Surface Flow Measurements From Drones

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Abstract

1 Drones are transforming the way we sense and interact with the environment.
2 However, despite their increased capabilities, the use of drones in geophysical
3 sciences usually focuses on image acquisition for generating high-resolution
4 maps. Motivated by the increasing demand for innovative and high perfor-
5 mance geophysical observational methodologies, we posit the integration of
6 drone technology and optical sensing toward a quantitative characterization
7 of surface flow phenomena. We demonstrate that a recreational drone can be
8 used to yield accurate surface flow maps of sub-meter water bodies. Specifi-
9 cally, drone's vibrations do not hinder surface flow observations, and velocity
10 measurements are in agreement with traditional techniques. This first in-
11 stance of quantitative water flow sensing from a flying drone paves the way
12 to novel observations of the environment.

Keywords: Flow measurement, Surface Hydrology, Large Scale Particle
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1. Introduction

Surface waters influence the way the landscape evolves, ecosystems develop, environmental risks arise, and epidemics propagate [1, 2, 3, 4]. Due to the complexity of surface water processes, a unique observational method for identifying and quantitatively monitoring flows is yet to be found [5]. Traditionally, surface flows are invasively monitored using current meters [6], tracing systems [7], and acoustic doppler instrumentation [8]. Water control structures, such as weirs and spillways, can also be used to estimate flow discharge [9].

Even if the efficacy of such methods has been demonstrated in the technical literature [10], their use is limited to easy-to-access environments. In addition, the measurement accuracy can be affected by the severity of natural rainfall events and by systematic errors associated with sensors interfering with the flow. To address some of these challenges, considerable efforts have been devoted toward the development and refinement of remote methods, including hand-held radars [11], microwave sensors [12], and satellites [13]. These approaches have highly benefitted the realm of hydrological observations; however, most of them are only applicable to large scale channel flows, may be expensive, and may not be suitable to frequently monitor water bodies.

To mitigate such issues, several methods based on the remote acquisition and analysis of flow images have been proposed and implemented in the last two decades [14]. Specifically, in [15], images of large scale riverine ecosystems are analyzed through high-speed cross-correlation to obtain surface flow velocity maps. These surface flow velocity maps can be complemented with

38 information on the bathymetry to allow for flow discharge estimations [16].
39 Such optical observational methods are challenged by practical difficulties,
40 such as the need for collecting ground reference points [17], and, therefore,
41 flow data are often not available at ungauged sites, such as extra-urban areas,
42 large-scale lakes and glaciers, coasts, and river estuaries. Despite practical
43 limitations, optical methods are inherently suited to enable continuous and
44 remote observations over diverse water bodies, spanning from rills to large
45 scale rivers. Notably, the potential of such image-based methods has been
46 assessed on a mountainous stream [18], a semi-natural hillslope [19], and a
47 large scale river [17].

48 Here, we propose a novel, fully remote approach for surface flow obser-
49 vations that overcomes practical difficulties related to the implementation
50 of optical methods in difficult-to-access environments. Specifically, we put
51 forward the integration of optical observational techniques and drones for
52 non-invasive quantitative flow measurement. With more than six billion
53 dollars a year spent in research and development around the world [20],
54 drones have transformed our capacity to remotely sense and access the en-
55 vironment [21, 22, 23, 24]. For instance, in the last decade, drones have
56 empowered multiple fields of science by enabling data collection in hostile
57 environments, such as volcanoes [25] and ice sheets [26], and by providing
58 footage over extended areas, such as forests [22] and natural reserves [27].
59 Just as aerial and satellite sensing have transformed scientific observations,
60 allowing the resolution of large-scale physical processes [28, 29], the pervasive
61 use of drones is set to revolutionise geophysical sciences through the rapid
62 and refined measurement of small to medium scale phenomena.

63 In the realm of hydrology, drones have the potential to enable remote and
64 distributed flow measurements in difficult-to-access water environments dur-
65 ing adverse hydro-meteorological events. In our vision, a drone is deployed
66 in natural environments and is remotely piloted (or, alternatively, guided
67 through GPS waypoint trajectory) above the water body of interest upon
68 request/need of the operator. An onboard camera oriented with its axis per-
69 pendicular to the water surface captures videos of the water surface, whereby
70 a ground user identifies a region of interest through a wireless monitor in real
71 time. Once the ground user selects an area of interest, the drone is set to the
72 hovering mode, and the platform stationkeeps above the region while taking
73 high-resolution videos of the water surface. Pictures extracted from the drone
74 footage can be processed off-line through several optical-based algorithms to
75 extract the surface velocity field.

76 To demonstrate the potential of our approach, here, we present the design
77 and preliminary assessment of a novel aerial sensing platform. The platform
78 features a low-cost recreational drone equipped with a miniature camera and
79 a system of lasers to remotely assign metric dimensions to images (remote
80 photometric calibration in the rest of the note) without the acquisition of
81 ground reference points. To assess the feasibility of the hovering capability
82 of the drone for reliable flow velocimetry, we execute preliminary experiments
83 on an ad hoc developed outdoor controlled facility at University of Tuscia.
84 Finally, we perform surface flow observations in a small scale stream (less
85 than 1 m wide and a few centimeters deep) in the Italian Alps. Interestingly,
86 few noninvasive techniques are currently available to monitor small scale sur-
87 face flows in natural environments. We remotely capture and calibrate videos

of the stream from the drone and apply the Large Scale Particle Image Velocimetry (LSPIV) high-speed cross-correlation algorithm [16] that extracts usable flow velocity maps from the motion of stream floaters. Such drone-based surface flow velocity estimates are compared to benchmark values from a current meter to demonstrate the validity of airborne flow velocimetry.

Our method is expected to help in hydrological monitoring in ungauged areas by providing information on the kinematics of surface waters. Differently from standard drone-based monitoring where image mosaicing techniques are used to assemble maps [30], our approach treats captured videos as quantitative data and analyzes them to measure the surface flow velocity. These observations could leverage current knowledge on the contribution of surface flows to the overall hydrological response of natural systems. Further, continuous technological advancements in battery life and camera storage capacity may foster observations at the catchment scale and in large scale and yet ungauged water systems, thus opening novel research avenues in hydrology.

The rest of the technical note is organized as follows. In Section 2, the aerial sensing platform, experimental settings, and image-based procedures are presented. In Section 3, we report experimental findings for the hovering assessment and the airborne flow velocimetry. In Section 4, we discuss the advancements of the proposed approach. Section 5 is left for conclusions.

2. Materials and Methods

Here, we present the aerial sensing platform utilized in the experiments. Further, we provide details for the hovering assessment and the airborne flow

112 velocimetry experiments.

113 *2.1. Aerial Sensing Platform*

114 The aerial sensing platform features a DJI Phantom 2 quadrotor [31]
115 mounting a Zenmuse H3-2D gimbal and a GoPro Hero 3 camera oriented
116 with its axis along the perpendicular. This configuration allows for compen-
117 sating the drone vibrations about the pitch and roll axes, while minimizing
118 distortions in video capture due to the inclination of the camera axis with
119 respect to the field of view (FOV). Remote photometric calibration is en-
120 abled through four green lasers (532 nm in wavelength and less than 5 mW
121 in power) installed at the four corners of the fuselage along the drone’s yaw
122 axis. The platform is less than 1.5 kg in weight and its overall cost is €1,300.

123 The relative distances of the laser pointers are measured upon assembly
124 of the sensing platform with a precision caliper. This system of lasers has
125 the twofold objective of: i) focusing points at known distances in the FOV
126 for remote image calibration and ii) indicating possible elevation and atti-
127 tude changes during hovering from the relative distance of the laser traces
128 in the images [17]. With respect to i), the traces of the lasers in captured
129 videos are used to estimate pixel dimensions in metric units. With respect to
130 ii), inaccurate hovering leads to images that depict slightly different FOVs.
131 However, high-speed cross-correlation should be applied on images display-
132 ing consistent regions of the fluid domain [32]. To this aim, lasers can be
133 instrumental to automatically identify portions of footage captured while the
134 drone is hovering at a given location. In fact, the traces that lasers determine
135 on the ground vary, based on the elevation and attitude of the drone; there-
136 fore, sequences of images displaying similar traces can be directly processed

137 for surface flow velocity estimation.

138 *2.2. Hovering Assessment*

139 A preliminary experiment assessment is conducted to assess the feasibility
140 of using a commercial low-cost platform for airborne flow velocimetry. The
141 aerial sensing platform presents limited hovering capability (vertical: ± 0.8 m
142 and horizontal: ± 2.5 m [31]). Therefore, airframe changes in attitude and
143 elevation may lead to variable image FOVs [33, 34]. To evaluate such FOV
144 variations, we fly the platform in the hovering mode above a large scale grid
145 in an outdoor facility at the University of Tuscia, Italy. We perform a 22 s
146 flight, whereby the onboard GoPro frame rate is set to 60 Hz and the FOV
147 to medium (focal length equal to 21 mm). The experiment is conducted at
148 dusk and during light air wind conditions (2.19 km/h wind speed) [35].

149 Hovering capability is assessed by estimating the relative variations in the
150 pixel area of the grid cells captured by the drone during the flight. Slight
151 variations in the pixel areas of the grid cells during the flight would suggest
152 that changes in the drone’s elevation and attitude can be mitigated with
153 minimal image processing, and, therefore, drone-based videos are compatible
154 with accurate surface flow observations. To provide a reliable assessment, the
155 experimental time is set to 22 s, whereas airborne flow velocimetry tests only
156 last up to few seconds (given the high camera frame rate, video data recorded
157 in few seconds are largely sufficient for accurate measurements).

158 *2.2.1. Hovering Assessment Outdoor Facility*

159 The drone is flown above a 5×5 m² flat grid assembled in the outdoor
160 laboratory at University of Tuscia, Italy, out of a dark opaque ground cloth

161 and a structure of white strings. The strings are laid to create $1 \times 1 \text{ m}^2$
162 squared grid cells. The dark cloth minimizes reflections and enhances the
163 visibility of the white strings against the background. Figure 1 presents a
164 schematics of the setup. The drone is deployed to hover above the center of
165 the grid. The dashed red rectangle in Figure 1 shows the FOV captured by
166 the onboard camera. The laser-focused rectangle is indicated in yellow.

167 2.2.2. Image-based Hovering Evaluation

168 Captured video data are preliminary corrected for the camera lens dis-
169 tortion. The video fish eye distortion is removed through the freely available
170 GoPro Studio 2.0 Software. Then, the video is converted and decompressed
171 to extract Full HD frames. Image processing entails a preliminary phase in
172 which frames are converted to grayscale based on luminance information and
173 then converted to binary by imposing a threshold. Image segmentation is
174 then applied on binary images to retain essential features.

175 To estimate the pixel area of the grid cells, an artificial binary template
176 depicting a representative node of the grid is created. Normalized cross-
177 correlation is performed between the template and images extracted from
178 the experimental video. By retaining locations presenting high values of the
179 cross-correlation coefficient and repairing false correlations, the pixel loca-
180 tions of the grid nodes are obtained. Image-based algorithms [36, 37] are
181 utilized to compute the areas of the grid cells and the area of the rectangle
182 identified by the four lasers.

183 2.3. Airborne Flow Velocimetry

184 To ultimately demonstrate the potential of drone-based flow observa-
185 tions, surface flow measurements are conducted over a less than 1 m-wide
186 and 11 cm-deep mountainous stream in the Rio Cordon natural catchment,
187 Italy [18].

188 2.3.1. Airborne Flow Velocimetry Study Site

189 The Rio Cordon drains a 7.68 km² natural basin located in the Dolomites,
190 Northeastern Italy. The stream is a tributary of the Fiorentina stream that in
191 turn flows into the Rio Cordevole. The catchment drainage network extends
192 for approximately 19 km at an average slope of 47.85%. Tests are executed
193 at a local gauging station, which is equipped with water gauges, a coarse
194 sediment grille, and a diversion pool for water and finer material. The gaug-
195 ing station is located at 1763 m above sea level where the area drained by
196 the stream is approximately 5 km² large. At the time of the experiments, a
197 nearby meteorological station recorded a wind speed of 0.9 m/s.

198 2.3.2. Airborne Flow Velocimetry Procedure

199 The drone is flown above an artificially channeled stream reach located
200 in the proximity of a stream gauge. The selected stream reach is a rectilinear
201 tract with a concrete rectangular section that extends for approximately
202 10 m. Surface velocity is measured using both artificial and natural tracers.
203 Ten repetitions are performed for each type of tracer. Similar to [38, 39],
204 artificial tracers are high-visibility in-house fabricated particles synthesized
205 from biocompatible and buoyant children-friendly dough. Particle size ranges
206 from 0.5 up to 1 cm, and beads are red, yellow, orange, and green in color.

207 Also, experiments are conducted using natural leaves as tracers. In both
208 classes of experiments, the drone captures Full HD videos at 60 Hz frame
209 rate. On average, the FOV extends for $9 \times 5 \text{ m}^2$.

210 Drone-based data are compared to benchmark flow velocities obtained
211 using an OTT C2 small current meter. Current meters yield accurate and
212 repeatable open channel flow measurements up to a few centimeters from
213 the water surface and, differently from more costly non-contact radars, are
214 widely used by researchers and practitioners in environmental monitoring.
215 In the experiments, the instrument is set to the time measurement mode,
216 whereby the number of impulses recorded in 10 s are counted and related to
217 flow velocity. The velocity is measured at a cross-section of the stream a
218 few centimeters upstream the subarea used for comparing the drone tests.
219 Benchmark values are obtained by measuring the flow at 0.5 m from the
220 right stream bank (that is, in the center of the stream) and 3 cm underneath
221 the water surface and averaging over three repetitions. Obtained values are
222 relative to the uppermost layer of the stream (top 30% of the stream depth),
223 where the velocity is less influenced by wind effects and, therefore, it is likely
224 higher than surface velocity.

225 *2.3.3. Airborne Flow Velocimetry Video Processing*

226 Similar to Section 2.2.2, drone-based videos are fish-eye undistorted and
227 sequences of Full HD images are extracted. Similar to the image-based hover-
228 ing evaluation, lasers' traces onto the stream surface are utilized to manually
229 identify stable image sequences within videos captured from the drone. The
230 lasers afford remote photometric calibration of experimental images. Specifi-
231 cally, the pixel distance between lasers traces is manually estimated in several

frames and validated with respect to objects of known dimensions that are visible in the field of view.

Untrimmed images depicting the transit of the tracers are processed using the high-speed cross-correlation edPIV software [40], where frame acquisition rate is set to 60 Hz, interrogation window size to 32×32 pixels, and grid size to 16×16 pixels. On average, the pixel area displaying the surveyed stream reach corresponds to 20% of the picture. Surface flow velocity maps are developed by averaging velocity estimations in time over the sequence of images analyzed in the experiment.

Due to imperfect hovering of the drone during image acquisition, image portions lying outside the stream presented non-null velocities. To remove such false readings, the average velocity of nodes outside the stream is automatically computed and subtracted from the entire set of velocity values. Given the stability of the aerial platform and the short duration of experimental flights, airframe vibrations do not excessively impact velocity estimation. In particular, velocities estimated without subtracting values of nodes outside the flow are 5 – 8% larger than measurements herein reported. Comparison between measurements executed with the two classes of tracers is performed by considering a subarea of the stream that is consistently captured in each video. Then, time-averaged velocities are computed over the frame sequence and the maximum value of the velocity field in the subarea is used for comparison.

254 3. Results

255 3.1. Hovering Assessment

256 Analysis of images recorded during the hovering test demonstrates that
257 the platform stability is compatible with airborne flow velocimetry. During
258 the flight time, consistent portions of the grid are captured by the camera.
259 Specifically, the 11 grid cells enclosing colored markers in the left panel of
260 Figure 2 are always visible in frames during the flight. Colored markers inside
261 such grid cells indicate the average pixel area of each cell over the flight time.
262 Squares 2, 5, 6, 9, and 10 present smaller areas than squares on the left hand
263 side of the grid, suggesting that the drone is closer to the left portion of the
264 grid.

265 In Figure 2 (right), the time series of the areas of the grid cells (colored
266 dots) and of the laser focused rectangle (black dots) are shown. Due to
267 illumination conditions, the trace of the four laser beams on the grid is not
268 always visible (76% of the total number of frames depicted four laser traces).
269 Notably, the cell areas slightly vary in time, with a maximum coefficient
270 of variation of 0.89%. On the other hand, external vibrations lead to a
271 coefficient of variation as large as 2.94% in the time series of the area identified
272 by the lasers. This is due to the fact that lasers are directly installed on the
273 drone fuselage, whereas the camera gimbal efficiently mitigates the drone's
274 vibrations, thus abating the coefficient of variation to less than a third of its
275 value. We remark that improved stability is crucial for correlation-based flow
276 velocity estimation, where the similarities between consecutive images are
277 used to infer the displacement of depicted objects. Therefore, slight changes
278 in the image FOV due to the drone's vibrations while hovering suggest that

279 reliable cross-correlation is feasible.

280 3.2. Airborne Flow Velocimetry

281 Proof of concept velocity observations in the Rio Cordon show the po-
282 tential of the drone-based approach for surface flow measurement. Aerial
283 platform velocities measured in the subarea located in between the dark cross-
284 sectional stripe and the dark inclined stripes (approximately $0.76 \times 0.83 \text{ m}^2$),
285 Figure 3 (left), are in line with benchmark values, Table 1. Underestimations
286 with respect to the impeller flowmeter readings may be due to the fact that
287 the flowmeter is slightly below the water surface (3 cm out of the total depth
288 of 11 cm), where wind effects are negligible and velocities are expected to be
289 larger than surface flows.

290 With regards to the two sets of drone measurements in Table 1, differences
291 between them are not statistically different as determined through one-way
292 ANOVA ($F = 2.43$ and $p = 0.14$). The slightly higher uncertainty obtained
293 in case of natural floaters is attributed to the fact that they were heavily de-
294 ployed in the stream and, therefore, involved longer flights. Therefore, since
295 the hovering performance of the drone is reduced over longer flight times, the
296 use of natural tracers yields the higher standard deviation in Table 1.

297 As shown in the velocity map in Figure 3 (left), the aerial platform is suc-
298 cessful in monitoring extended portions of the stream and the flow physics
299 across the stream is accurately captured, Figure 3 (right). Maps from the
300 drone are slightly affected by local water reflections and areas of poor illumi-
301 nation, since the onboard camera offers extended FOVs with diffused, rather
302 than direct, illumination.

303 4. Discussion and Remarks

304 Here, we propose a novel surface flow observation concept based on a
305 stand-alone sensing platform that integrates drone technology and optical
306 methods. Not only are image data captured from the platform, but a sys-
307 tem of lasers enables remote photometric calibration, thus circumventing the
308 need for time-consuming and expensive field campaigns for GRPs acquisi-
309 tion. Specifically, in this study, a laser system is utilized for pixel calibration
310 and for flow velocimetry analyses. Indeed, the stationarity of the time se-
311 ries of the area identified by the lasers is used to isolate stable sequences for
312 flow measurements, whereby small variations are associated with instances
313 of stable hovering.

314 Notably, the laser apparatus paves the way for unsupervised rapid obser-
315 vations in large scale hydrological systems. Indeed, instances of airborne flow
316 velocimetry currently rely on the acquisition of fixed objects in the FOV for
317 photometric calibration and for video stabilization due to imperfect hover-
318 ing [41, 42, 43]. On the other hand, the use of the laser system will leverage
319 pixel calibration in the absence of fixed reference objects, thus enabling low
320 cost observations in large scale systems, such as estuaries and limnological
321 environments. In such large scale settings that may exceed the maximum dis-
322 tance range allowed by the remote control, a priori planned GPS waypoint
323 navigation may facilitate observations.

324 Beyond pixel calibration and video stabilization, analysis of the laser’s
325 traces in the FOV can be used to complement onboard built-in altimetry
326 measurements. For instance, a smaller area corresponds to a higher distance
327 of the drone from the ground and, thus, to the drone increasing its vertical

328 position. Therefore, changes in the area and shape of the laser’s traces on
329 the ground can help in estimating the altitude of the drone with respect to
330 the ground, thus opening the way for refined photometric calibration and
331 enhanced measurement accuracy.

332 The presented system is inherently suited for real-time analysis in un-
333 gauged environments. Data acquisition is feasible in rather limited intervals
334 of time (few seconds) and surface flow velocity map generation is an unsu-
335 pervised process that can be afforded in 5-10 minutes. In addition, given
336 the limited cost of the equipment and its ease of implementation (medium
337 flight skills can be achieved after some hours of training), the approach is
338 versatile and likely sustainable for most research groups. With regards to
339 the use of tracers, even if highly-visible artificial tracers enable rapid velocity
340 estimations, their use requires either the presence of operators or installation
341 of remotely-operated devices to deploy the particles [18].

342 The dependence of LSPIV measurements on the presence of homoge-
343 neously distributed tracers may pose a significant technical challenge to prac-
344 tical implementations of the proposed approach. To overcome this issue, we
345 envision the development of machine learning techniques to automatically
346 de-noise pictures [44] and to emphasize floaters’ contrast against the image
347 background. Alternative image-based flow velocimetry algorithms that yield
348 the trajectory of individual floaters, such as particle tracking velocimetry,
349 should be explored [45]. In the case of floods or severe events, naturally-
350 occurring debris and sediments may be sufficient to obtain surface flow ve-
351 locity measurements [46].

352 The proposed approach may be readily implemented to provide fully

remote and rapid flow discharge estimates in inaccessible areas and large scale ecosystems. For instance, in [47, 48, 49], an entropy-based method is proposed to estimate flow discharge based on the maximum velocity observed on the stream surface. This approach establishes a linear relationship between the maximum surface velocity and mean velocity in natural rivers [50, 51]. The integration of such entropy-based approach and drone-enabled distributed surface velocity observations may lead to flow discharge estimates in complex environments. Further, application of image mosaicking and FOV reconstruction techniques may enable surface flow velocity gauging over large water areas.

5. Conclusions

In this work, we demonstrated the potential of integrating an aerial platform and optical sensing for surface flow measurements in natural environments. We designed the aerial platform to enable completely remote measurements, thus circumventing the need for on site surveys that are typically required by traditional measurement techniques, and enabling novel observations in inaccessible areas. By investigating the hovering capability of the aerial platform during a flight of more than 20 s, we found that the approach is suitable for remote flow observations. Further, surface flow velocity measurements performed from the drone on a small scale mountainous stream were in good agreement with data from on site flow sensing systems.

We expect drones to be a forward-looking addition to the experimental toolbox currently available to hydrologists and geophysicists. As technology progresses toward better performing drones, current limitations, such

377 as imperfect hovering capabilities, constrained flight time and payload, will
378 be easily overcome, and this approach should enable new avenues in hydro-
379 logical observations. Future studies will be devoted to the application of
380 the presented methodology to the kinematic characterization of alternative
381 environmental settings, such as channel and rill flows.

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Figure 1: Sketch of the experimental setup. Analysis of the squares of the grid was used to assess the ability to capture stable videos.

Table 1: Velocity measurements performed on the natural stream. Symbols v_m and σ stand for average maximum velocity and standard deviation, respectively. Average maximum velocities and standard deviations from the drone are obtained from LSPIV time-averaged maps by averaging over the yellow dashed subarea reported in Figure 3.

	v_m [m/s]	σ [m/s]
Flowmeter	2.54	0.09
Drone		
artificial tracers	2.29	0.09
natural tracers	2.15	0.27

Figure 2: Left, experimental grid for assessing the drone's hovering capability. Colored markers inside each square indicate the average area in pixels. Right, time histories of the area of each of the 11 squares visible during the flight (colored dots), and of the area of the rectangle focused by the laser beams (black dots). Raw data are smoothed through a local regression filter with weighted linear least squares and a parabolic model.

Figure 3: Left, representative surface flow velocity maps from the aerial platform based on the use of natural floaters. The yellow star indicates the location at which measurements with the impeller flowmeter are taken. Right, time-averaged cross-sectional profiles corresponding to the green, red, and blue cross-sections highlighted in the map. Shaded areas indicate standard deviations. The yellow dashed box in the left panel highlights the subarea used for measurement comparison.