at the Wesenitz River with the Canon 1200D1 Camera (a) with coefficient of determination between ADCP with openrivercam model (b) and tractrac model (c)

The strong correlation between image-based velocimetry approaches with actual observation is calculated with coefficient determination visualized in scatter plots in **Figure 6**b and **Figure 6**c. A moderate positive correlation ($R^2 = 0.571$) from the LSPIV technique delivered by openrivercam software can be found with a dense circle around the trendline. It should be noted that although the gap between estimation and measurement values has declined, trend fluctuation from both values illustrates a coarse connection, resulting in a lower R^2 value from this model. Tractrac analysis output demonstrates a rougher correlation with the ADCP measurement with only 0.1509 estimation match with actual dataset. This low correlation value is presented with scattered points from the trendline, indicating that greater variability and noises do not fit the trend of what observation instrument was provided.

In the next graph, **Figure 7**a reveals the comparison between various techniques of surface velocity measurement and estimation with different devices and camera perspectives, even though the dataset still corresponds to the same river. As with the previous plot, the ADCP will be noted as the reference for surface velocimetry with image or pixel estimation. The actual flow dynamics still illustrate a relatively stable velocity in the middle of the profile with a high fluctuation on each side of the river. The data of openrivercam follows the ADCP trends with consistently higher values, reaching at fastest flows at approximately 1.0 m/s. The trend line is closely mirroring the ADCP measurement profile in terms of shape and flow pattern. However, the overestimation analysis output was computed across the entire range of the river. From tractrac computation, an extreme magnitude of surface current starting from 0.1 m/s to 4.9 m/s spread into 94 observation points. Discursive motions with large spikes and dips with some sections aligning the actual data indicate that tractrac possibly is more sensitive to local flow disturbances and capturing more noises.

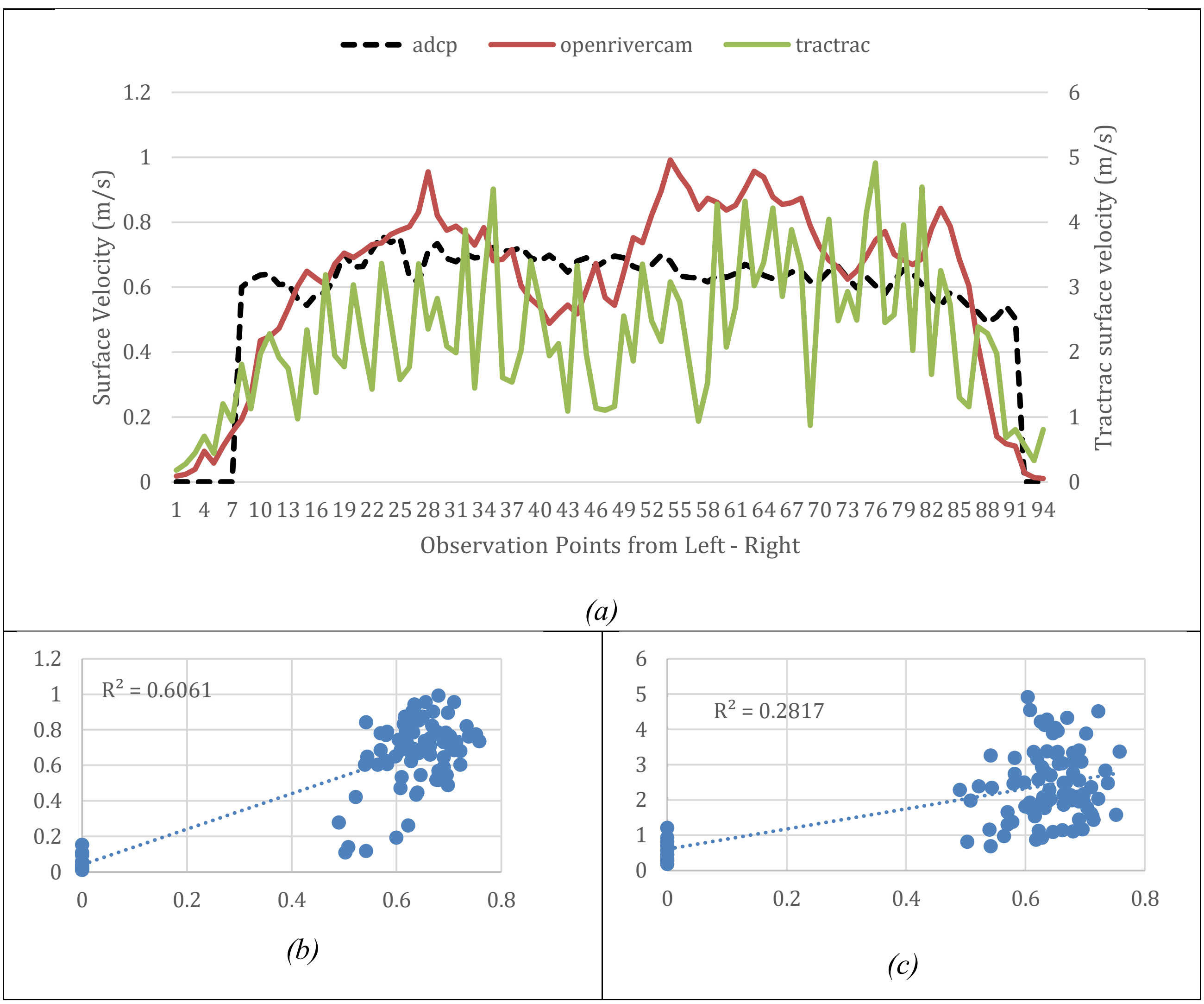
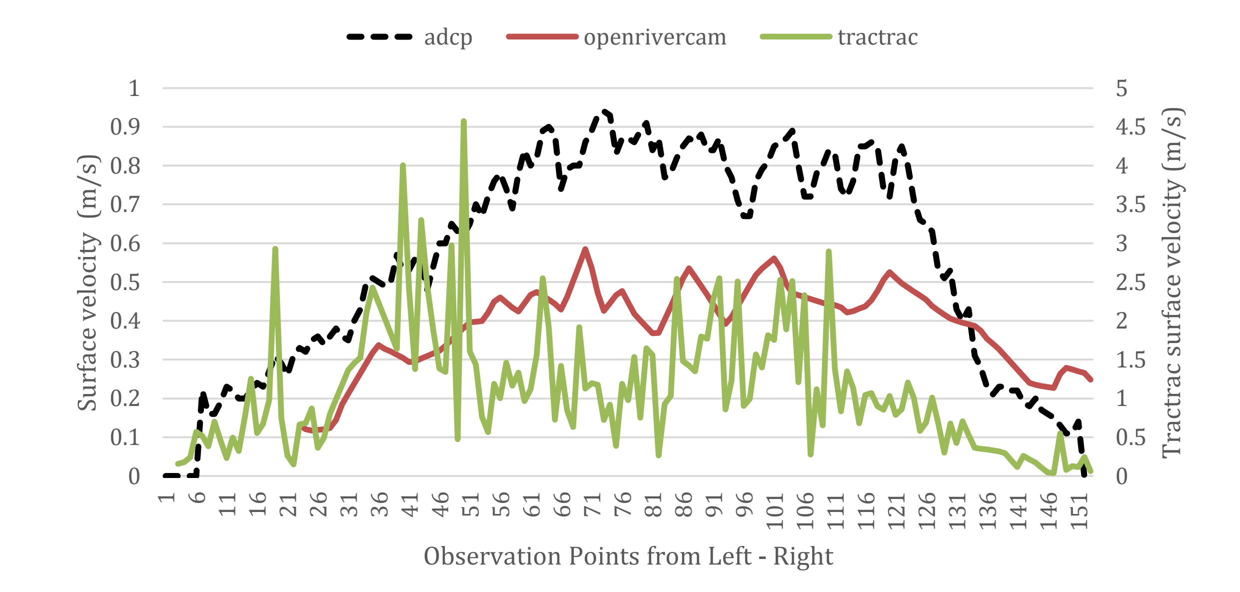


Figure 7 Field measurement (ADCP) values and surface velocimetry model (openrivercam and tractrac) comparison at the Wesenitz River with the Canon 1200D2 Camera (a) with coefficient of determination between ADCP with openrivercam model (b) and tractrac model (c)

Coming with a resembling statistical correlation output, a reliable coefficient determination is generated by the analysis of openrivercam with the R^2 reaching 0.6061 compared with the ADCP dataset. Although several fields show over and underestimation trends, the profile of the model establishes the pattern of the actual river flow, highlighted by dense clusters around the line. With dispersed correlation points in the tractrac model computation, a weaker coefficient is found (0.2817). While the number is quite modest, this is the highest value among the other tractrac and ADCP correlations. It can be stated that this image-based velocimetry model has a higher performance in analyzing with this type of camera device.

A comparison between model estimation and ADCP measurement for surface velocity measurement at Freiberger Mulde River is presented in the graph below. With a total of 151 points of velocity observations, it can be seen that a gentle rise starts on the left side of the river until it reaches approximately 60 points at 0.8 m/s of sur-face velocity. The flow becomes more stabilized with less fluctuation in the middle of the river ranging between 0.7 m/s and 0.9 m/s, before it sharply weakens to 0.2 m/s and its loss the power at the end of the right bank. The velocity profile computed by openrivercam generally presents a smooth trend following the movement of the actual river regime at the site. Visualizing a high match in terms of fluctuation shape, the gap between two values is shown in underestimation of the model estimation, with the peak only reaching 0.6 m/s, then the ADCP values which soar above 0.9 m/s. Tractrac analysis, with a much dissimilar velocity fluctuation with dips and spikes, on the other hand, offers high flow estimations stretching from 0 m/s to 4.5 m/s.



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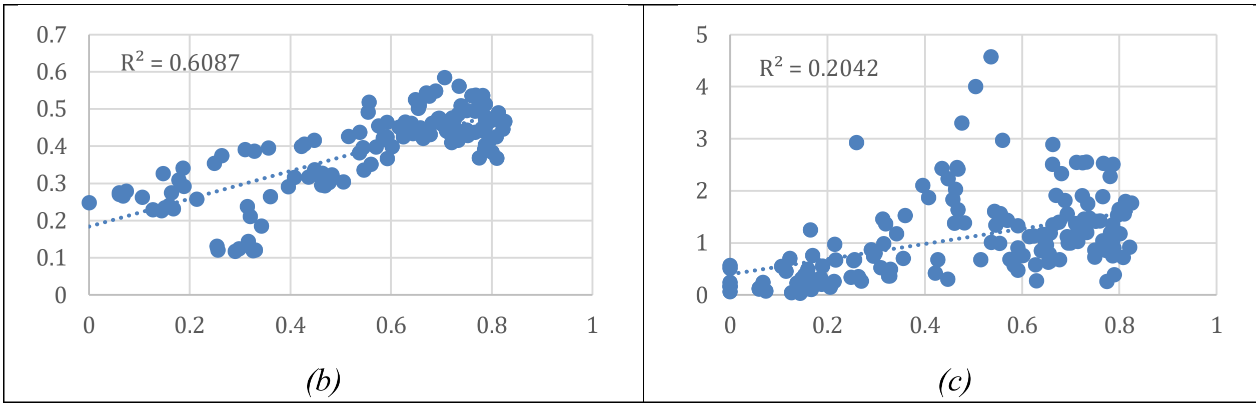


Figure 8 Field measurement (ADCP) values and surface velocimetry model (openrivercam and tractrac) comparison at the Freiberger Mulde River (a) with a coefficient of determination between ADCP with openrivercam model (b) and tractrac model (c)

A more delicate distribution of correlation points can be seen at the coefficient of determination between ADCP measurement with openrivercam estimation in **Figure 8**b. It can be explained that the flow rate fluctuates gentler than what we have at Wesenitz River. A positive correlation with a moderate strength is a prove that this software can deliver a proper velocimetry analysis with the image-based approach in real experiments. However, the tractrac approach (**Figure 8**c) still generates a weak correlation even in the new river site. With several outliers spotted, the 0.2042 coefficient of determination indicates that the flow estimation from this algorithm cannot reflect the actual Freiberger Mulde flow condition.

3.2. Spatial Error Distribution

An accuracy assessment by evaluating the error distribution was carried out to quantitatively measure the performance of openrivercam and tractrac programs in the previous section, reflecting the actual observation of surface water flow velocity magnitudes. Reference measurements were collected for each of the four samples in the form of transect lines. Based on this approach, a cross-section was established on each region of interest of the locations, with provided points obtaining both velocity information from the actual measurement and image-based computations. The detailed information retrieved from the transect points is summarized in **Table 2**, while a comparison of error metrics for each location is drawn in **Figure 9**.

Table 2 RMSE scores from reference measurement of surface flow velocities for each location.

River	RMSE (m/s)	
	Openrivercam	Tractrac
Wesenitz 500	0.34	0.68
Wesenitz 1200D1	0.17	1.74
Wesenitz 1200D2	0.17	1.94
Freiberger Mulde	0.28	0.91

The RMSE values reflect the average magnitude of the error between estimated velocities (from openrivercam and tractrac program) and the reference ADCP measurement. From **Table 2** above, lower RMSE values can be found in the openrivercam evaluation from all four site observation analyses. It demonstrates that this model consistently delivers a better performance than tractrac in providing a more accurate estimation of surface velocities with lower error values. The relatively smaller divergent error between the model with the actual river assessment is computed in the Wesenitz site with Canon 1200D1 and Canon 1200D2 devices which makes it possible to mistakenly predict the flow velocity only in 0.17 m/s. On the contrary, the highest error values also can be highlighted from this site with the same devices, but a different approach. Tractrac estimation gives more than 1.7 m/s error of flow velocity, possibly due to increased variability or noise in its computation, resulting in difficulties in capturing accurate surface flow dynamics.

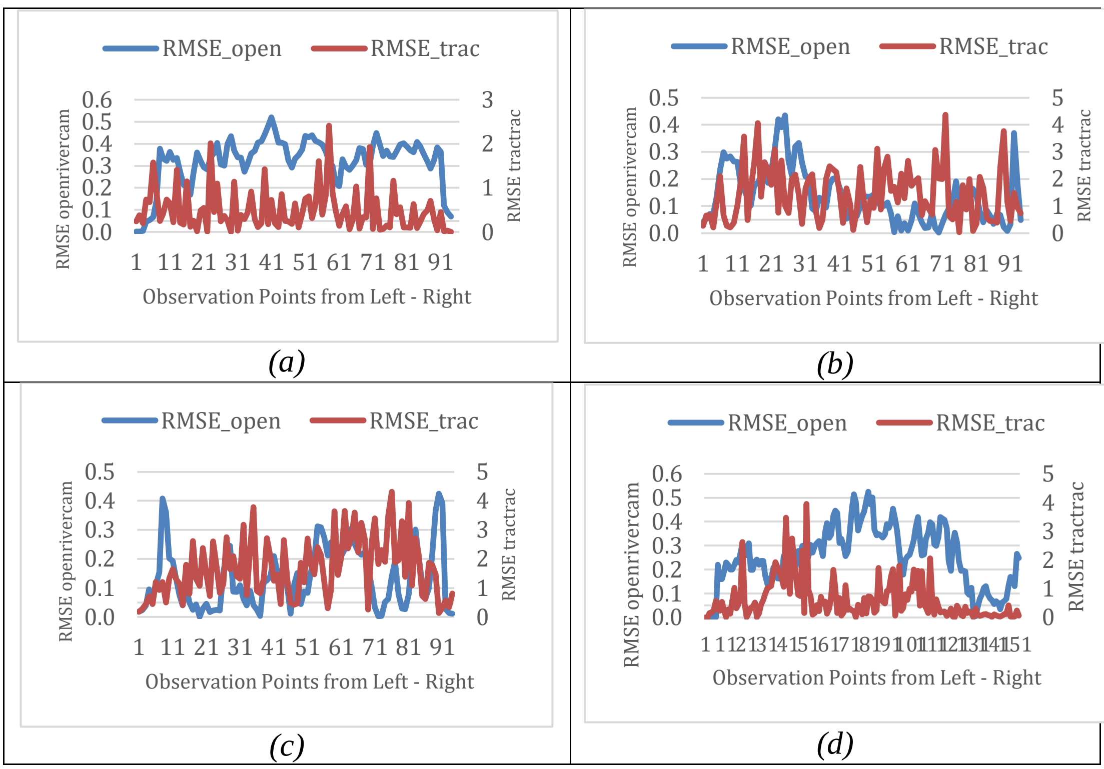


Figure 9 Root Mean Square Error (RMSE) values from models' output and actual campaign observations from Wesenitz river with Canon 500 (a), Canon 1200D1 (b), and Canon 1200D2 (c) devices, and from Freiberger Mulde river (d)

Figure 9 visualizes the distribution of statistical deviation in four observation sites from openrivercam and tractrac estimation against ADCP measurement. In general, tractrac produces higher errors than the openrivercam. In section (a), it can be seen that the magnitude between the model's estimation with the actual assessment distributes from 0 to 0.5 m/s and from 0 to above 2.0 m/s in openrivercam and tractrac respectively. While there is a notional variability of square error in tractrac analysis, the fluctuation in openrivercam draws a pattern where the low error appears on both sides of the river while rapid ups and downs can be found in the middle of the river. In the Canon 1200D1 represented by **Figure 9**b, an abstract variation is illustrated by both model's outputs. However, it is notable that the square error provided by openrivercam reaches approximately 0.4 m/s while the highest number of errors from tractrac rises above 4.0 m/s. Another Canon 1200D device in section (c) shows, in the tractrac model, an extreme increase in movement of the error values from the left side of the bank, before it intensively fluctuates in the middle of the river until the square error reaches more than 4.0 m/s, and it starts to decline on the right of the banks. On the contrary, openrivercam analysis highlights that the highest error values can be found on both sides of the banks with error values more than 0.4 m/s while lower values are established in the middle of the river. In Freiberger Mulde River shown in **Figure 9**d, openrivercam software illustrates a gentle rise of a square error on the left of the river. It reaches the maximum value at less than 0.6 m/s and starts to dive on the right of the banks. Another model gives a notion of fluctuation with the highest square error climbing until almost reaches 4.0 m/s.

3.3. Computational Efficiency

The time required to process the image-based velocimetry analysis for surface velocity estimation using openrivercam and tractrac across various datasets is presented in **Table 3** below. This dataset illustrates the computational performance differences between the two models by reporting the time needed to process different quantities of frames in seconds for each river transect.

Table 3 Time needed to process the image-based analysis

	Number frames	Time needed (s)	
		Openrivercam	Tractrac
Wesenitz 500D	200	547.58	114.03
Wesenitz 1200D	200	767.00	210.10
Wesenitz 1200D II	200	408.83	150.03
Freiberger Mulde	180	174.52	139.03

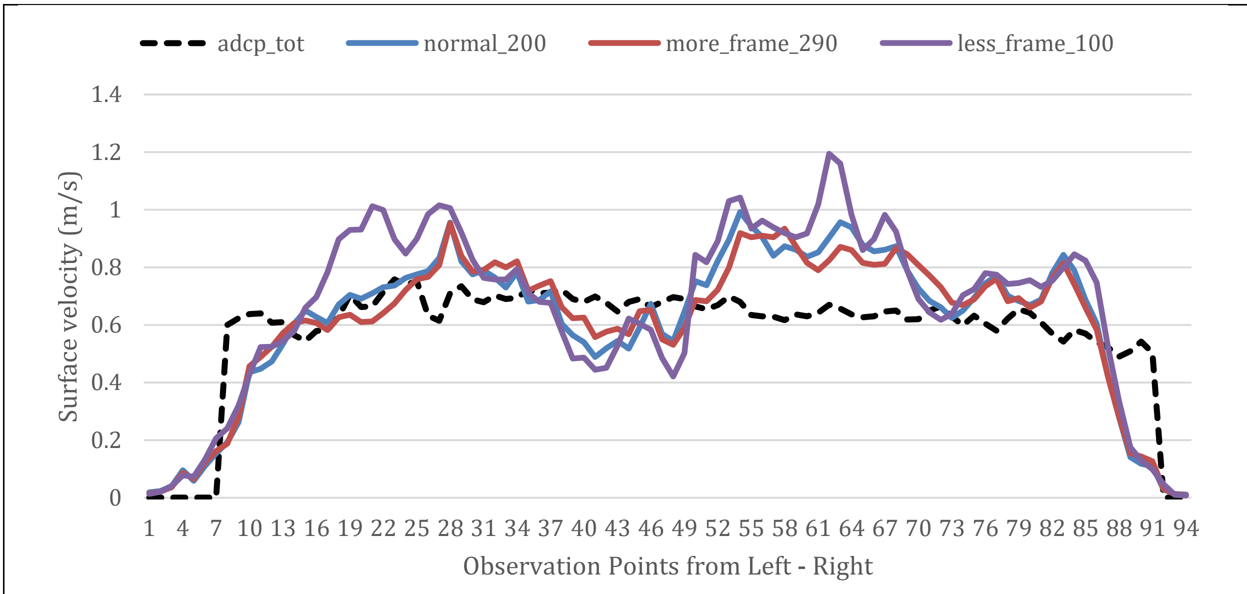
In general, the result in **Table 3** above shows that openrivercam software is consistently outperformed by tractrac in terms of the speed in footage data processing. Tractrac requires less time to process image-based surface velocity estimation with most of the time needed less than 200 seconds. Meanwhile, despite the high accuracy estimation by openrivercam, the computation speed becomes the trade-off that requires the user to spend more time using this software. In comparison, velocimetry processed in Wesenitz River which has 200 frames with a generally higher resolution than the Freiberger Mulde site by openrivercam took roughly 2.7 – 4.8 times longer than the time needed for tractrac to generate the same analysis. For the Freiberger Mulde dataset, with fewer frames (180) and less spatial resolution value, the gap between the two models narrows. Openrivercam completes the analysis in 1.25 times longer than tractrac with 174.52 seconds against 139.03 seconds.

3.4. Sensitivity Analysis

After extensive comparison with other methods, such as tractrac, and examination of data accuracy, we have selected openrivercam as the preferred model due to its smoother and closer alignment with observed river dynamics from ADCP measurement. In this section, we focus on evaluating the flexibility and sensitivity of the model under various experimental conditions. The study site chosen for further evaluation is the Wesenitz River which provides a diverse flow environment ideal for testing different model configurations. The analysis will be conducted using a Canon 1200D2 camera, which has been selected for its high-quality image-capturing capabilities, ensuring precise data collection for the selected model. As the primary objective here is to understand how well openrivercam performs under varying conditions, the specific purpose of this section is to explore how well the model's behavior with changes in temporal and spatial resolution, and by shifting the cross-section location of the river.

3.4.1. Higher and lower time resolution

The velocimetry analysis from image-based starts as cameras capturing the dynamics of the liquid surface in a sequence of consecutive frames, allowing the reconstruction of the local flow velocity by identifying the movements of the tracer particles between pairs of subsequent frames (Pumo, Alongi, Ciraolo, & Noto, 2021).The evaluation to know how the model reacts with the shifting of time resolution in this analysis is determined by the variation of frame quantity supplied into the model. The evaluation was conducted at the same observation site along the Wesenitz River, where 94 observation points were analyzed. The model was tested under three different time resolutions: normal conditions with 200 frames, more time resolution with 290 frames, and only 100 frames inputted to see how less time resolution influences the model performance. Overall, the alteration of frame amount follows the normal trend as expected, with velocities increasing towards the middle of the river and decreasing near the banks. There are two spikes spotted and it can be seen that the fewer frame conditions gave a higher surface velocity estimation of around 1.2 m/s while the others only reached less than 1.0 m/s. Reducing the number of frames also decreases the smoothness of the model, which impacts the model's ability to capture rapid changes in flow velocity. On the contrary, increasing the number of frames improves the detailed flow of information over time. It can be shown that the red profile, representing more time resolution, gives a smoother profile, particularly in areas with previously fluctuating velocities. The comparison output can be depicted in **Figure 10** below.



(a)

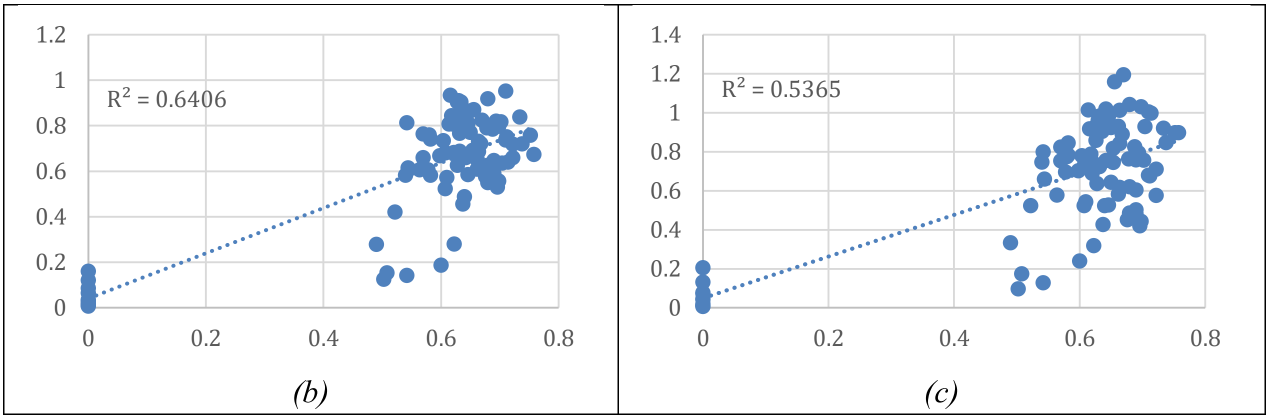


Figure 10 Surface velocity values comparison between the normal (200 frames) and treated image-based process (a) with the coefficient of determination for the increased number (b) to 290 frames and reduced number (c) to 100 frames

The relation between the actual assessment of river dynamics with the changed models in terms of frames' quantity is determined with the coefficient of determination analysis. For base comparison, the normal time resolution with 200 frames supplied to the model gives a strong correlation with R^2 reaching 0.6061, capturing the velocity variation and following the general current regime across the river. A slight improvement in model accuracy is reflected by adding more frames to the model. The higher frame rate provides better data consistency and reduces noise to give a more precise estimation. In contrast, reducing the number of frames from the video footage resulted in lower accuracy compared to the normal resolution with a 0.5365 coefficient of determination. The reduced frame rate brings more variabilities and noises which results in less reliable velocity predictions.

3.4.2. Higher and lower spatial resolution

In this section, the investigation of the effects of varying spatial resolution on the accuracy of the openrivercam model in estimating surface velocities across a river cross-section along the Wesenitz Rivers is established with several computed pixel settings (**Figure 11**). The normal condition configures a 25 cm x 25 cm pixel resolution in each PIV computation, while 12 cm x 12 cm and 50 cm x 50 cm grids are used for the finer and the coarser inputted resolutions respectively in this image-based analysis. From the line graph we can see that, generally, the treated models show underestimation trends compared with the normal model. In the middle of the section, the variability flows computed by these algorithms range only from 0.3 m/s to 0.8 m/s. However, this estimation can match more with the actual ADCP measurement, providing smoother profiles along the river, but still capturing localized flow patterns.

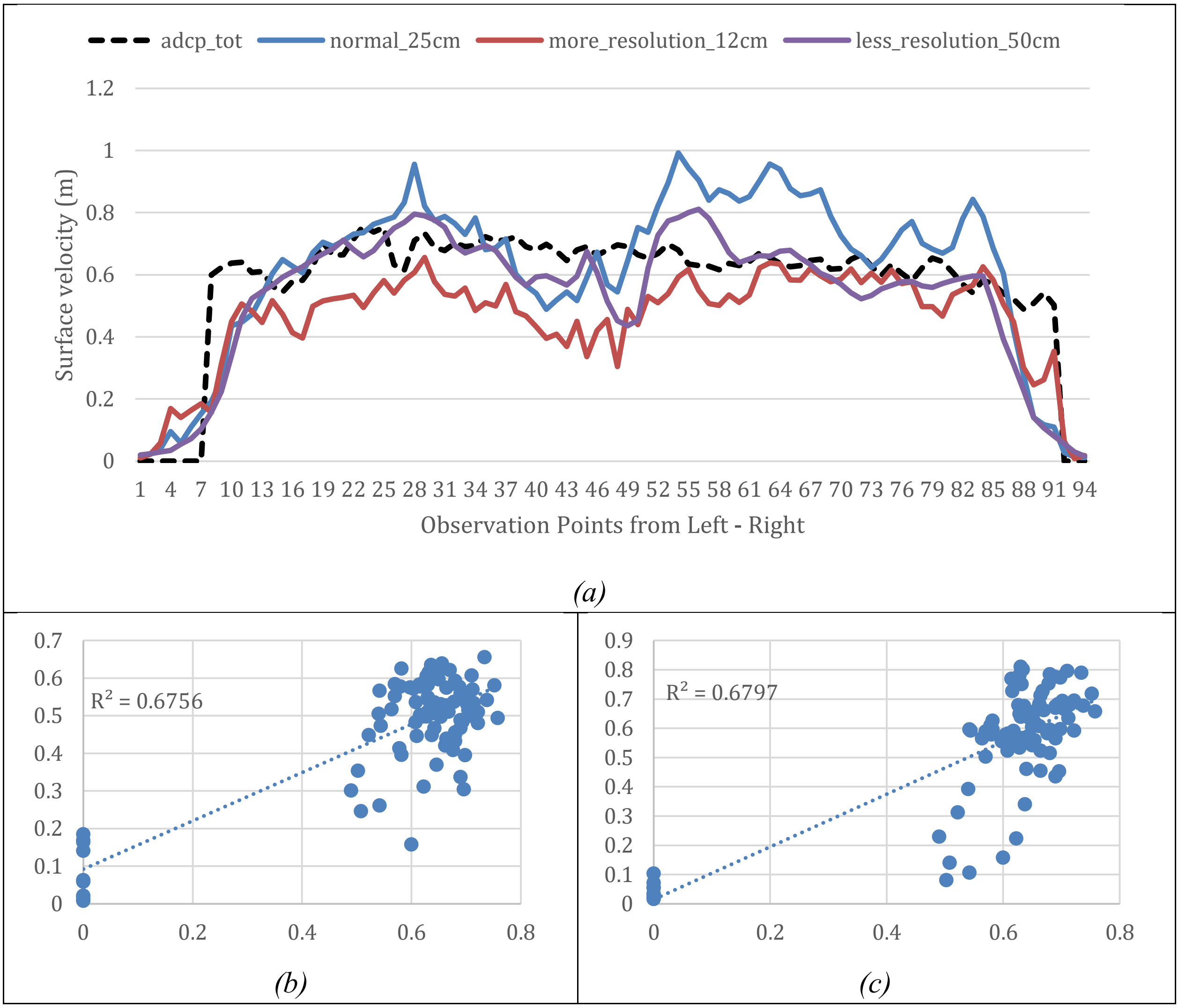


Figure 11 Surface velocity values comparison between the normal (20 cm) and treated image-based process (a) with the coefficient of determination for the increased value (b) to 12 cm and reduced value (c) to 50 cm of spatial resolution.

A surprising output comes from the coefficient of determination resulted from both spatial resolution conditioned models. With a normal grid, the correlation between openrivercam computation with actual ADCP measurement has shown a robust performance with a 0.6061 coefficient. However, significant increases in model accuracy are reflected by both actions in reducing and increasing the grid size of the frame. The improvement of R^2 to 0.6756 from increased spatial resolution occurs from a finer resolution (**Figure 11**b), allowing for a more detailed representation of the flow. It leads to a smoother and closer alignment between the model with the reference ADCP data. Surprisingly, a coarser quality of the spatial resolution also provides the improvement of the R^2 value to 0.6797 in **Figure 11**c. This result suggests that in certain conditions, a coarser pixel grid can still capture the general flow trends effectively. It can be implemented if the observation site's flow dynamics are relatively smooth across the cross-section.

3.4.3. Movement of the cross-section

Transect location is an important requirement to comprehend a surface velocity across the river site. With more than 90 points of observation at the Wesenitz site, a slight error in locating the cross line potentially influences the output of the computation of surface velocity. In this part, the sensitivity of the model for transect shifting is explored to recognize what impact appears compared with the initial condition. Firstly, the normal transect position is located in pixel number four on the x-axis. Then, the line was shifted to pixels one and three along the x-axis to know what profiles are generated with these conditions. In general, moving the transect does not seem to have much difference in terms of velocity trends. Some gentle fluctuation can be recognized in the middle of the river, with three of the models sharing similar behavior. However, in the moved transect number one, the greater variability is depicted in the middle of the river surface, creating the highest and the lowest values which deviate from the ADCP reference data. Meanwhile in another treated model, although at first glance it shares an identical profile, the yellow line captures the movement slightly later than the normal situation. It creates discrepancies with the flow variation between normal and shifted transect surface current estimation.

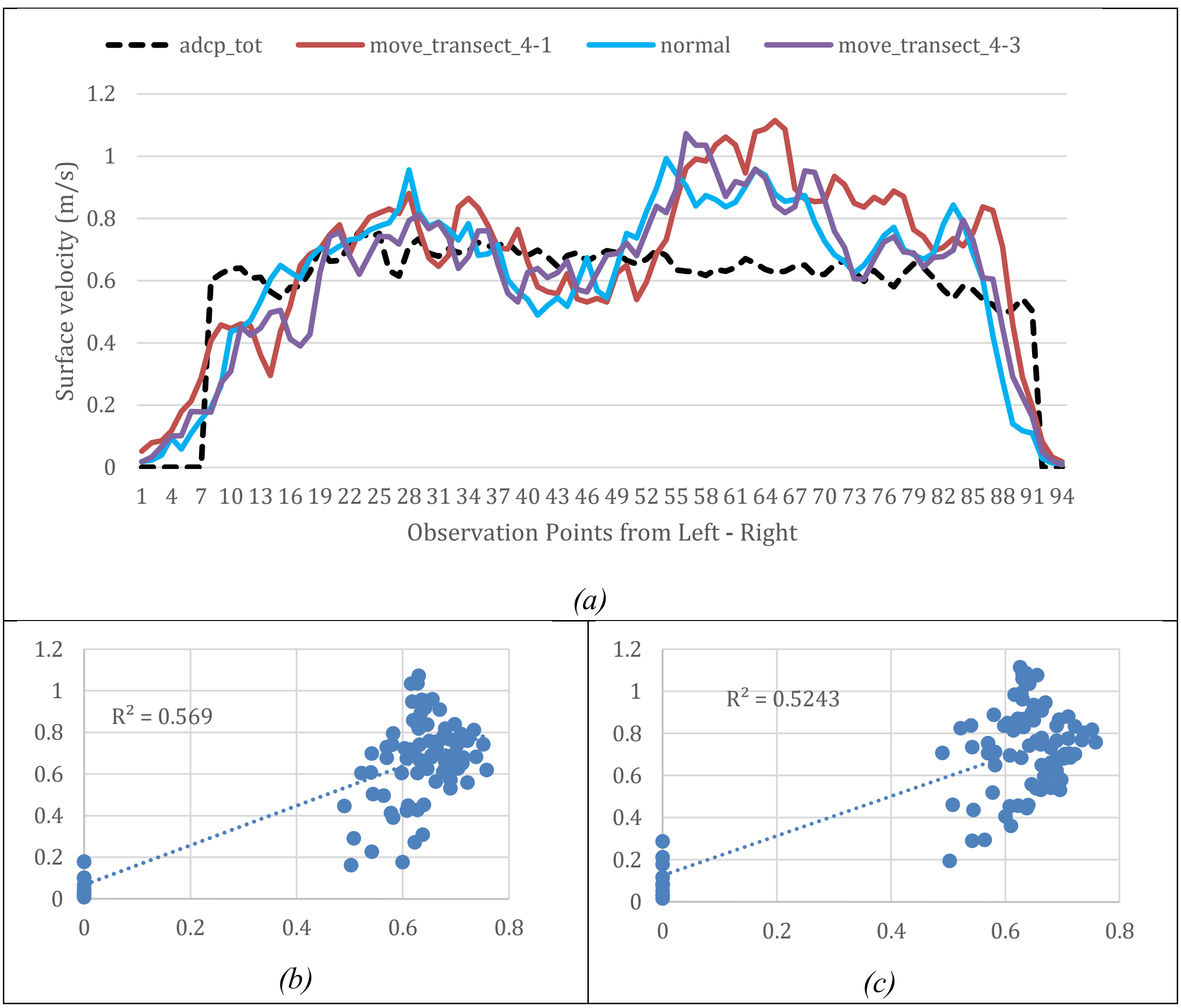


Figure 12 Surface velocity values comparison between the normal and treated image-based process (a) with the coefficient of determination for the displacement of the transect to pixel number 3 (b) and pixel number 1 (c)

With a strong initial correlation with the previous transect, changes in the coefficient of determination value from the transect shifting are expected. Although this treatment results in a reduction of accuracy in the velocity prediction, shifting the transect location has a notable finding that relates between the accuracy point with the water direction. In the normal line scenario, the cross-section is positioned in the lower stream and gives a strong correlation with the actual river dynamics. Placing the line to the upper stream on pixel number 3 provides a slightly less accurate value than the normal one with a 0.569 correlation, presented in **Figure 12**b. However, once the observation line is shifted to a further upstream location, the R^2 declines sharply to 0.5243 on pixel number 1, as it is illustrated in **Figure 12**c. This analysis indicates that the model's performance is sensitive to the location of the transect with areas closer to the riverbank introducing more complexity and reducing predictive accuracy.

4. Discussion

The result of this study provided insight into the accuracy and latency differences between two image-based velocimetry programs, openrivercam with its LSPIV approach and tractrac utilizing the PTV method. Comparative analysis from this study reveals distinct performance characteristic from both application that inform their optimal applications. LSPIV approach through openrivercam application presents an excels in natural river monitoring operational, demonstrating superior accuracy (R^2 = 0.57-0.62 vs. PTV's 0.13-0.28) in capturing large-scale flow patterns across all field sites. It produced more stable velocity estimation (RMSE 0.11-0.34 m/s) by analyzing image patterns rather than individual particles from PTV approach, proving it robust against natural tracer variability (Tauro et al., 2017). Significant research also refines this finding, with a study by (Bradley, Kruger, Meselhe, & Muste, 2002) showed the water regime measurement with LSPIV in a stage station provides high accuracy within the estimated standard error for the current meter compared with direct observation for a stream in Iowa with a drainage area of around 150 km². Research by (Creutin, Muste, Bradley, Kim, & Kruger, 2003) also presented a high estimation of LSPIV measurement with a stationary remotely operated camera for instantaneous discharge data set in a 70 m cross-section of the Iowa River. On another hand, tractrac offers niche advantages for more detailed studies. This system suffered from inaccuracy result caused by several reasons, such as particle misidentification from reflection, supported by (Hauet, Creutin, & Belleudy, 2008), stated that several parameters that still hinder the extraction of accurate PIV-based velocities are illumination conditions, sunlight reflection, and image ortho-projection process. Another potential drawback comes from its sensitivity to illumination changes during normalization process (Aguirre-Pablo, Alarfaj, Li, Hernández-Sánchez, & Thoroddsen, 2017). Despite all the shortfalls, PTV approach showed potential laboratory and small-scale studies where controlled seeding is possible and turbulence analysis outweighs absolute accuracy needs (Tauro et al., 2017). This research also reveals unexpected insights from camera specifications applied in the observation site. While higher-resolution cameras (1920×1080) generally improved LSPIV accuracy with the turndown of 18% of RMSE, performance of PTV was more affected by environmental and field condition, highlighted by the research of (Sutarto, 2015), with orthorectification process.

Based on the comparative and sensitivity analysis, guidelines for implementing image-based velocimetry in real-world scenarios can be proposed. Openrivercam (LSPIV) is the preferred choice for routine river monitoring and discharge estimation due to its robust accuracy (R^2 = 0.57–0.62) and stability across varying natural conditions. Optimal results are achieved with more than 280 frames and a less fine 50 cm² interrogation area to balance processing time and spatial resolution. Supplying the velocimetry process with 280 frames (9 to 10 seconds) can drop the error points, as well as reduce the percentage of it against the average of the stream flow score, while generating the computation with an increased dimension of interrogation area can lift the accuracy point and reduce the error ratio. The last action to perform an ideal velocimetry analysis is to make sure the cross-section position is not shifting at all. While a small misplacement impacts only a small amount of error addition, the fluctuation of inaccuracy performance increases as far as the position changes from its original place. For more detailed turbulence or sediment transport studies, PTV from tractrac tool offers finer-scale velocity data, but requires more controlled environments to mitigate errors from reflections and particle misidentification. A minimum of 30 fps is recommended to capture rapid flow dynamics. A hybrid approach is suitable to perform emergency flood monitoring analysis with LSPIV for reliable bulk discharge calculations and PTV for identifying localized hazards. This strategy aligns with SDGs targets by enabling adaptive water resource management in data-scarce regions (Ovink, Rahimzoda, Cullman, & Imperiale, 2023).

Several limitations appeared in this study must be acknowledged. Flow conditions available during the analysis were low-to-moderate flow velocity (<1.5 m/s). Field tests in high-velocity or sediment laden rivers are remained uncertain. The environmental dependencies also hamper the output accuracy, which are influenced by lighting conditions and natural tracer availability, which is not well-covered in this paper. Customization on applying image stabilization and correcting tracers' movement potentially reduce the streamflow rate measurement by 20% to 30% (Detert, 2021), pointing how importance tracer and video quality. Coming from those limitations and expand the applicability of image-based velocimetry, extreme flow testing and tracer deployment system should be applied. The future project can validate techniques in flash floods (>2 m/s) and hyper concentrated flow to assess robustness under extreme condition. Developing hybrid approaches combining natural tracer for LSPIV and biodegradable artificial particles for PTV can improve accuracy in low-tracer environments. These recommendations address key operational trade-offs between accuracy, resolution, and computational efficiency, providing a framework for practitioners to select context-appropriate tools. Future work should also explore real-time integration with low-cost sensors to enhance accessibility.

5. Conclusion

The focus of this study was to generate a comprehensive evaluation of two open-source image-based velocimetry techniques, openrivercam (LSPIV) and tractrac (PTV), for river flow monitoring under real-world conditions. Our findings demonstrate that openrivercam delivers superior accuracy (R^2 = 0.57–0.62) and reliability for large-scale surface velocity estimation, making it particularly suitable for operational monitoring in diverse river environments. While tractrac offers finer spatial resolution, its sensitivity to environmental noises and particle tracking errors limits its standalone use for field applications, though it remains valuable for laboratory-scale turbulence studies. The research highlights critical trade-offs between accuracy, computational efficiency, and environmental adaptability, providing practitioners with evidence-based guidelines for technique selection. Key operational factors such as frame count (> 280), spatial resolution (50 cm²), and precise transect placement significantly influence performance outcomes. These insights address a pressing need for accessible, non-invasive flow monitoring tools, particularly in resource-limited regions where traditional methods are impractical. With several limitations occurred on this study, future work should focus on validation in extreme flow conditions, with hybrid tracer availability, and explore on real-time system integration to further bridge the gap between scientific innovation and practical resource water management. By advancing scalable, cost-effective monitoring solutions, this study contributes directly to global efforts in sustainable water governance and climate resilience under SDG 6.

Author Contributions:

In this research, several contributions from authors are provided below. Conceptualization, Farhan Kurniawan and Sebrian Beselly; methodology, Farhan Kurniawan; software, Farhan Kurniawan, Sebrian Beselly, and Claudia Bertini; validation, Piet Lens and Sebrian Beselly; formal analysis and investigation, Farhan Kurniawan; resources, Piet Lens and Sebrian Beselly; writing – original draft preparation, Farhan Kurniawan; writing – review and editing, Farhan Kurniawan; supervision, Piet Lens, Sebrian Beselly, and Claudia Bertini. All authors have read and agreed to the published version of the manuscript.

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