

River Surface Velocity Estimation Using UAS-Borne Doppler Radar and Continuous Wavelet Transform

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Abstract—Reliable estimation of river surface velocity is essential for hydrological monitoring, flood forecasting, and water resource management, yet conventional in situ measurements remain spatially limited and operationally demanding. Unoccupied aerial systems (UASs) equipped with Doppler radar provide a promising remote sensing solution for rapid, contactless velocity measurement. However, mixed ambient wind and propeller-induced airflow (propwash) introduce significant distortion in radar returns, leading to composite velocity estimates that mix true river flow with locally induced air motion. To address this challenge, we develop a bidirectional observation framework for UAS-borne Doppler radar measurements. The same surface footprint is observed from two opposing viewing directions, and Doppler spectra from each acquisition are analyzed using the continuous wavelet transform (CWT) to resolve mixed velocity components. An analytical integration of the bidirectional measurements is then applied to remove the propwash-induced interference, enabling retrieval of the true river surface velocity under light wind conditions. The proposed approach was

evaluated using field experiments conducted across more than 50 cross sections (XSs) in five rivers, spanning a wide velocity range from 20 to 250 cm/s. Retrieved velocities were validated against independent in situ measurements obtained with an OTT-MFPro current meter, acoustic Doppler current profiler (ADCP), and FlowTracker. Results demonstrate strong agreement with reference observations, with the bidirectional measurement configurations achieving normalized root-mean-square errors (NRMSEs) below 20%. These results highlight the capability of UAS-borne Doppler radar combined with bidirectional observations and wavelet-based spectral analysis to mitigate propwash-induced velocity bias and enable accurate river surface velocity retrieval. Larger uncertainties were observed for single-direction measurements, particularly at low velocities.

Index Terms—Bidirectional measurements, continuous wavelet transform (CWT), Doppler radar, river surface velocity, unoccupied aerial systems (UASs).

I. INTRODUCTION

ACCURATE estimation of river surface velocity plays a critical role in hydrological monitoring, flood forecasting, and water resources management [1], [2]. Surface velocity observations are widely used for discharge estimation [3], hydraulic model calibration [4], and understanding river dynamics [5]. Reliable velocity measurements are therefore essential for both scientific research and operational water management. Conventional river velocity measurements are typically obtained through in situ instruments such as the acoustic Doppler current profiler (ADCP) [6], the SonTek FlowTracker acoustic Doppler velocimeter [7] (hereafter referred to as FlowTracker), and electromagnetic current meters such as the OTT-MFPro [8]. These instruments provide high measurement accuracy and have become standard tools for hydrological observations. However, these measurements are typically point-based and require direct contact with the water, which restricts their spatial coverage and operational efficiency. In particular, in situ observations are difficult or even impossible to obtain during extreme flow events and in remote or inaccessible areas. This lack of reliable in situ data has become a major bottleneck in global-scale hydrological research and applications.

To overcome these limitations, remote sensing techniques have increasingly been explored for river surface velocity

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monitoring, particularly optical [9], [10] and thermal [11], [12] velocimetry methods that enable noncontact measurements over large spatial domains. Particle image velocimetry (PIV) and large-scale PIV (LSPIV) have been widely used to estimate flow velocities from image sequences acquired by fixed cameras or mobile platforms such as unoccupied aerial systems (UASs) and helicopters [13], [14]. Stereoscopic PIV (SPIV) further extends conventional 2-D PIV to 3-D measurements by reconstructing surface velocity fields from multiview observations based on stereoscopic vision principles [15]. Alternatively, space–time image velocimetry (STIV) estimates 1-D surface velocities along predefined search lines by constructing space–time images from grayscale intensity variations across consecutive frames, offering improved computational efficiency and robustness under textured flow conditions [16], [17]. Despite their advantages, the optical-based velocimetry remains strongly dependent on favorable illumination conditions, the presence of visible surface tracers, and is susceptible to wind-induced disturbances. Meanwhile, the thermal-based velocimetry is subject to environmental constraints, most notably the air–water temperature gradient. Both approaches are further limited in large-river applications, where multiple video scenes must be mosaicked to obtain complete spatial coverage. Furthermore, the substantial computational cost associated with processing large image datasets may limit their applicability in real-time and operational monitoring scenarios, highlighting the need for alternative sensing approaches that are less sensitive to environmental constraints.

Radar-based techniques have emerged as a robust solution for river surface velocity retrieval due to their all-weather and day–night operational capability, enabled by the weak sensitivity of microwave signals to illumination and atmospheric conditions [10], [18]. Doppler radar systems estimate surface velocity by measuring the Doppler frequency shift of electromagnetic waves backscattered from moving water surfaces, enabling noncontact flow monitoring without disturbing the flow field [19], [20], [21]. Based on deployment configuration and operational scenarios, Doppler radar systems for river velocity monitoring can be broadly categorized into three types. *Fixed-station systems*, typically installed on bridges or riverbanks, enable continuous long-term monitoring with stable observation geometry, supporting time-series analysis of flow dynamics [22]. Although measurement accuracy on the order of 10 cm/s has been reported, such systems are inherently limited by fixed spatial coverage and infrastructure requirements, which may restrict deployment in remote environments [23]. *Mobile systems*, including handheld or vehicle-mounted configurations, enable rapid deployment for emergency surveys such as flood monitoring [24], [25]. However, these systems typically provide limited spatial coverage and may suffer from geometric inconsistencies due to manual operation [26]. *UAS-borne systems* provide enhanced flexibility for rapid surveys over large or inaccessible river reaches. By leveraging aerial mobility, these systems enable efficient measurements in hazardous or complex terrain [27]. Recent studies indicate that reliable velocity retrieval can be achieved when appropriate signal processing techniques are applied to compensate for platform motion effects [28].

Despite the operational flexibility of UAS-borne Doppler radar for hydrometric monitoring, propeller-wash (propwash)-induced interference remains a critical factor affecting measurement accuracy [28], [29]. The downward momentum flux generated by multicopter propulsion systems produces complex airflow–water interactions, generating secondary wind–wave fields that can significantly perturb the Bragg-scale capillary waves, which constitute the dominant backscattering mechanism at K- and Ka-band frequencies [30], [31]. Consequently, the received radar signals may be contaminated by localized clutter, reflecting both intrinsic streamflow dynamics and turbulence induced by near-field aerodynamic forcing. Strong ambient wind conditions may further modulate the short-scale surface roughness and Bragg scattering, increasing Doppler uncertainty and complicating the separation of hydraulic and aerodynamic velocity components. This effect introduces nonstationary spectral distortions, including frequency bias and spectral broadening. Conventional centroid-based Doppler estimators [32] often lack the capability to distinguish hydraulic velocity signatures from aerodynamic disturbances, particularly under low-flow conditions where the propwash-induced velocity bias (hereafter, propwash bias) may approach or exceed the ambient stream velocity. The Gaussian two-peak model has been used to separate true river surface velocity from propwash effects in Doppler spectra. However, the nonuniqueness of the fitting solution and the limited validity of the bimodal assumption under high-velocity conditions (>80 cm/s) restrict its general applicability [28]. Furthermore, the lack of electromagnetic scattering models that account for near-field aerodynamic effects [33], as well as the absence of robust blind source separation (BSS) methods [34], continues to limit the accuracy of river surface velocity measurements. These challenges highlight the need for physically informed scattering analysis and advanced signal separation approaches to enable robust Doppler-based flow measurements under UAS operating conditions.

To address these challenges, this study proposes a bidirectional observation framework for river surface velocity retrieval using UAS-borne Doppler radar. The approach relies on observing the same water surface footprint from two opposing viewing directions in sequence. In this configuration, the river surface velocity produces distinct Doppler shifts in each observation, whereas the airflow component induced by propwash remains largely symmetric. By exploiting this asymmetry, the true river velocity (under light-wind conditions) can be analytically separated from the mixed Doppler measurements. To further enhance the extraction of velocity components, a signal processing strategy based on the continuous wavelet transform (CWT) [35], [36], [37], [38] is employed. The wavelet-based spectral analysis enables precise identification of velocity signatures within the Doppler signal, facilitating robust separation of hydraulic and aerodynamic contributions.

The proposed method was evaluated through extensive field experiments conducted at more than 50 cross sections (XSSs) across five rivers, covering a wide range of flow conditions with surface velocities ranging from 20 to 250 cm/s. The retrieved velocities were validated against independent in

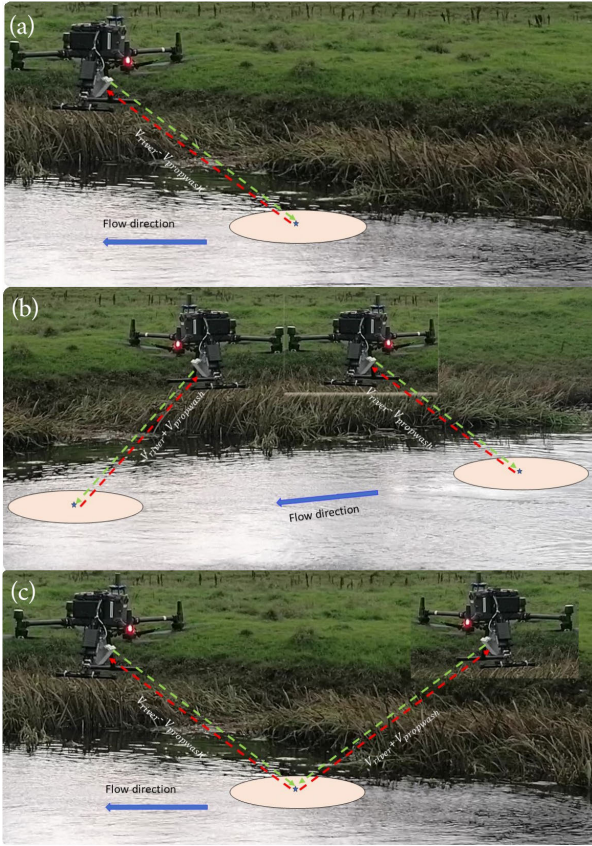


Fig. 1. Three measurement configurations. (a) Single-direction measurements (upstream-looking). (b) Bidirectional measurements with different radar footprint areas. (c) Bidirectional measurements with identical footprint areas.

situ measurements obtained from an ADCP, an OTT-MFPro current meter, and a FlowTracker velocimeter.

The main contributions of this study are summarized as follows. First, a bidirectional observation strategy is proposed to address propwash-induced contamination in UAS-based Doppler radar measurements. Second, a CWT-based spectral analysis method is developed to extract velocity components from Doppler signals. Third, the proposed framework is validated through extensive field experiments across multiple rivers and flow conditions, demonstrating its capability for practical river monitoring applications.

The remainder of this article is organized as follows. Section II introduces the UAS-borne Doppler radar measurement system and data acquisition procedure. Section III describes the proposed bidirectional observation framework and the CWT-based signal processing method. Section IV presents the field experiments and validation datasets. Section V presents experimental results. Section VI discusses performance evaluation. Finally, Section VII summarizes the conclusions and outlines potential directions for future research.

II. UAS-BORNE DOPPLER RADAR SYSTEM AND DATA ACQUISITION

A. UAS-Borne Doppler Radar System

In this study, a Geolux RSS-2-300W Doppler radar was mounted on a DJI Matrice 300 RTK UAS (see Fig. 1). The radar operates as a continuous-wave (CW) K-band system

at 24.125 GHz (wavelength: 12.5 mm) and measures river surface velocities in the range of 0.02–15 m/s, with a velocity resolution of 7.3 mm/s. The system exhibits a repeatability error below 1%. The Doppler radar provides direct access to raw Doppler spectra, output as a sequence of individual traces. Each trace consists of the return power of 4096 frequency bins (4096 16-bit samples) acquired at a rate of 10 Hz, and the raw data are stored in SEG-Y format for subsequent processing. Trace selection was then applied to remove invalid measurements and retain reliable spectra for velocity estimation. The system has recently evolved into a commercial configuration, with radar parameter optimization planned within the UAWOS project.

B. Data Acquisition

During measurements, the platform hovered at predefined waypoints for approximately 60 s to ensure stable data acquisition. Flight trajectories were planned such that the UAS heading remained perpendicular to the river flow direction to maintain a consistent observation geometry. The Doppler radar (see white box in Fig. 1) was mounted at a fixed incidence angle of 45° relative to the water surface. According to the Doppler principle, the frequency shift between the transmitted and backscattered electromagnetic waves is proportional to the relative velocity between the radar and the water surface within an elliptical measurement area, hereafter referred to as the footprint [39], [40], [41].

During hovering, the UAS maintained a stable position using the RTK positioning system and onboard flight controller, minimizing platform motion effects on the Doppler measurements. Radar data, including raw Doppler spectra and derived velocity estimates, were continuously recorded at a sampling frequency of 10 Hz. Each measurement location was typically sampled for 50–60 s to ensure sufficient temporal averaging and improve measurement robustness.

Three measurement configurations were designed to evaluate the effects of flight altitude and observation geometry.

- 1) During the 2023 Rönne Å campaign, the influence of flight altitude (1.5–6.1 m) on radar measurements was investigated with the radar pointing upstream [see Fig. 1(a)] [28]. The effect of signal direction at multiple flight altitudes was evaluated only in this campaign. Based on these results, a fixed flight altitude of approximately 4 m was adopted for all subsequent surveys in other rivers.
- 2) Radar measurements were conducted in both upstream and downstream viewing directions under identical flight conditions (altitude ≈ 4 m), resulting in different surface footprint areas [see Fig. 1(b)].
- 3) Radar measurements were conducted in both upstream and downstream viewing directions under identical flight conditions (altitude ≈ 4 m), resulting in identical radar footprint areas [see Fig. 1(c)].

A flight altitude of approximately 4 m above the water surface was adopted for all bidirectional measurements as a compromise among UAS-induced propwash, radar footprint size, signal quality, spatial resolution, waypoint configuration,

and field measurement efficiency [28]. In addition, all measurements were conducted under relatively stable hydrological and meteorological conditions (light winds of approximately 6–20 km/h), avoiding periods of strong wind or rainfall to ensure data quality.

III. METHOD

This methodology integrates bidirectional observation, wavelet-based spectral decomposition, and analytical combination, providing a robust framework for accurate, repeatable, and minimally biased river surface velocity retrieval from UAS-borne Doppler radar measurements.

A. Bidirectional Observation Framework

To mitigate the influence of drone-induced airflow on surface velocity retrieval, a bidirectional observation framework was implemented [see Fig. 1(c)]. In the optimized measurement protocol, each river surface footprint was sequentially measured from two opposing directions under identical flight conditions. It should be noted that the measurement protocol evolved throughout the different field campaigns. The optimized protocol described above was implemented only in the later surveys, after insights were gained from the initial campaigns.

The drone moved along the XS reference in one direction, starting from one riverbank to the other, without rotating at waypoints, and then flew back along the same line in the opposite direction, again without rotation. The maximum time interval between the two measurements at the same waypoint was within 30 min, confirming that flow conditions remained stable. By comparing Doppler spectra obtained from upstream- and downstream-oriented measurements, the contribution of propwash bias can be isolated and removed, enabling estimation of the true river surface flow while neglecting the influence of ambient wind.

This approach provides systematic correction for platform-induced perturbations, ensuring that the retrieved velocities accurately reflect the river surface flow while minimizing measurement bias inherent in single-direction observations.

B. CWT-Based Velocity Extraction

The CWT of a signal $S(v)$ is defined as

$$W(a, b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} S(v) \psi\left(\frac{v-b}{a}\right) dv \quad (1)$$

where $W(a, b)$ denotes the wavelet coefficient at scale a and translation b , $S(v)$ represents the Doppler velocity spectrum, and $\psi(\cdot)$ is the mother wavelet. The scale parameter a controls the spectral resolution, while b corresponds to the velocity location of spectral features. The normalization factor ensures energy consistency across different scales. Mexican hat (Mexh) wavelet (also known as the Ricker wavelet) is the second derivative of a Gaussian function. Due to its symmetric shape, strong localization capability, and sensitivity to spectral peaks, it is well suited for identifying localized energy distributions and extracting dominant velocity components from Doppler spectra using CWT [42], [43].

Raw Doppler spectra from each directional measurement were processed using the CWT to separate mixed velocity components. The procedure consisted of three main steps.

- 1) *Trace Selection*: For each waypoint, traces corresponding to the radar footprint were identified based on start and end traces.
- 2) *Normalization and Averaging*: Selected traces were normalized and averaged to generate a representative 1-D velocity–amplitude spectrum for each footprint.
- 3) *CWT Application*: The CWT with a Mexh wavelet was applied to the averaged 1-D spectra.

This approach provides simultaneous localization in both velocity and velocity resolution, enabling robust identification of mixed velocity components associated with river surface flow and platform-induced airflow effects. Dominant velocity peaks are then extracted to derive representative footprint-scale velocities, improving the stability of velocity retrieval under transient disturbances and dynamic airborne observations.

Low-velocity gaps frequently appear in Doppler spectra due to weak or missing returns near zero velocity. To mitigate this issue, a synthetic 1-D spectrum was used to evaluate the impact of different gap-reconstruction strategies (see Fig. 2). Following Fulton et al. [30], a minimum velocity threshold (15 cm/s) was applied, and the gap region was reconstructed using either zero filling or spline interpolation. To further clarify, we updated the shape of the synthetic 1-D spectrum (see Fig. 3), filling the gap region $[-15, 15 \text{ cm/s}]$ using spline interpolation. The final analysis demonstrates that combining CWT-based spectral decomposition with this gap reconstruction enhances the robustness of velocity retrieval from spectra affected by low-velocity gaps, achieving a normalized root-mean-square error (NRMSE) of 2.58%.

C. Analytical Combination for Propwash Bias Removal

Following spectral decomposition, bidirectional measurements were analytically combined to isolate the true river surface velocity. Let V_{up} and V_{down} be the velocities measured in the upstream and downstream directions, respectively, each consisting of the true river velocity V_{river} , the ambient velocity V_{wind} , and the propwash bias $V_{propwash}$. Here we define the mixed velocity $V_{river,wind}$ as the combination of V_{river} and V_{wind} , with a constant direction equal to the true river velocity under light wind conditions. Under the linear superposition assumption, the Doppler velocity represents the projection of both $V_{river,wind}$ and $V_{propwash}$ along the radar line of sight (LOS)

$$\begin{cases} V_{up} = V_{river,wind} - V_{propwash} \\ V_{down} = V_{river,wind} + V_{propwash} \end{cases} \quad (2)$$

where the sign reflects the relative motion direction along the radar LOS. Note that the measured velocity may become negative when the propwash bias exceeds the river velocity, indicating that the dominant motion component is directed opposite to the river flow.

Solving (2) yields

$$\begin{cases} V_{river,wind} = \frac{V_{up} + V_{down}}{2} \\ V_{propwash} = \frac{V_{down} - V_{up}}{2} \end{cases} \quad (3)$$

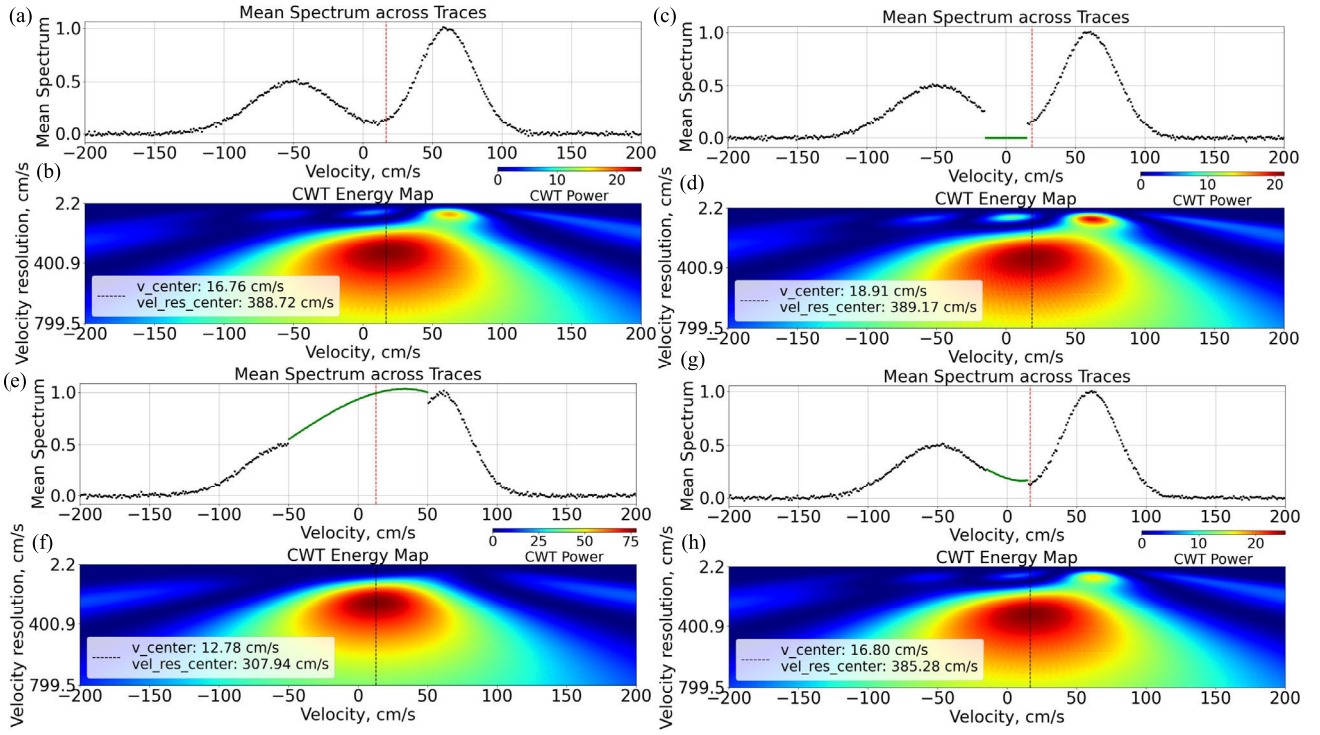


Fig. 2. Synthetic demonstration of low-velocity gap reconstruction in Doppler spectra using CWT. (a) Mean synthetic spectrum. (b) Corresponding CWT power distribution showing the estimated center velocity and velocity resolution. (c) and (d) Small-gap reconstruction (-15 to 15 cm/s) using zero filling. (e) and (f) Large-gap reconstruction (-50 to 50 cm/s) using spline interpolation. (g) and (h) Small-gap reconstruction using spline interpolation. Green markers indicate reconstructed spectral regions.

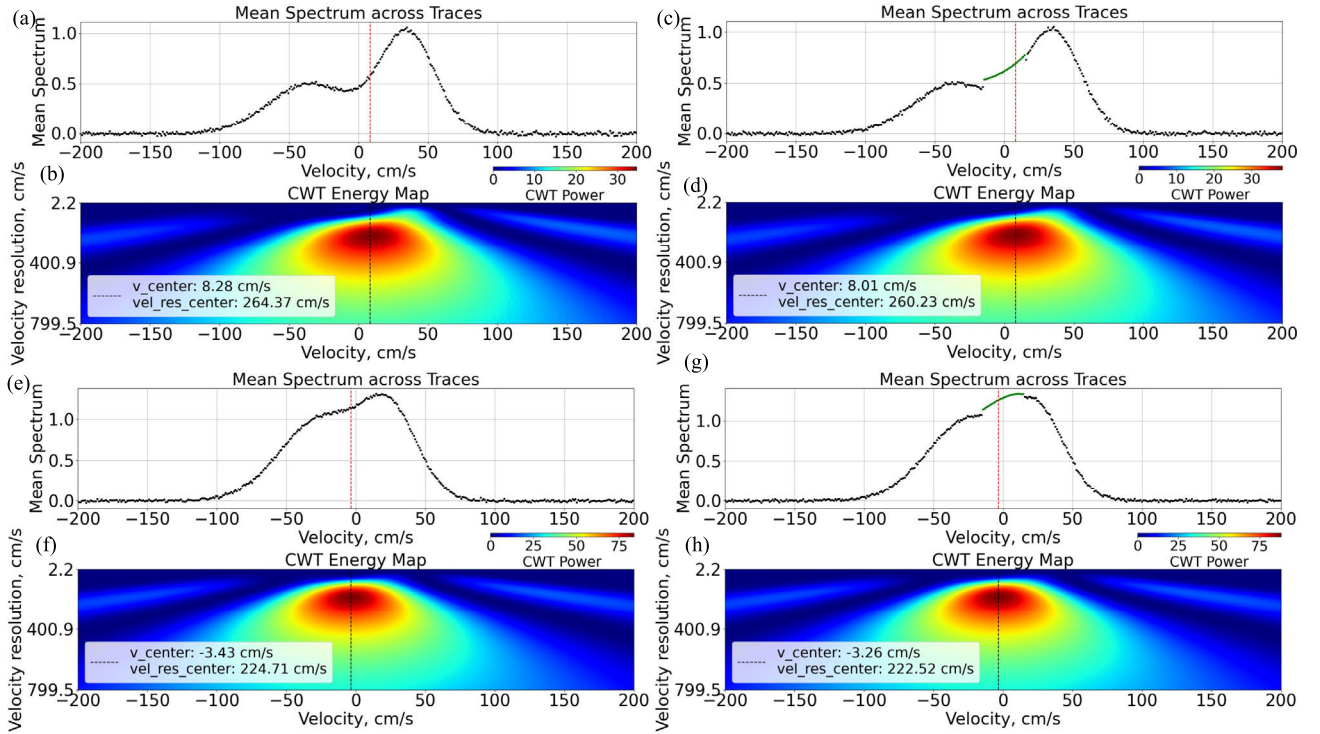


Fig. 3. Comparisons of other synthetic models. (a) Mean synthetic spectrum. (b) Corresponding CWT power distribution showing the estimated center velocity and velocity resolution. (c) and (d) Gap reconstruction (-15 to 15 cm/s) using spline interpolation results. (e)–(h) Other compared example. Green markers indicate reconstructed spectral regions.

This formulation remains valid regardless of the relative magnitude of river velocity and propwash bias. Representative

examples under different flow conditions are shown in Figs. 4 and 5, demonstrating that the proposed bidirectional

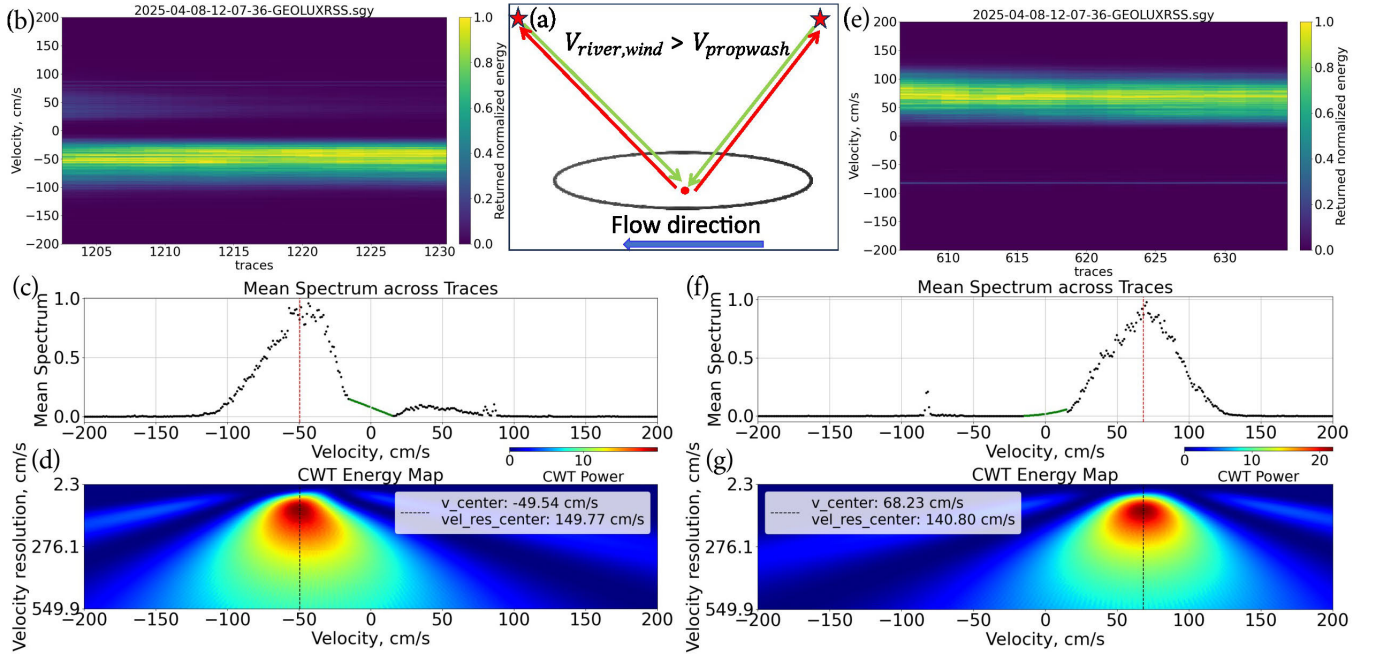


Fig. 4. CWT analysis of upstream- and downstream-looking Doppler measurements ($V_{river,wind} > V_{propwash}$). (a) Measurement geometry. Upstream-looking results: (b)–(d) return-normalized energy map, mean Doppler spectrum, and CWT power map, respectively. (e)–(g) Corresponding downstream-looking results.

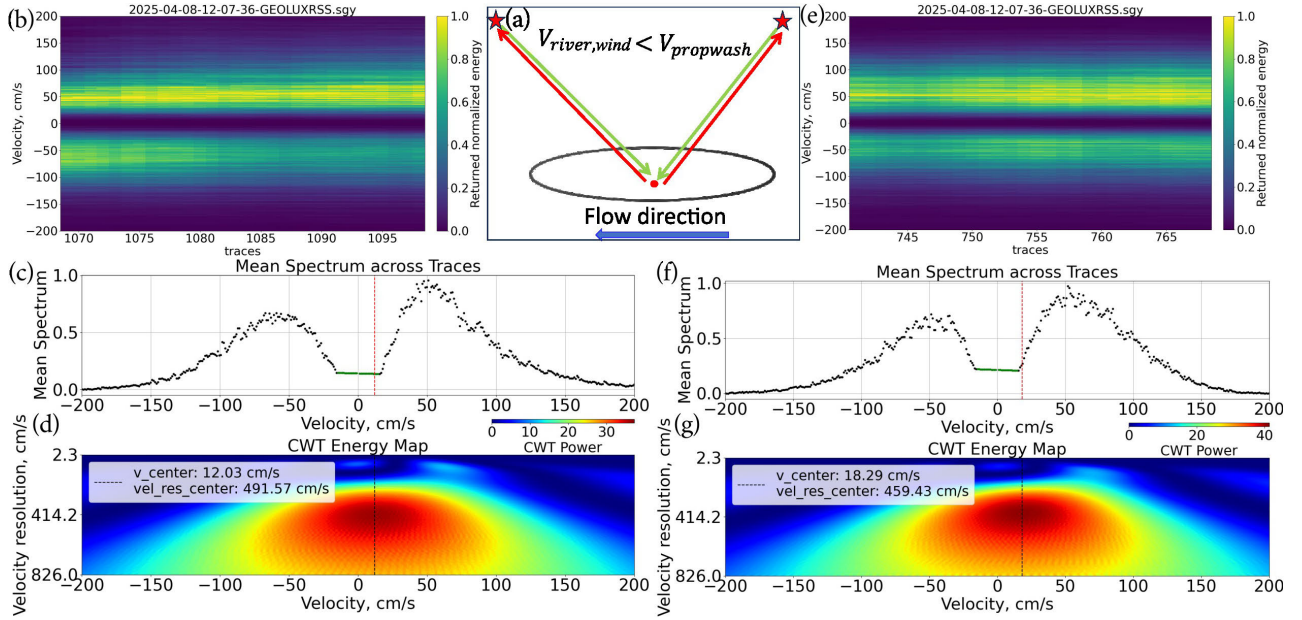


Fig. 5. CWT analysis of upstream- and downstream-looking Doppler measurements ($V_{river,wind} < V_{propwash}$). (a) Measurement geometry. Upstream-looking results: (b)–(d) return-normalized energy map, mean Doppler spectrum, and CWT power map, respectively. (e)–(g) Corresponding downstream-looking results.

observation framework can effectively separate river flow and propwash contributions whether the river velocity exceeds the propwash bias or vice versa.

IV. FIELD EXPERIMENTS AND VALIDATION DATASETS

The experimental dataset comprises UAS-borne Doppler measurements and co-located in situ reference velocities under diverse hydraulic conditions. It includes single-direction and bidirectional measurements with identical or varying radar footprints, providing a comprehensive basis to assess the accuracy and robustness of the proposed velocity retrieval framework. The measurement protocols varied among field

sites due to the progressive optimization of the UAS radar observation strategy. The initial campaigns were designed to investigate the influence of flight altitude and signal direction, while the later campaigns adopted the optimized configuration identified from these experiments, including a flight altitude of approximately 4 m and paired bidirectional measurements at each waypoint.

A. Study Sites and Hydraulic Conditions

Field experiments were conducted across five European rivers under different hydraulic conditions to evaluate the performance and robustness of the proposed UAS-borne Doppler

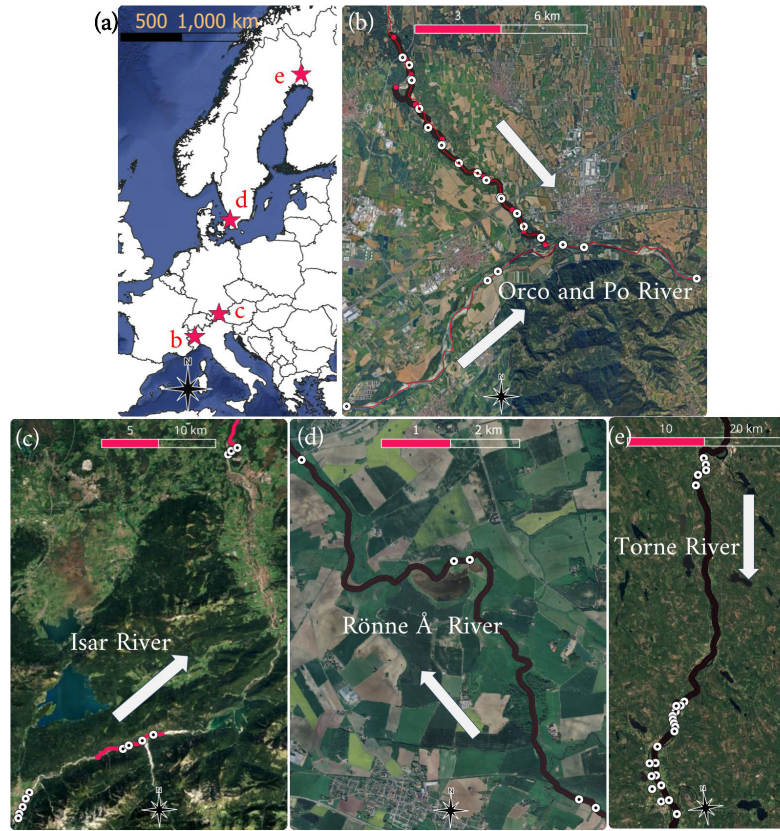


Fig. 6. (a) Map showing the measured locations of selected five different rivers. (b)–(e) Overview of measured XSs.

radar velocity retrieval method. The study sites include the RönneÅ and Torne rivers in Sweden, the Orco and Po rivers in Italy, and the Isar river in Germany (see Fig. 6). These rivers represent a range of river sizes, hydraulic regimes, and channel morphologies, providing diverse testing conditions for airborne surface velocity measurements.

The measurement campaigns were carried out between August 2023 and July 2025 under relatively stable hydrological conditions. Depending on the experimental objectives, both single-direction and bidirectional observation modes were implemented.

The geographic locations of the surveyed XSs were determined using the onboard RTK-GNSS positioning system and referenced to the local projected coordinate systems used at each study site. The specific coordinate reference systems (CRSs) and EPSG codes are listed in Table I.

A total of more than 50 XSs were surveyed, covering river surface velocities from approximately 20 to 250 cm/s. The selected sites encompass both hydraulically uniform reaches and sections with complex channel morphology, providing representative conditions for evaluating airborne velocity measurements. All surveys were conducted under quasi-steady flow and low-wind conditions to minimize temporal variability and surface disturbances. The dataset spans typical hydrological monitoring scenarios, including low-, moderate-, and relatively high-flow regimes. The UAS Doppler radar and reference velocity measurements were acquired within short time intervals, and stable hydraulic conditions were confirmed by consistent UAS-derived water surface elevation (WSE) and

water penetrating radar (WPR) water depth measurements collected before and after each survey.

B. UAS Doppler Radar Measurements

UAS-based Doppler radar measurements were conducted following the data acquisition strategy described in Section II. At each XS, the UAS hovered at predefined waypoints to collect Doppler spectra of the river surface. Multiple footprints were sampled across the river width to capture the spatial variability of surface velocity.

Three measurement configurations were adopted across the study sites based on the experimental objectives described in Section III. For the identical footprint configuration, the Torne river site provides a representative example, where only three upstream-looking waypoints were used to represent the upstream footprint due to battery life and operational efficiency constraints, while downstream-looking waypoints covered the full observation range to ensure consistent measurements and enable bidirectional comparison.

The raw Doppler spectra were processed using the CWT approach to extract dominant velocity components, with low-velocity gaps (<15 cm/s) reconstructed when necessary. Missing spectral values were filled using linear interpolation, and a power-based threshold (80% of the maximum CWT power) was applied to retain dominant spectral components. Based on the upstream- and downstream-looking CWT velocities at each pair of waypoints, as defined in (3), the mixed true river surface velocity, under light ambient wind, and the

TABLE I
SUMMARY OF FIELD EXPERIMENTS

Rivers	Number of XSs	Velocity range (cm/s)	River width range (m)	Reference coordinate system	Measurement Mode	Reference instruments	Measured date
Rönne Å River 2023	5	15-120	8.8-15.4	EPSG:3006	Single-direction (pointing upstream)	OTT-MFPro	29-31 August 2023
Isar River 2024	9	20-150	3.4-45.3	EPSG:25832	Bidirectional, different footprint	OTT-MFPro	24–27 February 2024
Torne River 2024	14	15-160	135.7-524.9	EPSG:3006	Bidirectional, identical footprint (3 upstream waypoints)	OTT-MFPro, ADCP, PIV	5-8 September 2024
Isar River 2025	3	150-250	21.4-35.9	EPSG:25832	Bidirectional, identical footprint	ADCP	29–30 July 2025
Orco River 2025	11	15-190	18.2-53.9	EPSG:32632	Bidirectional, identical footprint	FlowTracker	8-10 April 2025
Orco & Po River 2024	13	15-250	18.0-135.1	EPSG:25832	Bidirectional, identical footprint	N/A	14-15 July 2024

platform-induced propwash bias was subsequently derived. The resulting velocity datasets provide a robust basis for subsequent validation against independent in situ measurements.

C. In Situ Reference Measurements

To validate river surface velocities retrieved from the UAS-borne Doppler radar system, independent in situ measurements were acquired using established hydrological instruments, including an OTT-MFPro electromagnetic current meter, ADCPs, and a FlowTracker acoustic Doppler velocimeter. The OTT-MFPro and FlowTracker were used in shallow, wadable areas, whereas ADCP measurements were collected from a boat in deeper sections.

Table I summarizes the in situ measurements conducted at the corresponding field sites. It should be noted that neither the ADCP nor the point-velocity instruments (OTT-MFPro and FlowTracker) directly measure the true water surface velocity. For the ADCP, the reference velocity was taken as the streamwise velocity of the topmost valid depth cell after standard QRevInt quality control, rather than the QRevInt-extrapolated surface velocity, whereas the OTT-MFPro and FlowTracker provide point velocities at the measurement depth only.

Reference in situ measurements were conducted as close as possible in time to the UAS observations to minimize temporal discrepancies in flow conditions. For the ADCP measurements, multiple velocity observations were collected around each reference location along the XS due to the continuous movement of the ADCP during the survey. These measurements were projected onto the reference line and grouped according to their nearest reference positions. Therefore, point-based in situ velocity measurements were first averaged at identical locations to obtain representative values. These averaged velocities were then linearly interpolated to estimate the flow velocity at the Doppler radar waypoint positions, enabling a direct comparison with the UAS-derived velocities.

The UAS Doppler radar and in situ instruments have different spatial sampling scales. The radar-derived velocity represents a footprint-scale surface velocity, whereas OTT-MFPro, FlowTracker, and ADCP measurements represent localized or volume-averaged velocities. Therefore, discrepancies between these measurements may partly arise from spatial variability within the radar footprint, particularly under heterogeneous flow conditions.

V. RESULTS

A. Single-Direction Mode

For the Rönne Å river in 2023, single-direction observations with the radar pointing upstream were conducted at five XSs (XS1–XS3, XS5, and XS6) using multiple flight altitudes to evaluate the baseline performance of the UAS-borne Doppler radar for river surface velocity retrieval (see Figs. 6(d) and 7). Table II summarizes the velocity statistics derived from both the CWT and Gaussian fitting methods [28], including average, minimum, and maximum velocities for each XS, together with mean bias error (MBE), root-mean-square error (RMSE), and NRMSE relative to co-located OTT-MFPro measurements. The number of waypoint samples per XS is also reported.

As shown in Fig. 7, the underestimation of CWT velocities varies with flight altitude. Overall, lower altitude flights (1.5 and 2.1 m) tend to experience stronger propwash effects, leading to a greater negative bias, whereas higher altitude flights (4.1, 5.1, and 6.1 m) exhibit less underestimation. However, at some waypoints, this altitude-dependent trend does not hold because the enlarged radar footprint at higher altitudes captures more heterogeneous flow while experiencing weaker propwash-induced airflow. The altitude-dependent bias is therefore attributed to both the radar footprint size and the relative contributions of mixed velocity components within each footprint. Despite this systematic underestimation, both the Gaussian fitting and CWT-derived velocities exhibit strong linear correlations with OTT-MFPro measurements (see Fig. 7

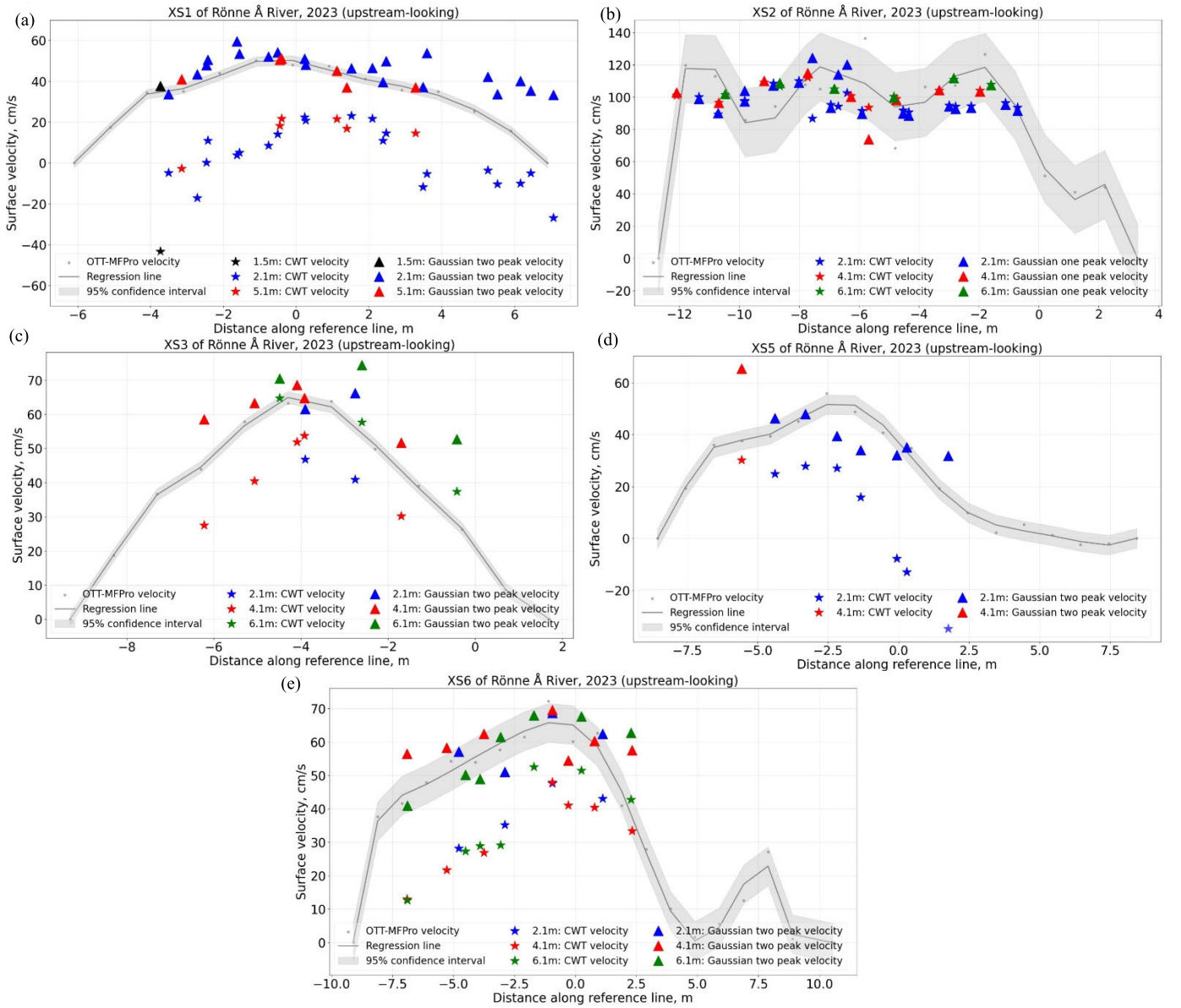


Fig. 7. Rönne Å river: comparisons between OTT-MFPro results (gray points), velocities derived from Gaussian mode fitting (triangle), and CWT velocities (stars). The regression line and the corresponding 95% confidence interval are represented by the gray line and shaded area, respectively. (a)–(e) XS1–XS3, XS5, and XS6, respectively. Different colors represent different drone flight altitudes.

and Table II), confirming that the CWT approach reliably captures the dominant velocity trends.

Table II provides a quantitative assessment of CWT-derived velocities under single-direction observations, with Gaussian fitting results included as a reference to illustrate the limitations of single-direction measurements. The CWT results show systematic underestimation, particularly under low-flow conditions (<50 cm/s), as reflected by large negative MBE values (-33.11 and -13.59 cm/s) and high NRMSE (93.4% and 70.2%) at XS1 and XS5. In contrast, XS2, characterized by higher flow velocities (>80 cm/s), shows reduced bias (MBE = -4.76 cm/s and NRMSE = 14%), indicating that the relative influence of the propwash decreases at higher velocities. Although the Gaussian fitting method reduces these errors to some extent, both approaches remain affected by propwash contamination because they rely on single-direction observations.

These results highlight that, while single-direction processing can capture general velocity trends, it cannot fully separate river flow from UAS-induced airflow effects. This limitation motivates the use of bidirectional measurements, which provide the additional geometric constraints needed to explicitly estimate and correct propwash contributions.

B. Bidirectional Mode With Different Footprints

Bidirectional measurements with different radar footprint areas were conducted to evaluate the influence of measurement geometry on the extraction of river surface velocity and propwash-induced flow components. Representative XSs were selected across the Isar river in 2024 [see Fig. 6(c)], where upstream- and downstream-looking waypoints covered nonoverlapping areas of the river surface [see XS32 shown in Fig. 8(a)]. Upstream- and downstream-pointing Doppler

TABLE II
OVERVIEW OF THE FIRST MEASURE PATTERN (ONLY POINTING UPSTREAM) RESULTS FOR ALL XSs

Study Area	Cross sections	CWT average velocity (cm/s)	CWT min/max velocity (cm/s)	MBE (CWT) (cm/s)	RMSE (CWT) (cm/s)	NRMSE (CWT)	Calculated waypoints samples	MBE (Gaussian) (cm/s)	RMSE (Gaussian) (cm/s)	NRMSE (Gaussian)
Rönne Å River 2023	XS1	3.89	-43.26/23.18	-33.11 ⁺	35.63 ⁺	93.40%	27	6.97 ⁺	11.05 ⁺	28.98%
	XS2	99.56	86.82/112.33	-4.76 ⁺	14.65 ⁺	14.04%	33	-3.28 ⁺	15.15 ⁺	14.52%
	XS3	45.16	27.58/64.75	-8.99 ⁺	13.06 ⁺	24.13%	10	9.09 ⁺	12.06 ⁺	22.27%
	XS5	6.89	-34.76/30.29	-13.59 ⁺	26.74 ⁺	70.24%	22	12.09 ⁺	17.70 ⁺	46.50%
	XS6	34.63	12.69/52.53	-20.60 ⁺	22.88 ⁺	41.43%	18	3.58 ⁺	9.56 ⁺	17.31%

⁺ means the MBE and RMSE were calculated between CWT/Gaussian fitted velocity and OTT-MFPro velocity under each waypoint along the corresponding XS.

TABLE III
OVERVIEW OF THE SECOND MEASURE PATTERN (POINTING TWO DIRECTIONS BUT HAVING DIFFERENT FOOTPRINT AREAS) RESULTS FOR ALL XSs

Study Area	Cross sections	Propwash average bias (cm/s)	CWT corrected average velocity (cm/s)	CWT corrected min/max velocity (cm/s)	MBE (cm/s)	RMSE (cm/s)	NRMSE	Calculated waypoints samples
Isar River 2024	XS9	3.05	70.28	48.75/78.80	N/A	N/A	N/A	N/A
	XS10	5.25	67.57	10.40/91.31	N/A	N/A	N/A	N/A
	XS12	23.23	75.41	63.63/82.30	2.07 ⁺	2.07 ⁺	3.36%	1
	XS15	10.27	87.90	50.21/121.55	N/A	N/A	N/A	N/A
	XS19	10.65	90.97	20.81/147.98	N/A	N/A	N/A	N/A
	XS21	6.24	83.55	48.31/107.43	-19.28 ⁺	21.02 ⁺	20.00%	5
	XS23	2.20	156.24	106.33/175.88	3.59 ⁺	9.92 ⁺	6.54%	5
	XS30	10.40	72.91	59.97/106.98	N/A	N/A	N/A	N/A
	XS32	3.33	76.59	54.70/100.09	-7.34 ⁺	18.67 ⁺	19.21%	2

⁺ means the MBE and RMSE were calculated between CWT corrected velocity and OTT-MFPro velocity under each waypoint along the corresponding XS.

measurements were processed using the CWT approach, and propwash bias was estimated according to the analytical framework described in Section III. Subsequently, the CWT-corrected velocities were obtained and considered as the true river surface flow under the light ambient wind conditions [see Fig. 8(b)].

Table III summarizes the results of this second measurement pattern for the Isar river in 2024, as shown in Fig. 8(b) and (c). Estimated propwash bias ranged from 2.2 to 23.2 cm/s across the surveyed XSs, reflecting the combined effects of platform-induced airflow and ambient wind. The CWT-corrected velocities demonstrate good agreement with the in situ OTT-MFPro measurements, with MBE ranging from -19.28 to 3.59 cm/s and RMSE from 2.07 to 21.02 cm/s. It should be noted that the MBE and RMSE computed from the selected XSs may underestimate the actual error. The limited number of CWT-corrected waypoint samples, compared with the in situ measurements, reduces statistical representativeness, and the selected samples may not fully capture flow variability or propwash-induced disturbances. For instance, at XS23, with a maximum of five samples, the MBE, RMSE, and NRMSE

values are unusually low (MBE = 3.59 cm/s, RMSE = 9.92 cm/s, and NRMSE = 6.54%), reflecting limited spatial coverage rather than inherently higher accuracy.

Overall, the above measurement pattern provides a means to separate the true river surface velocity from UAS-induced propwash, while neglecting the spatial heterogeneity of flow velocity along the streamwise direction. This limitation motivated the development of the one-to-one bidirectional footprint matching strategy presented in this study, which minimizes spatial inconsistency between opposing observations and provides a more robust basis for propwash correction.

C. Bidirectional Mode With Identical Footprints

1) *Limited Upstream Reference Waypoints*: To further evaluate the effectiveness of the propwash separation framework, bidirectional measurements with identical radar footprints were conducted along multiple XSs of the Torne river during the 2024 campaign [see Fig. 6(e)]. In this configuration, only three upstream-looking waypoints were available due to operational constraints, while downstream-looking measurements covered a larger number of locations along each

TABLE IV
OVERVIEW OF THE THIRD MEASURE PATTERN (ONLY THREE WAYPOINTS POINTING UPSTREAM) RESULTS FOR ALL XSs

Study Area	Cross sections	Propwash average bias (cm/s)	CWT corrected average velocity (cm/s)	CWT corrected min/max velocity (cm/s)	MBE (cm/s)	RMSE (cm/s)	NRMSE	Calculated waypoints samples
Torne River 2024	XS2	26.99	76.66	53.34/104.99	N/A	N/A	N/A	N/A
	XS3	0.93	45.48	14.68/58.48	-21.27*	25.12*	37.65%	19
	XS4	22.84	67.96	-2.43/113.65	-0.51**	13.24**	20.19%	22
	XS5	0.73	121.37	58.13/159.68	N/A	N/A	N/A	N/A
	XS6	6.64	113.59	53.49/160.05	22.80&	25.12&	29.10%	23
	XS7	3.25	46.49	-0.89/61.81	N/A	N/A	N/A	N/A
	XS8	-9.06	99.57	32.53/156.93	N/A	N/A	N/A	N/A
	XS9	10.85	53.77	19.30/78.41	N/A	N/A	N/A	N/A
	XS14	20.92	41.21	19.44/51.91	-1.82*	11.75*	27.76%	21
	XS20	-1.50	71.07	27.06/118.94	N/A	N/A	N/A	N/A
	XS21	-3.29	27.00	-45.85/66.39	N/A	N/A	N/A	N/A
	XS22	3.21	76.29	41.60/112.77	N/A	N/A	N/A	N/A
	XS23	4.23	67.33	27.35/88.72	N/A	N/A	N/A	N/A
	XS24	3.88	62.49	25.19/79.85	2.33**	18.13**	30.61%	21

* means the MBE and RMSE were calculated between CWT corrected velocity and ADCP velocity under each waypoint along the corresponding XS.

& means the MBE and RMSE were calculated between CWT corrected velocity and PIV velocity under each waypoint along the corresponding XS.

** means the MBE and RMSE were calculated between CWT corrected velocity and OTT-MFPro velocity under each waypoint along the corresponding XS.

XS [see XS4 shown in Fig. 9(a)]. Representative upstream measurements and their corresponding downstream observations were first selected to estimate the propwash contribution. The resulting three propwash bias estimates were averaged to obtain a representative propwash bias. This mean value was then applied to the remaining downstream measurements to correct the CWT-derived downstream velocities under the assumption of spatially uniform propwash effects. Fig. 9(b) shows a comparison of the CWT-corrected velocities with the available in situ measurements (ADCP and OTT-MFPro), demonstrating good agreement along the XS4. The downstream-looking CWT velocities tend to be slightly higher, whereas the upstream-looking velocities are generally lower, mainly due to the asymmetric influence of propwash bias components on the Doppler measurements. The distribution of the CWT-corrected velocities along the remaining XSs of the Torne river is shown in Fig. 10(a) and (b).

Table IV summarizes the results of this measurement configuration. The estimated propwash bias varies between approximately -9.06 and 26.99 cm/s, indicating that UAS-induced airflow effects vary depending on local wind conditions and flight stability. The negative propwash bias is likely attributed to opposing directions between the river flow and the ambient wind during the measurements. The CWT-corrected average velocities range from 27.00 to 121.37 cm/s, demonstrating that the proposed correction framework can be applied across a wide range of hydraulic conditions. Comparisons with available in situ measurements (ADCP, OTT-MFPro, and PIV) show reasonable agreement after propwash bias correction. For example, at XSs with available reference data, MBE ranges from -21.27 to 22.80 cm/s, RMSE spans 11.75–25.12 cm/s,

and NRMSE varies between approximately 20% and 38%. The remaining XSs lack direct in situ comparison due to measurement availability but still provide useful information on the spatial variability of corrected surface velocities.

It should be noted that the use of only three upstream-looking waypoints limits the statistical robustness of the propwash bias estimation. However, because these waypoints were selected to represent typical flow conditions and shared identical footprint geometry with downstream measurements, they still provide a reasonable basis for propwash bias estimation. Increasing the number of matched bidirectional waypoints would likely further improve the robustness of the correction.

Overall, the results confirm that even with a limited number of upstream reference measurements, the identical footprint bidirectional framework can effectively estimate propwash effects and improve the consistency of UAS-derived velocities with independent in situ observations.

2) *One-to-One Bidirectional Footprint Matching*: To further evaluate the performance of the proposed bidirectional correction framework under optimal observation conditions, additional experiments were conducted using bidirectional measurements with identical radar footprints. In this configuration, upstream- and downstream-looking measurements were acquired at the same reference locations across the XS, but with a slight offset along the river flow direction, ensuring that velocity observations were derived from nearly identical hydraulic conditions and radar footprint geometries [see Fig. 1(c) and XSTO07 shown in Fig. 11(a)]. This one-to-one footprint match minimizes geometric uncertainties and allows a more reliable estimation of propwash bias components.

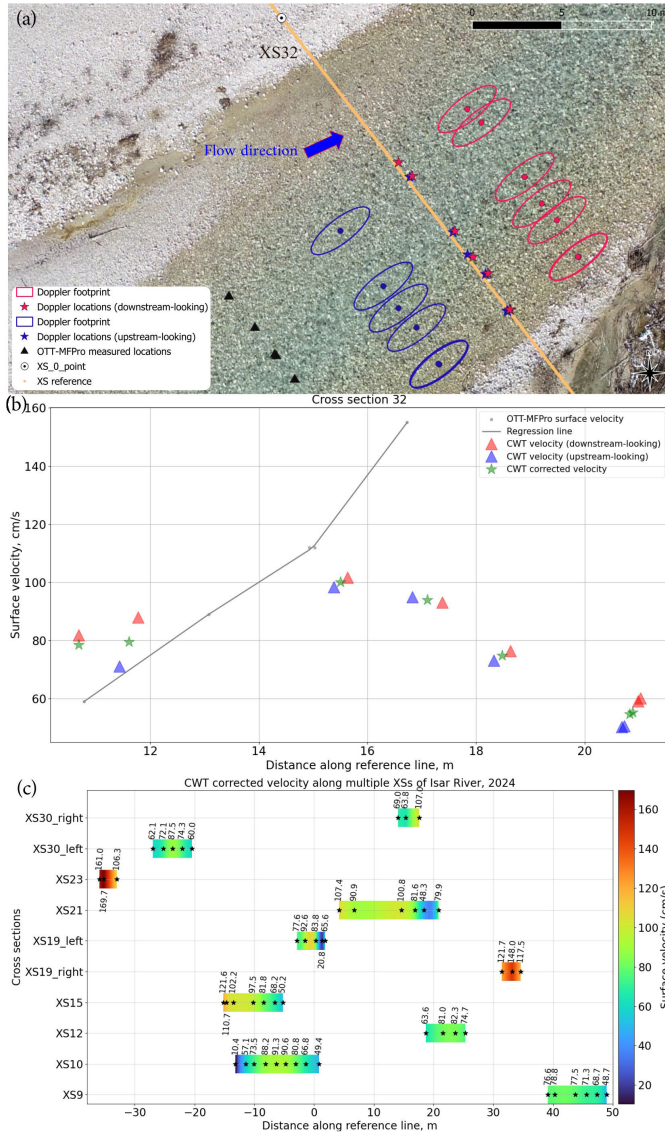


Fig. 8. Isar river. (a) Locations of UAS-Doppler radar waypoints (stars) and in situ OTT-MFPro measurements (triangles) along the XS32 reference line (orange points). Red ellipses denote the downstream-looking radar measurement footprints, and blue ellipses denote the upstream-looking radar measurement footprints. (b) Comparison of CWT-derived velocities from both pointing directions (triangles), CWT-corrected velocities (green stars), and OTT-MFPro measurements (gray dots) along XS32. The gray line shows the linear regression. (c) CWT-corrected velocity distribution along each XS, measured in the Isar river in 2024, is shown as a heatmap.

Fig. 11(b) shows an example from XST007 at the Orco river in 2025 [see Fig. 6(b)], where CWT velocities were derived from the two pointing directions. Based on (3), the CWT-corrected ($V_{river,wind}$) and propwash bias ($V_{propwash}$) were computed for each pair of waypoints, and the CWT-corrected velocities were subsequently compared with FlowTracker reference measurements. The results demonstrate that the corrected velocities generally fall within the 95% confidence interval of the in situ measurements and follow the spatial velocity distribution along the XS. This indicates that the proposed correction approach effectively reduces directional bias caused by platform-induced airflow. It should be noted that some negative CWT-derived velocities (upstream-looking, blue triangles) correspond to low-velocity zones, indicating

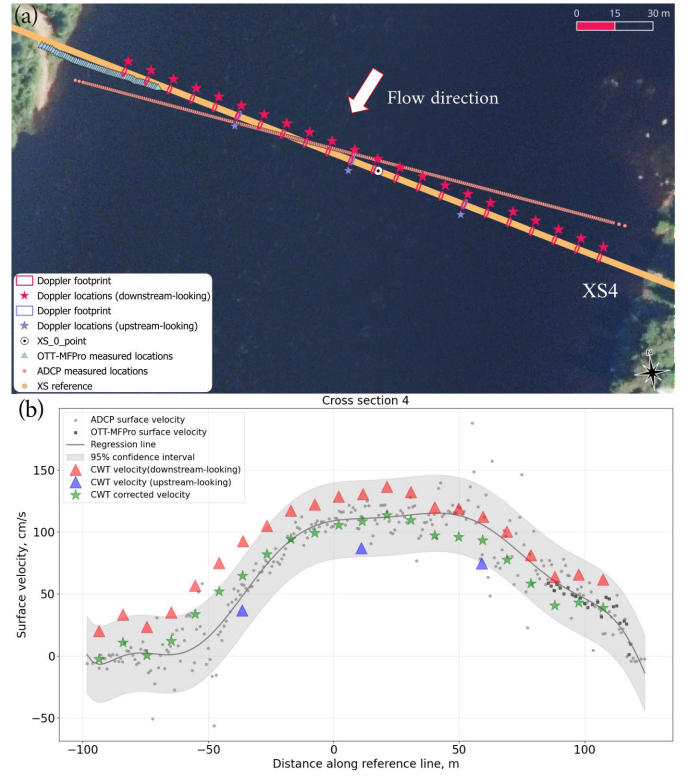


Fig. 9. Torne river. (a) Locations of the UAS-Doppler radar waypoints (stars) and in situ measurements obtained using an ADCP (brown points) and an OTT-MFPro (triangles) along the XS4 reference line (orange points). Red ellipses indicate the measurements pointing downstream, whereas blue ellipses indicate the measurements pointing upstream. (b) Comparison of estimated CWT surface velocities from the two pointing directions (triangles), CWT-corrected velocities (green stars), and in situ (combined ADCP and OTT-MFPro) velocity distribution along the XS4 tagline. ADCP and OTT-MFPro measurements are shown as gray dots and black squares, respectively. The regression line and the in situ corresponding 95% confidence interval are represented by the gray line and shaded area, respectively.

that the radar signals were dominated by the propwash during the measurements.

Fig. 12 and Table V summarize the distribution of CWT-corrected velocities across multiple XSs at the Orco, Po, and Isar rivers. The estimated propwash bias ranges from approximately -1.23 to 32.33 cm/s, reflecting variations in drone flight conditions (e.g., ambient wind velocity and flight altitude), river local turbulence, and flow regimes. The CWT-corrected velocities show good consistency with the available in situ measurements (FlowTracker or ADCP), with MBE ranges from -13.43 to 3.64 cm/s, RMSE values typically ranging from about 10.06 to 22.9 cm/s, and NRMSE values around 10.77% – 19.17% for the XSs where sufficient reference samples are available. These results confirm that the CWT-corrected velocities achieve reasonable agreement with in situ measurements under identical footprint conditions.

In addition, compared with the limited upstream sampling configuration described in Section V-C1, the one-to-one bidirectional footprint matching approach provides improved consistency and reduced uncertainty. These results demonstrate that identical footprint bidirectional observations represent the most reliable configuration for separating river flow velocity

TABLE V

OVERVIEW OF THE THIRD MEASURE PATTERN (POINTING TWO DIRECTIONS AND HAVING THE SAME FOOTPRINT AREA) RESULTS FOR ALL XSs

Study Area	Cross sections	Propwash average bias (cm/s)	CWT corrected average velocity (cm/s)	CWT corrected min/max velocity (cm/s)	MBE (cm/s)	RMSE (cm/s)	NRMSE	Calculated waypoints samples
Orco River 2025	TO01	8.47	56.84	47.30/65.45	N/A	N/A	N/A	N/A
	TO02	17.71	91.25	49.84/132.22	N/A	N/A	N/A	N/A
	TO03	17.84	71.34	52.20/82.65	N/A	N/A	N/A	N/A
	TO04	12.53	59.88	52.25/65.22	N/A	N/A	N/A	N/A
	TO05	1.88	122.93	99.38/146.41	N/A	N/A	N/A	N/A
	TO06	21.74	110.31	4.96/152.70	3.64 [#]	22.90 [#]	19.11%	8
	TO07	12.59	51.08	3.13/94.38	-1.39 [#]	10.06 [#]	19.17%	19
	TO09	11.90	84.81	2.27/140.02	N/A	N/A	N/A	N/A
	TO10	32.33	36.75	10.43/80.60	N/A	N/A	N/A	N/A
	TO11	24.88	70.46	16.04/100.91	N/A	N/A	N/A	N/A
	TO12	3.85	160.05	139.68/183.36	N/A	N/A	N/A	N/A
Orco River 2024	Orco1	16.68	100.31	70.41/110.03	N/A	N/A	N/A	N/A
	Orco2	14.18	113.26	63.72/138.11	N/A	N/A	N/A	N/A
	Orco5	5.18	114.54	48.54/142.81	N/A	N/A	N/A	N/A
	Orco7	11.97	84.68	6.80/153.17	N/A	N/A	N/A	N/A
	Orco8	21.16	62.14	1.02/115.54	N/A	N/A	N/A	N/A
	Orco9	22.54	44.49	3.30/79.85	N/A	N/A	N/A	N/A
	Orco10	6.69	156.95	103.43/203.67	N/A	N/A	N/A	N/A
Po River 2024	Po2	-1.23	160.69	59.28/251.18	N/A	N/A	N/A	N/A
	Po3	11.25	114.18	71.37/141.02	N/A	N/A	N/A	N/A
	Po6	25.42	51.34	14.91/81.78	N/A	N/A	N/A	N/A
	Po7	4.89	45.94	22.14/61.56	N/A	N/A	N/A	N/A
	Po11	21.47	70.44	32.59/92.51	N/A	N/A	N/A	N/A
	Po12	13.97	112.16	95.11/127.30	N/A	N/A	N/A	N/A
Isar River 2025	CS1	9.73	170.56	151.84/180.91	-13.43*	19.82*	10.77%	13
	CS2	4.60	236.88	207.93/247.48	N/A	N/A	N/A	N/A
	CS4	3.96	225.69	178.06/250.95	N/A	N/A	N/A	N/A

[#] means the MBE and RMSE calculated between CWT corrected velocity and Flowtracker velocity under each waypoint along the corresponding XS.

* means the MBE and RMSE calculated between CWT corrected velocity and ADCP velocity under each waypoint along the corresponding XS.

from UAS-induced propwash effects and achieving accurate river surface velocity retrieval.

D. Overall Performance Evaluation

The one-to-one bidirectional footprint matching framework described in Section V-C2 was evaluated over multiple rivers and XSs to investigate the correspondence among the estimated propwash bias, the upstream- and downstream-looking CWT velocities, and the CWT-corrected velocities. Fig. 13(a) shows the fitting relationship between the CWT-corrected velocity and the propwash bias. To eliminate outliers induced by measurement noise, a RANSAC regression with a linear base model [44] was employed, which iteratively fits the model to random subsamples and retains only the inliers. A fixed random seed was adopted to ensure reproducibility, and a residual threshold of 7 cm/s was used for inlier identification. The linear regression between the CWT-corrected velocities and the estimated propwash bias yields a clear negative trend, with a coefficient of determination $R^2 = 0.796$ and an RMSE of 3.62 cm/s. This indicates that the estimated propwash bias decreases as the CWT-corrected velocities increase, which explains why the single-direction measurement is particularly bad for slow-flowing rivers.

Furthermore, Fig. 13(b) and (c) shows the fit relationships between the CWT-corrected velocities and the upstream- and downstream-looking CWT velocities, respectively. Both cases exhibit a strong positive trend, with $R^2 \geq 0.90$ and RMSE = 3.62 cm/s. When the CWT-corrected velocity is zero, the estimated propwash biases are 30.62 cm/s for the bidirectional regression [see Fig. 13(a)], upstream-looking configuration [see Fig. 13(b)], and downstream-looking configuration [see Fig. 13(c)], indicating consistent propwash-induced velocity biases across different radar orientations. In contrast, the propwash bias derived from the Gaussian two-peak model is -17.11 ± 32.04 cm/s at a flight altitude of 4 m [28], indicating substantially larger uncertainty. These results demonstrate that the proposed CWT-based bidirectional approach provides a more reliable and constrained estimate of propwash bias.

The bidirectional footprint framework enables correction of the propwash bias and improves single-direction measurements. As shown in Table VI, applying the linear fitting derived from Fig. 13(b) substantially reduces underestimation in upstream-looking CWT velocities. For instance, at XS1 of the Rönne Å river, the corrected average velocity increased from 3.89 to 30.74 cm/s, reducing MBE from -33.11 to -7.41 cm/s and RMSE from 35.63 to 13.90 cm/s. Similar

TABLE VI

COMPARISON OF THE RESULTS OF THE FIRST MEASURE PATTERN (ONLY POINTING UPSTREAM) RESULTS WITH THE CORRECTED CWT RESULTS OBTAINED USING THE FITTING LINE IN FIG. 13(B) FOR ALL XSs

Study Area	Cross sections	CWT and fitting average velocity (cm/s)	CWT and fitting min velocity (cm/s)	CWT and fitting max velocity (cm/s)	MBE (cm/s) compared to in-situ	RMSE (cm/s)	NRMSE	Calculated waypoints samples
Rönne Å River 2023	XS1	3.89	-43.26	23.18	-33.11 ⁺	35.63 ⁺	93.40%	27
	XS1 Fitting	30.74	-10.90	46.38	-7.41 ⁺	13.90 ⁺	36.42%	27
	XS2	99.56	86.82	112.33	-4.76 ⁺	14.65 ⁺	14.04%	33
	XS2 Fitting	112.23	101.24	123.23	7.90 ⁺	15.52 ⁺	14.88%	33
	XS3	45.16	27.58	64.75	-8.99 ⁺	13.06 ⁺	24.13%	10
	XS3 Fitting	65.32	50.17	82.22	11.18 ⁺	14.31 ⁺	26.43%	10
	XS5	6.89	-34.76	30.29	-13.59 ⁺	26.74 ⁺	70.24%	22
	XS5 Fitting	47.50	-3.57	89.17	9.43 ⁺	21.66 ⁺	56.90%	22
	XS6	34.63	12.69	52.53	-20.60 ⁺	22.88 ⁺	41.43%	18
	XS6 Fitting	56.25	37.34	71.68	1.02 ⁺	8.98 ⁺	16.25%	18

⁺ means the MBE and RMSE were calculated between CWT (fitting CWT) velocity and OTT-MFPPro velocity under each waypoint along the corresponding XS.

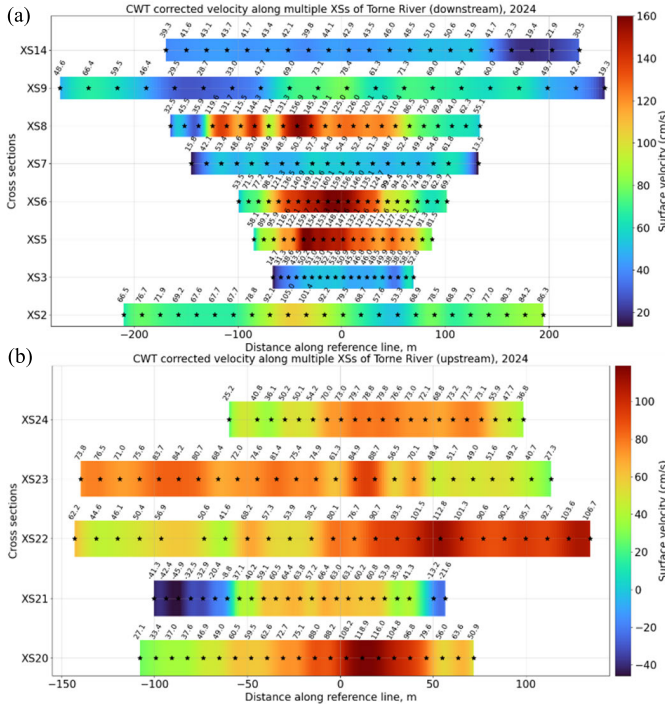


Fig. 10. Torne river: the CWT-corrected velocity distribution along each XS, measured under the third measurement pattern (pointing in two directions with the same footprint area, but only three waypoints pointing upstream), is shown as a heatmap. (a) and (b) XSs measured in the downstream and upstream parts in the Torne river in 2024, respectively. Note that approximately 400-m upstream of XS3, a widened river reach with a mid-channel island is present, which results in overall lower surface velocities at this XS (see Fig. 14).

improvements were observed across other XSs, especially at low-velocity locations, with NRMSE decreasing accordingly. These results demonstrate that bidirectional measurements provide robust, physically realistic surface velocities and can effectively correct single-direction observations when full bidirectional coverage is unavailable.

For the Torne river, bidirectional observations with only three upstream-pointing waypoints were compared with CWT-corrected velocities using the fitting line from Fig. 13(c). As summarized in Table VII, the fitting generally adjusts for

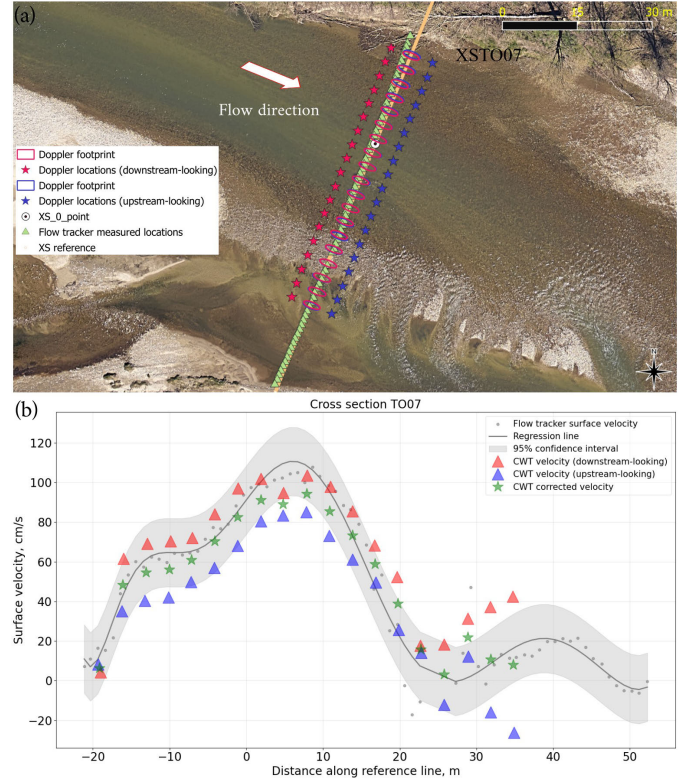


Fig. 11. Orco river. (a) Locations of the UAS-Doppler radar waypoints (stars) and in situ measurements obtained using a FlowTracker (triangles) along the XS007 reference (orange points). Red ellipses indicate the measurements pointing downstream, while blue ellipses indicate the measurements pointing upstream. (b) Comparison of estimated CWT surface velocities from the two pointing directions (triangles), CWT-corrected velocities (green stars), and FlowTracker velocity distribution along the XS tagline. FlowTracker measurements are shown as gray points, while the regression line and the corresponding 95% confidence interval are represented by the gray line and shaded area, respectively.

propwash effects, with mixed results depending on the site. At XS4 and XS6, the corrected averages remain close to in situ measurements, while RMSE and NRMSE are slightly reduced compared with the CWT-corrected values in Section V-C1. However, at XS3 and XS24, the fitting produces larger

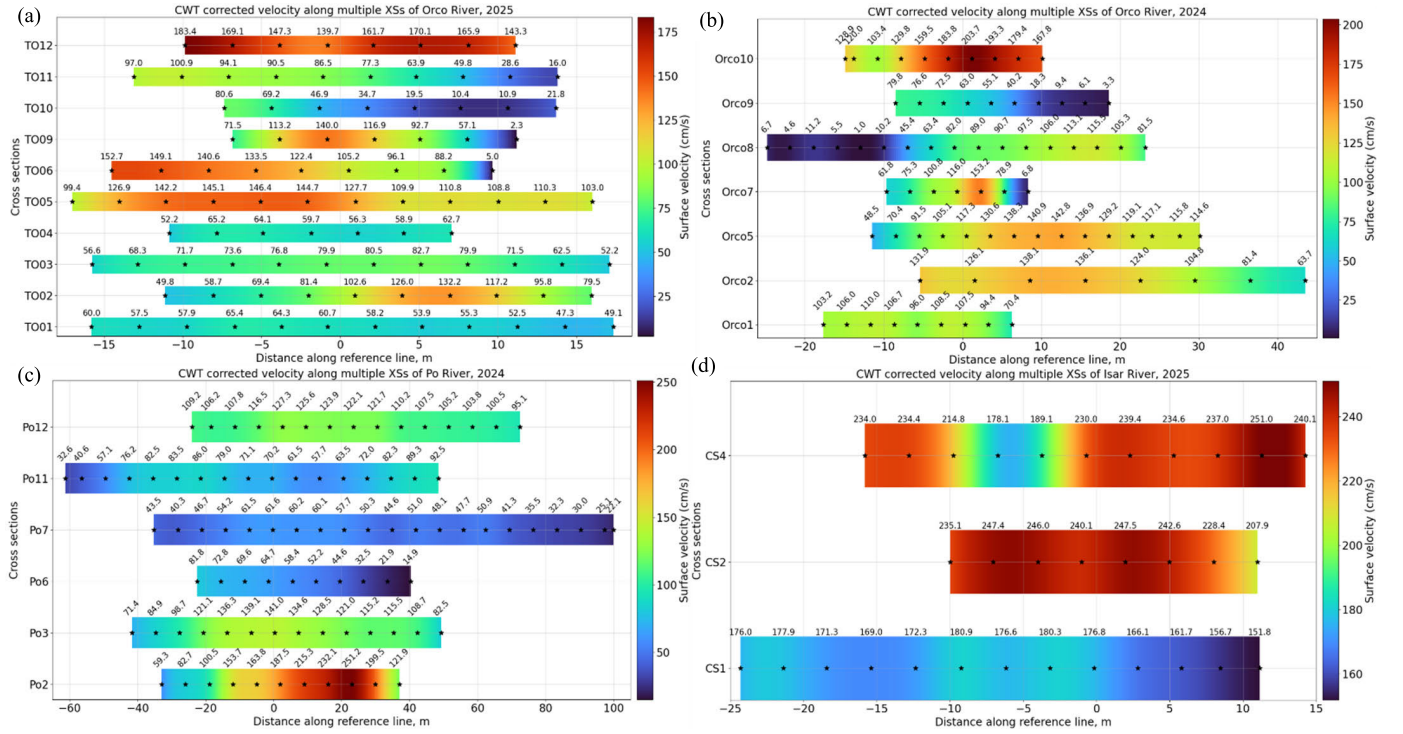


Fig. 12. CWT-corrected velocity distribution along each XS, measured under the third measurement pattern (pointing in two directions with the same footprint area) along each XS, is shown as a heatmap. (a) and (b) XSs measured in the Orco river in 2025 and 2024, respectively. (c) XSs measured in the Po river in 2024. (d) XSs measured in the Isar river in 2025.

deviations at some waypoints, particularly at XS3, reflecting local flow heterogeneity likely associated with channel morphology and upstream flow disturbances rather than wind forcing, as the wind-induced surface drift velocity was shown to be negligible (see Table VIII). These results demonstrate that even with minimal upstream-looking waypoints, bidirectional-based corrections can partially compensate for propwash-induced biases, though accuracy improves with more comprehensive footprint matching.

VI. DISCUSSION

The experimental results demonstrate that UAS-borne Doppler radar combined with CWT-based processing provides a robust approach for measuring river surface velocities across diverse hydraulic conditions. The separation of river velocity and propwash-induced bias assumes that the UAS-induced disturbance can be represented as an additional bias component superimposed on the Doppler-derived river velocity.

Single-direction observations (upstream-looking) generally underestimate velocities due to propwash effects, with the magnitude of underestimation varying with flight altitude and flow velocity. The Gaussian-mode fitting method partially mitigates this bias, but its general applicability is restricted by solution nonuniqueness and the limited validity of the bimodal assumption under low-velocity conditions (<80 cm/s).

Bidirectional measurements with different footprints enable the estimation of CWT-corrected velocities under the assumption of limited flow heterogeneity along the streamwise direction. However, this assumption may not be valid in mountain rivers with shallow flow depths, coarse beds, and strong local turbulence. In such cases, localized hydraulic

disturbances and rapidly varying surface velocities may lead to inconsistencies between upstream- and downstream-looking measurements, reducing the reliability of the propwash bias correction. This limitation suggests that identical footprint bidirectional measurements and increased waypoint density may be required in highly heterogeneous flow environments.

Bidirectional measurements with identical footprints, even with limited upstream waypoints, allow effective separation of river flow and propwash bias when lateral velocity variations are relatively small. This measurement can significantly improve field efficiency by reducing the number of required waypoints. However, in wide rivers, large lateral velocity variations are common due to strong ambient wind forcing, nonuniform flow distribution, and local turbulence, which increase cross-sectional flow heterogeneity. Under such conditions, propwash bias estimates derived from a limited number of upstream-downstream waypoint pairs may become less reliable. For example, in the Torne river, the accuracy of the CWT-corrected velocities could likely be further improved by increasing the density of upstream-looking waypoints. In addition, wider rivers are associated with longer wind fetch and stronger surface wind effects, which increase surface roughness and complicate the separation of true river velocity from propwash bias components in the radar Doppler spectra. This also explains why applying linear relationships derived from waypoints in narrower rivers (<100 m wide) [see Fig. 13(c)] to wider rivers may lead to larger residual errors.

Bidirectional measurements with identical footprints using one-to-one waypoint matching provide the most physically consistent configuration for separating river flow and propwash bias. By ensuring that upstream- and downstream-looking

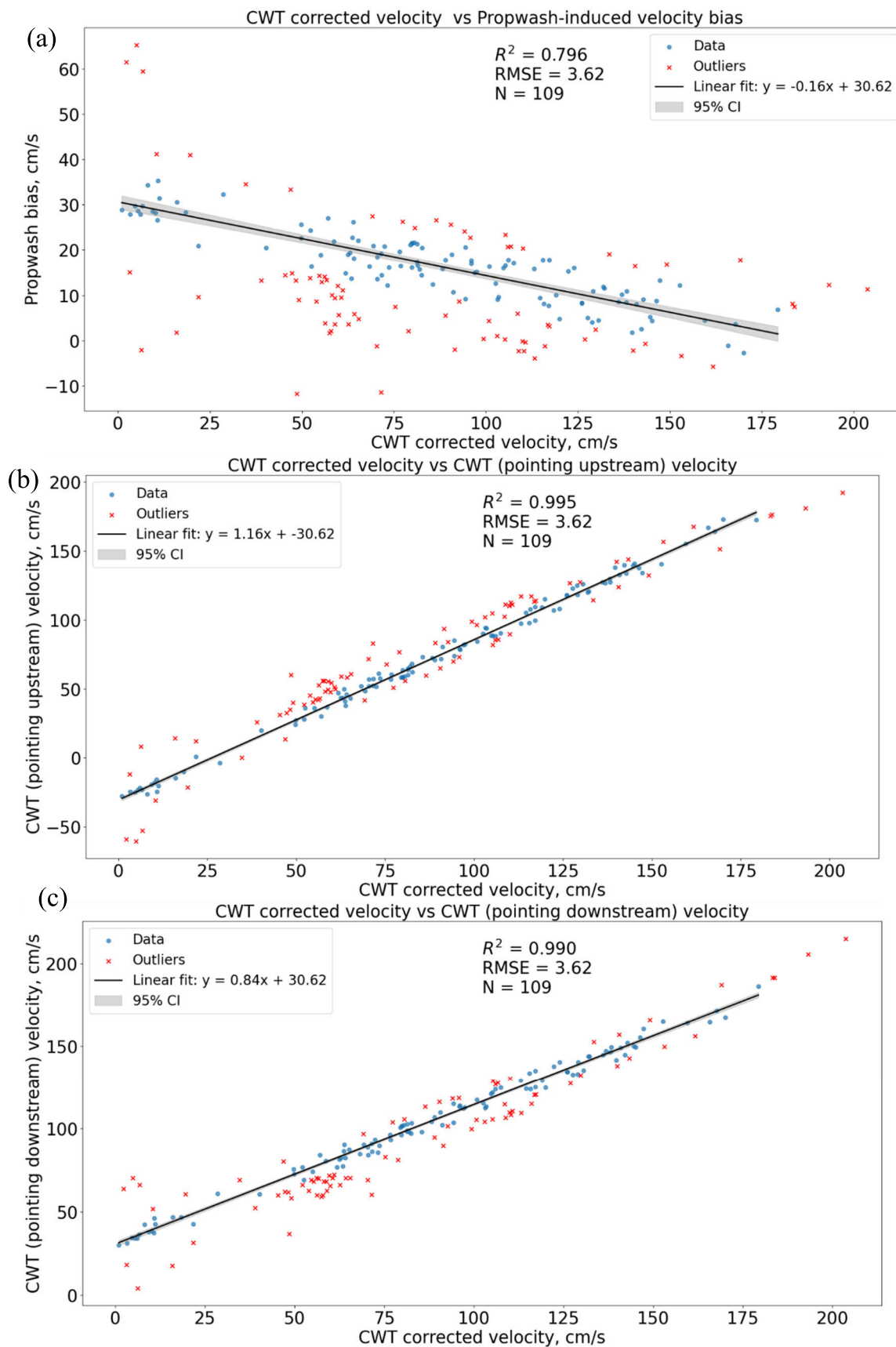


Fig. 13. (a)–(c) Scatter plots showing the relationships between the CWT-corrected velocity (x -axis) and the propwash-induced velocity bias, the upstream-looking CWT velocity, and the downstream-looking CWT velocity (y -axis), respectively. Only waypoints derived from the XSs shown in Figs. 11 and 12 were included in the analysis.

TABLE VII

COMPARISON OF THE RESULTS OF THE THIRD MEASUREMENT PATTERN (ONLY THREE UPSTREAM-POINTING WAYPOINTS) WITH THE CWT CORRECTED RESULTS OBTAINED USING THE FITTING LINE IN FIG. 13(c) FOR ALL XSs

Study Area	Cross sections	Propwash average bias (cm/s)	CWT corrected average velocity (cm/s)	CWT corrected min/max velocity (cm/s)	MBE (cm/s)	RMSE (cm/s)	NRMSE	Calculated waypoints samples
Torne River 2024	XS3	0.93	45.48	14.68/58.48	-21.27*	25.12*	37.65%	19
	XS3 Fitting	20.34	23.00	-17.86/52.08	-43.74*	46.39*	69.51%	19
	XS4	22.84	67.96	-2.43/113.65	-0.51*+	13.24*+	20.19%	22
	XS4 Fitting	19.70	68.22	-12.16/126.04	2.62*+	13.35*+	20.35%	22
	XS6	6.64	113.59	53.49/160.05	23.80&	25.12&	29.10%	23
	XS6 Fitting	12.81	103.43	35.14/161.99	17.11&	18.37&	21.28%	23
	XS14	20.92	41.21	19.44/51.91	-1.82*	11.75*	27.76%	21
	XS14 Fitting	24.76	36.65	11.60/50.25	-5.66*	11.74*	27.76%	21
	XS24	3.88	62.49	25.19/79.85	2.33*+	18.13*+	30.61%	21
	XS24 Fitting	19.14	44.11	-1.84/79.85	-15.11*+	25.41*+	42.91%	21

* means the MBE and RMSE were calculated between CWT corrected velocity and ADCP velocity under each waypoint along the corresponding XS.

& means the MBE and RMSE were calculated between CWT corrected velocity and PIV velocity under each waypoint along the corresponding XS.

+ means the MBE and RMSE were calculated between CWT corrected velocity and OTT-MFPPro velocity under each waypoint along the corresponding XS.

TABLE VIII

ESTIMATED WIND-INDUCED SURFACE DRIFT VELOCITY (CM/S) AT THE TORNE RIVER

Study Area	Cross sections	Propwash average bias (cm/s)	CWT corrected average velocity (cm/s)	CWT corrected min/max velocity (cm/s)	Windspeed (10 m high) (m/s)	Wind/riverflow from direction (North is 0°)	Wind drift velocity (cm/s)
Torne River 2024	XS2	26.99	76.66	53.34/104.99	1.41	162.62°/50.79°	-1.31
	XS3	0.93	45.48	14.68/58.48	3.26	263.61°/12.62°	-2.65
	XS4	22.84	67.96	-2.43/113.65	2.29	230.21°/12.68°	-4.54
	XS5	0.73	121.37	58.13/159.68	4.23	192.86°/359.94°	-10.31
	XS6	6.64	113.59	53.49/160.05	1.22	176.19°/358.06°	-3.05
	XS7	3.25	46.49	-0.89/61.81	3.34	226.26°/359.41°	-5.71
	XS8	-9.06	99.57	32.53/156.93	3.92	227.98°/31.56°	-9.4
	XS9	10.85	53.77	19.30/78.41	3.08	221.43°/58.81°	-7.35
	XS14	20.92	41.21	19.44/51.91	2.39	241.04°/348.61°	-1.8
	XS20	-1.50	71.07	27.06/118.94	3.13	160.37°/0.01°	-7.37
	XS21	-3.29	27.00	-45.85/66.39	3.78	159.85°/359.43°	-8.9
	XS22	3.21	76.29	41.60/112.77	4.05	160.86°/14.52°	-8.43
	XS23	4.23	67.33	27.35/88.72	3.86	160.77°/18.77°	-7.6
	XS24	3.88	62.49	25.19/79.85	3.19	170.51°/0.52°	-7.85

observations sample nearly identical surface areas, geometric inconsistencies and hydraulic variability are minimized, allowing propwash bias to be estimated individually for each waypoint pair. This configuration improves the robustness of the CWT-corrected velocities compared with the previously discussed measurement modes, while still maintaining acceptable field efficiency. Under conditions of both low river velocities and strong ambient winds, some waypoints exhibit upstream-looking CWT velocities that exceed the corresponding downstream-looking estimates. Consequently, the estimated propwash bias may become negative. Although this

negative value can still be used mathematically to correct the CWT-derived velocities, it should be interpreted as an effective compensation term rather than a physically realistic propwash bias magnitude.

Overall, the combination of bidirectional observation and CWT spectral analysis provides a practical and physically consistent framework for mitigating propwash effects, while the results emphasize the importance of appropriate flight configuration, footprint matching, waypoint density, high flow velocities, and light wind for reliable UAS-based river velocity measurements.

VII. CONCLUSION

This study systematically evaluated the capability of UAS-borne Doppler radar combined with CWT spectral analysis for retrieving river surface velocities under varying hydraulic and environmental conditions, with particular focus on mitigating propwash disturbances. The results show that single-direction measurements tend to underestimate (upstream-looking) or overestimate (downstream-looking) surface velocities due to the included airflow direction. Bidirectional observation strategies, especially those based on identical footprint matching, provide a more physically consistent approach by enabling the separation of true river flow and propwash bias components under light wind conditions.

A clear negative relationship between propwash bias and solved river velocity demonstrates that propwash effects are most significant under low-flow conditions and decrease as river velocity increases, as the natural flow progressively dominates the Doppler response. Strong linear relationships ($R^2 > 0.94$) between the corrected and uncorrected CWT velocities demonstrate that the proposed bidirectional framework effectively removes systematic propwash bias while preserving the dominant river flow characteristics.

The experiments further demonstrate that measurement accuracy depends primarily on waypoint configuration and flow velocity heterogeneity. Increasing waypoint density and ensuring footprint consistency were found to significantly improve the robustness of the CWT-corrected velocities, particularly in hydraulically complex or wide river sections. The effects of wind-induced surface drift velocity were quantitatively evaluated and found to be minor compared with other sources of uncertainty under the present conditions.

In summary, this study demonstrates that bidirectional CWT-based processing provides a practical and robust framework for improving the reliability of UAS-based river surface velocity measurements. The findings provide useful guidance for survey design and highlight the potential of UAS-Doppler radar as an efficient tool for high-resolution hydrometric monitoring. Future work will focus on extending the proposed approach to more complex flow environments and stronger wind conditions, and on developing compact radar systems for smaller UAS platforms while balancing the associated tradeoffs in payload, transmitted power, antenna size, and measurement performance.

APPENDIX

A. Wind-Induced Surface Drift Estimation

We take XS3 at the Torne river as an example to estimate the wind-induced surface drift velocity. The wind speed at 10 m above the water surface was 3.26 m/s, as derived from the ERA5 reanalysis dataset [45], [46]. The wind originated from 263.61° and the river flow from 12.62° , with directions referenced clockwise from true north (0°).

The river flow direction is therefore $12.62^\circ + 180^\circ = 192.62^\circ$, while the wind direction toward the surface is $263.61^\circ - 180^\circ = 83.61^\circ$. The angle between the wind and river flow directions is, thus,

$$\theta = |192.62^\circ - 83.61^\circ| = 109.01^\circ. \quad (\text{A.1})$$

The effective wind component parallel to the river flow is given by

$$U_{\text{wind,parallel}} = U_{\text{wind}} \cos \theta. \quad (\text{A.2})$$

Substituting the values into (A.2) yields

$$U_{\text{wind,parallel}} = 3.26 \times \cos(109.01^\circ) = -1.06 \text{ m/s} \quad (\text{A.3})$$

where negative sign indicates a headwind component relative to the river flow direction.

Based on the empirical formulation proposed in [47], the wind-induced surface drift velocity in open-channel flow can be approximated as follows:

$$U_{\text{drift}} \approx 0.025 \times U_{\text{wind,parallel}} = -2.65 \text{ cm/s}. \quad (\text{A.4})$$

Furthermore, the wind-induced surface drift velocities for all XSs along the Torne river were estimated using the same approach, and the results are presented in Table VIII. The ERA5 wind data used in this study are of relatively low/coarse resolution. While no in situ anemometer measurements were available, ERA5 wind data were used to provide a regional-scale estimate of wind conditions during the field experiments. The relatively low wind speeds indicated by ERA5 suggest that wind effects were unlikely to be the dominant source of velocity bias under the investigated conditions, although direct validation using local wind measurements is required in future studies.

B. Comparison of ADCP and UAS-Derived Velocities of XS3

From the above calculations, the estimated wind-induced surface drift velocity of XS3 at the Torne river is approximately -2.65 cm/s , which is relatively small. As shown in Fig. 14(c), a substantial discrepancy is observed between ADCP_1 (gray) and the Doppler-derived velocities, whereas the mean PIV results closely match the Doppler-derived measurements. A second ADCP measurement section (denoted ADCP_2) was located approximately 45-m upstream of the XS3 reference line [see Fig. 14(a) and (b)]. Comparison of ADCP_2 [black in Fig. 14(c)] with ADCP_1, Doppler-derived, and PIV velocities reveals that ADCP_2 exhibits lower velocities in the central part of the XS and agrees more closely with the UAS-derived velocities.

The primary explanation for these discrepancies lies in the hydrodynamic effects induced by an upstream island (approximately 400-m upstream), which generates a channel contraction followed by a sudden expansion. This flow configuration leads to the development of a central low-velocity zone and secondary circulation structures. Consequently, ADCP_1 records velocities that are higher than the surface velocities measured by PIV and Doppler radar.

In contrast, ADCP_2, located closer to the island, samples the central low-velocity region and therefore yields measurements that are more consistent with the surface-derived velocities.

These results further indicate that, under complex flow geometry conditions, the extrapolation of ADCP measurements toward the surface (particularly for ADCP_1) may not be reliable, leading to discrepancies with surface-sensitive techniques. Given that the wind-induced surface drift velocity

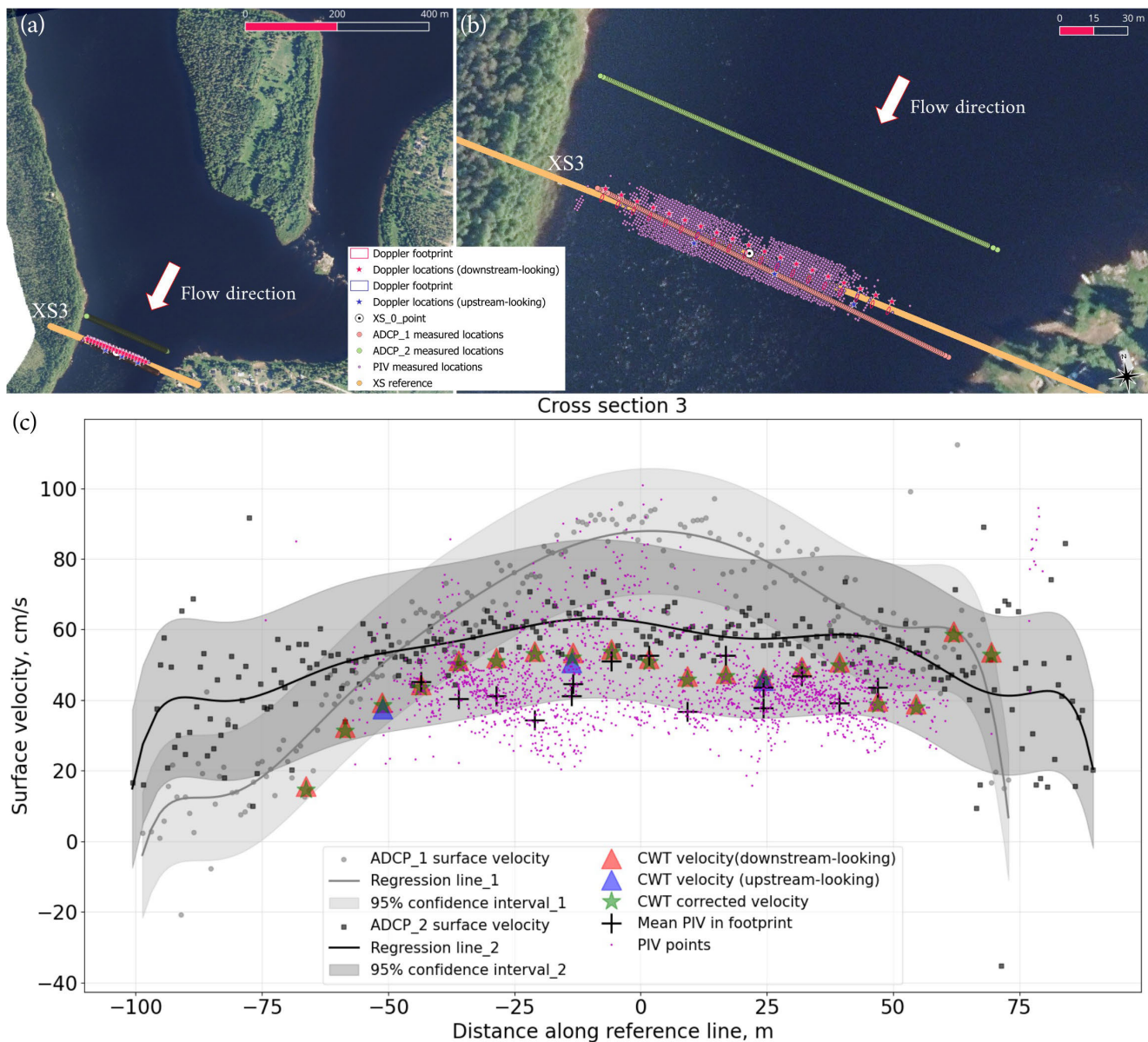


Fig. 14. Torne river. (a) and (b) Locations of the UAS-Doppler radar waypoints (stars) and in situ measurements obtained using an ADCP_1 (brown points) and an ADCP_2 (green points) along the XS3 reference (orange points). Red ellipses indicate the measurements pointing downstream, whereas blue ellipses indicate the measurements pointing upstream. Where (b) is an enlarged view of (a). (c) Comparison of velocity estimates along XS3 reference. CWT surface velocities from two pointing directions (triangles), CWT corrected velocities (green stars), PIV results (magenta points and black crosses), ADCP_1 (gray dots), and ADCP_2 (black squares). The gray line and gray shaded area represent the regression line and 95% confidence interval based on ADCP_1 data, while black represents the ADCP_2 results.

is negligible (≈ -2.65 cm/s), the observed differences are primarily attributed to channel geometry and the associated flow dynamics rather than wind effects.

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DATA AND CODE AVAILABILITY

The datasets and codes used in this study are publicly available in [48] and [49]. The repository contains the raw

measurements, processed datasets, and implementation codes for reproducing the main results.

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Villads Flendsted Jensen, photograph and biography not available at the time of publication.

Michael Andreas Pedersen, photograph and biography not available at the time of publication.

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