Response to Review 1 (Flavia Tauro)

We wish to thank Dr Flavia Tauro for her insightful comments and wider discussion concerning the application of UAVs and associated methodological developments for the quantification of flood processes. In the following we provide point by point responses to each of the reviewer's comments.

Comment 1. *The Materials and Methods Section should be simplified to improve on clarity. Paragraph 2.2 is sometimes difficult to read (the coordinates of GCPs and of the UAV starting position can be easily confused). Maybe a flow chart may help in better identifying the image processing steps*.

Reply 1. We agree that a flow chart would help to clarify the image processing steps. This is now included in this resubmission (Figure 1). We also explicitly specify differences between GCP co-ordinates and camera model co-ordinates to add clarity to Section 2.2 (see marked-up version).

Comment 2. *Further explanation should be provided on areas presenting poor transformation accuracy (p.5 of Paragraph 2.2). Why were 48% of the original velocity vectors eliminated? How do you plan to improve on that?*

Reply 2. 48% of the vectors were removed due to the apparent movement of the GCPs, or due to unsatisfactory error associated with georectification (Page 6 Lines 15 - 19). This is a result of persistent residual distortion effects following image correction, especially close to the image boundaries, due to the specified transformation parameters being sub-optimal (Page 7 Lines 11 – 13 and Page 11 Lines 4 - 7). This is likely a result of the actual radial distortion parameters of the lens within camera differing slightly from the manufacturers' specification. Assessment of this is not possible without performing manual calibration of the camera, which would have improved the transformational accuracy. To improve the transformational accuracy in future deployments this would be best achieved by using a calibrated camera with minimal lens distortion (Page 11 Lines 6 - 7).

Comment 3. *Details on the video footage should be included. Was it captured while the UAV was remotely piloted or on autonomous navigation? Why didn't you consider flying in the hovering mode to reduce vibrations? How is the camera connected to the platform? Camera gimbals sensibly reduce UAVs vibrations. Image resolution should be included in the Materials and Methods. Also, the footage should be added as supplementary material (I tried to access it on www.angusforbes.co.uk but I was not successful).*

Reply 3. The crowd-sourced video footage was collected by a standard DJI Phantom Vision 2 UAV in manual flight mode by a member of the public whose aim was to document the impacts of the floods across the inundated area (Page 3 Line 30 – Page 4 Line 1). The video itself was not collected with the intention of being used for PIV analysis. If this had been piloted by ourselves we would have sought to hover over each region of interest (ROI) for several seconds before moving on. The image resolution of the video footage is 960 x 540 pixels at 25 frames per second (Page 4 Line 1 - 2). We now provide the video footage as Supplementary Material.

Comment 4. *In my opinion, limitations of the proposed approach lay in the following:*

- *Numerous GCPs need to be surveyed in the aftermath of the event*
- *Distinct features are necessary to geo-reference the images and apply the tracking algorithm*

The need for GCPs tends to limit the approach to gauged or easily-accessible areas. Conversely, ungauged natural and rather extended regions would be difficult to monitor. On-site surveying hampers the use of UAVs in *wide and impervious areas. How do you plan to compensate for GCPs surveying in such areas? What is the degree of supervision required by the feature tracking procedure? Do users need to identify the features in images to start the tracking process? I agree with the Authors that Lagrangian-based algorithms may be beneficial in case of low seeding densities. However, they typically require higher supervision by users (a priori information on shape and size of the objects to be tracked). Finally, how long did it take to process the images and extract velocities? How do you plan (if you do) on automating the approach towards real-time analysis?*

Reply 4. We agree with the limitations of the approach that Reviewer 1 rightly mentions. This method requires the presence of GCPs that are observable across the camera frame, which must also be accurately surveyed following the event (Page 4 Lines 4 - 7). Within urbanised areas where naturally occurring features are available as GCPs (e.g. lamp-posts, fence lines, walls, etc.) this approach offers a potentially valuable method for quantifying flood flow processes beyond the range of events that can be captured typically using traditional flow measurement techniques. In areas where such GCP features do not exist a different approach would be required, whether it be through the use of lasers, or utilisation of on-board GPS systems in conjunction with additional sensors to facilitate in the transformation process (Page 10 Lines 1 - 2, and Page 10 Lines 10 - 11). Enhancement and adoption of these approaches are key to enable UAVs to be utilised for real-time capture of hydraulic properties of flow in the future (Page 10 Lines 11 - 12). The procedure we adopt requires some supervision. Specifically, during the tracking stage, GCP locations are added, checked and updated every 10 frames as the camera field of view and illumination of the image varies (Page 4 Lines 31 - 32). This procedure ensures that sufficient GCPs are visible throughout the video and that they are still accurately focussed on the correct object in question. In an optimal operation, purpose-built GCPs would be installed across the areas of interest with specific optical characteristics so that (semi-)automatic registration would be possible (Page 10 Lines 7 - 8). The features of interest do not necessarily need to be manually selected prior to tracking. Features across the entire frame are established and it is subsequently possible to specify a ROI, thereby ignoring tracked features beyond this area. Complete automation of the process (no supervision required), camera calibration and tracking of the 5.6 seconds of footage presented here took 87 minutes on a 64-bit Windows OS with a 3.2 GHz CPU and 8 GB installed RAM. The initial development of the master camera model accounted for 29% of this time, with the subsequent tracking, georectification and updates to the camera model accounting for 71% (Page 6 Line 23).

Response to Anonymous Review #2

We wish to thank Anonymous Reviewer #2 for their detailed critique of our paper and for their considered comments. In the following we provide point by point responses to each of the reviewer's comments.

Response to specific comments:

Comment 1. *First of all, an overview of the method is required, maybe between paragraph 2.1 and 2.2. The different steps of the calculations have to be presented, a small chart could be useful. Furthermore, more details on the algorithms should be given. For example, it is said that "a distorted camera model was generated", could you explain how? I also wonder if the user has to locate the GCPs manually on the pictures. Could you clarify what you call "prominent features"? The calculation of the flow velocities owing to the first steps of the method should be explained. I was also wondering if the water surface elevation is needed or not.*

Reply 1. We agree that an overview of the method and flow chart will be beneficial in helping to clarify the processing steps and to provide a clear overview of the method. This is now included in the resubmission (Page 3 Lines 15 – 20 and Figure 1). For brevity, we have not provided details of sub-steps of the approach where other authors have published details of the method. In the example that Reviewer 2 specifies, we adopt the method of Messerli and Grinsted (2015) for the development of the camera model (Page 4 Line 17). Details of this approach and examples of its use are provided within the cited publication. We have now removed the term 'prominent features' from the manuscript and make it clear that all features are utilised are those that are automatically extracted by the KLT algorithm (see marked-up version). GCPs are manually selected from the images (Page 4 Line 30 – Page 5 Line 2). GCPs must be level with the water surface, non-mobile, and clearly visible within the laser scan generated point cloud (Page 5 Lines 2 – 3). These features are then automatically tracked from frame-to-frame using the KLT algorithm. In the resubmitted manuscript we explicitly state how the flow velocities are calculated (Section 2.5). By selecting GCPs that intersect with the water surface elevation, we are assuming that the water surface slope is negligible across the image frame (Page 9 Lines 24 - 26). Whilst this assumption is appropriate for relatively small areas such as this application, this may not be appropriate in other applications. We discuss the errors associated with transformation in Section 4.2.

Comment 2. *The method lacks a clear validation step. The obtained flow velocities should be compared with measurements performed with other devices. It could be very interesting to apply the technic on a low flow event to control the results. The proposed validation is only based on optically tracked features; more details are required about this major operation. A small map with the measurement area and the trajectory of the UAV could be helpful in the beginning of the paper.*

Reply 2. Due to the localisation of this flash flood within an ungauged catchment we do not have any data that could be used as validation. Indeed, this was the motivation behind our approach. However, the data presented in Figure 4 clearly replicates observations of how the flow interacts with features and structures which modify the flow path e.g. blocked bridge resulting in flow being diverted along the road, while the reported standard deviations show how stable the velocity field is over the 5.6 seconds of recording. However, we do agree that a quantitative validation of this approach is required moving forward. This is something that we intend to assess in forthcoming research activities. In this resubmission we now provide a map of the UAV trajectory and the camera viewshed within Figure 1.

Comment 3. *Could you also specify how you code the different steps (matlab, fortran?). Are the codes open-source?*

Reply 3. The entire work-flow is coded in MATLAB R2016a (Page 4 Line 17). Although the code is not currently open-source this is something that we seek to achieve in time.

Comment 4. *In the introduction, you should cite the works dealing with measurements of surface flow velocities from helicopters images. You should also cite the different technics of image analysis such as LSPIV, LSPTV*

Reply 4. We now cite the works of Fujita and Kunita (2011) whom utilise helicopters and LSPIV for flood monitoring (Page 2 Line 17), and we also highlight the different approaches (LSPIV and LSPTV) for image analysis (Page 2 Lines 27 – 29).

Comment 5. *At the end of paragraph 2.1, the error is for all the directions x, y and z?*

Reply 5. Yes the error that we cite at the end of Section 2.1 relating to the stitching of point clouds and the transformation to real world co-ordinates is the total error across the x, y, and z planes. This is clarified in the revised manuscript (Page 4 Lines 10 - 11)

Comment 6. *Some of the Figures (1 and 4 for example) and table 1 are not cited in the text*

Reply 6. This is an oversight on our part and this has been rectified in the revised manuscript (see marked up version).

Comment 7. *The UAV acronym should be make explicit in the abstract (especially for non-English speaking people).*

Reply 7. In the revised manuscript, the term 'UAV' is properly defined in the title, abstract, and first occurrence in the main body of the text (see marked-up version).

Technical Note: Advances in flash flood monitoring using Unmanned Aerial Vehicles (UAVs)

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Abstract Unmanned aerial vehicles (UAVs) have the potential to capture information about the earth's surface in dangerous and previously inaccessible locations. Through image acquisition of flash flood events and subsequent object-based analysis, highly dynamic and oft-immeasurable hydraulic phenomenon may be quantified at previously unattainable spatial and temporal resolutions. The potential for this approach to provide valuable information about the hydraulic conditions present during dynamic, high-energy flash floods has until now not been explored. In this paper we adopt a novel approach, utilising the Kande-Lucas-Tomasi (KLT) algorithm to track features present on the water surface which are related to the free-surface velocity. Following the successful tracking of features, a method analogous to the vector correction method has enabled accurate geometric rectification of velocity vectors. Uncertainties associated with the rectification process induced by unsteady camera movements are subsequently explored. Geo-registration errors are relatively stable and occur as a result of persistent residual distortion effects following image correction. The apparent ground movement of immobile control points between measurement intervals ranges from 0.05 - 0.~~13m~~13 m. The application of this approach to assess the hydraulic conditions present in Alyth Burn, Scotland during a 1:200 year flash flood resulted in the generation of an average 4.2 measurements m^{-2} at a rate of 508 measurements s^{-1}. Analysis of these vectors provide a rare insight into the complexity of channel-overbank interactions during flash floods. The uncertainty attached to the calculated velocities is relatively low with a spatial average across the area of ± 0.~~15m~~15 m s^{-1}. Little difference is observed in the uncertainty attached to out-of-bank velocities (± 0.~~15m~~15 m s^{-1}), and within-channel velocities (± 0.~~16m~~16 m s^{-1}), illustrating the consistency of the approach.

1 Introduction

The occurrence of flash flooding from intense rainfall in Western Europe is predicted to increase throughout first half of the 21st Century (Beniston, 2009; Rojas et al., 2012). These events pose severe risks to society, transform communities and under extreme conditions can permanently alter the state of the river system (Doocy et al., 2013; Milner et al., ~~2013;Doocy et al.,~~ 2013). Flash floods in fluvial systems pose high risks to communities especially when they occur in small, upland catchments where orographic effects can enhance precipitation intensity with runoff being concentrated rapidly along narrow and steep flow pathways (~~Garambois et al., 2014;Sangati et al., 2009;~~Bracken and Croke, 2007; Sangati et al., 2009; Garambois et al., 2014). Despite a substantial body of work on physical flood processes observed in research catchments (e.g. Quinn and Beven, 1993;~~Mayes et al., 2006;~~ Soulsby et al., 2000; Mayes et al., 2006), there is currently a paucity of data describing the antecedent and concurrent processes associated with extreme flash flood events. This is mainly due to conventional monitoring networks often failing to adequately sample small, responsive catchments (Borga et al., 2008; Gaume and Borga, 2008; Soulsby et al., 2008; Braud et al., 2014~~;Borga et al., 2008~~). Measurement and monitoring of these events is therefore largely responsive rather than active, opportunistic rather than strategic, and hindered by practical difficulties (Borga et al., 2008; Tauro et al., 2015b). Making observations of peak flood discharge ~~(Q_{peak})~~ in real-time remains a significant practical challenge.

Given current operational constraints, favourable sources of process-data during flash floods ~~and particularly at Q_{peak}~~ in ungauged catchments often rely on *post-hoc* analyses of air and space borne earth observation sensors (e.g. visible, near-infrared and multispectral imaging and synthetic aperture radar). Increasing availability of these ~~remote~~remotely sensed data has furthered our understanding of floodplain inundation processes (e.g. Wright et al., 2008); enabled hydraulic properties such as roughness (Simeonov et al., 2013), river stage and discharge (Liu et al., 2015) to be successfully modelled; provided justification for the incorporation of spatially and temporally varied roughness values (Mason et al., 2003; Schumann et al., 2007~~;Mason et al., 2003~~); and enabled calibration and validation of hydrodynamic models (e.g. Martinis et al., 2009; Refice et al., 2014). Various contributions have been enabled by the fortuitous availability of archived satellite and aerial records (e.g. Chen and Mied, 2013; Kääb and Leprince, 2014~~;Chen and Mied, 2013~~). However, the highly transient temporal and spatial domains of flash floods, combined with the significant lead times required to mobilise monitoring resources, has up until now limited the use of ~~archived satellite and aerial records to larger, more slowly responding catchments (e.g. Wong et al., 2015)~~satellite and aerial records to larger, more slowly responding catchments (e.g. Fujita and Kunita, 2011; Wong et al., 2015).

The widespread availability of unmanned aerial vehicles (UAVs) has, in recent years, increased our ability to monitor and quantify higher magnitude, lower frequency environmental phenomena (e.g. Niethammer et al., 2012; Ryan et al., 2015), whilst at the same time reducing operational costs of traditional environmental monitoring (Fekete et al., 2015). The potential for the use of UAVs for non-contact flow measurement has been identified (Kääb and Leprince, 2014), leading to proof-of-concept studies utilising UAVs for monitoring of low-flow conditions (e.g. ~~Patalano et al., 2015;Tauro et al., 2015a;~~Pagano et al., 2014; Detert and Weitbrecht, 2015; Patalano et al., 2015; Tauro et al., 2015a; Tauro et al., 2015b). However, the potential for this approach to provide valuable information about the hydraulic conditions present during dynamic, high-energy flash floods has yet to be realised.

Image based non-contact methods of flow estimation utilise algorithms (e.g. Large-Scale Particle Tracking Velocimetry (LSPTV) and Large-Scale Particle Image Velocimetry (LSPIV)) designed to track optically visible features of the free-surface to determine the rate of fluid flow in artificial, or natural open-channels (~~Pentari et al., 2014;~~Jodeau et al., 2008; Kim et al., 2008;~~Sun et al., 2010;Le Boursicaud et al., 2015;~~ Le Coz et al., 2010; Sun et al., 2010; Dramais et al., 2011; Puleo et al., 2012; Pentari et al., 2014; Le Boursicaud et al., 2015). The rate at which naturally occurring features (e.g. foam, seeds, woody debris and turbulent structures) or artificially introduced tracers (e.g. Ecofoam chips, fluorescent micro-spheres, etc.) are displaced downstream can be used to estimate the free-surface velocity, which may be related to depth-averaged flow characteristics (e.g. Jodeau et al., 2008; Dramais et al., 2011; Fujita and Kunita, 2011; Simeonov et al., 2013; Le Boursicaud et al., 2015~~;Fujita and Kunita, 2011;Dramais et al., 2011;Jodeau et al., 2008~~). Conceptually, terrestrial and airborne tracking of surface water features are similar; however the uncertainties associated with rectification of captured images to account for perspective, radial, and tangential distortions are compounded when using a UAV for image acquisition. This is due to unsteady camera movement, which must be accounted for if accurate geometric rectification of velocity vectors or oblique images is to be achieved (Kantoush et al., 2008; Kim et al., 2008). A second source of uncertainty is introduced in situations where low seeding densities prevail resulting in a lack of stable and identifiable surface features (Lewis and Rhoads, 2015). However in the case of flash floods, coherent flow structures at the free-surface and presence of washed-in floating material may produce favourable seeding conditions (Jodeau et al., 2008; Dramais et al., 2011~~;Jodeau et al., 2008~~).

This paper presents a novel methodology for the derivation of key hydraulic data during flash floods using imagery captured by a low-cost, commercially available UAV platform. Our approach overcomes uncertainties associated with image rectification, transformation and feature tracking to determine river surface velocity during flash floods. Our approach yields fundamental process data, invaluable for flash flood reconstruction in ungauged river catchments. The adoption of this technique has the potential to significantly advance our understanding of high flow stage processes during flash floods.

2 Materials and Methods

The materials presented in the following section describe the entire work-flow for the extraction of surface water velocities from a UAV through the utilisation of image based non-contact methods. This method is organised in five sub-sections, which are presented sequentially: (i) primary data collection; (ii) development of an initial camera model, and (iii) updated camera models for projective transformations; (iv) assessment of transformation accuracy and apparent movement of GCPs; and finally, (v) surface velocity calculation. A schematic overview of this method is provided in Figure 1, wherein each heading corresponds with the homonymous section within the main text.

Figure 1. A schematic of the proposed methodology for tracking surface water features from UAVs and their conversion to velocities.

2.1 Primary data collection

~~A Phantom Vision 2 UAV, equipped with a FC200 camera unit was deployed over~~ On 17th July 2015, the Alyth Burn, Perthshire, Scotland (324600, 748600 OS BNG) ~~on 17th July 2015 at ~11:00 BST. At this time, the river~~ breached its banks as a result of a prolonged period of rainfall over the catchment. While rainfall totals were not in themselves extreme (~~41mm~~41 mm over a 6 hour period), the prolonged nature of the precipitation event coupled with the particular catchment configuration upstream of the town, resulted in over 70 properties being flooded and four footbridges in the town centre being destroyed (Perth & Kinross Council et al., 2015)~~.~~. During this flood event, a Phantom Vision 2 UAV, equipped with a FC200 camera unit was deployed over Alyth Burn in manual flight mode by a member of the public at ~11:00 BST. The video footage itself was not collected with the intention of being used for flow reconstruction, rather to document the impacts of the floods across the inundated area. Footage of the event was collected at 960 x 540 pixel (px) resolution at an acquisition rate of 25 frames per second (FPS).

Ground control points (GCPs) for the area of interest were required to convert the image (px) co-ordinates into geographical co-ordinates (OS BNG m). The deployment of a Leica MS50 multi-station shortly after the flood event enabled the generation of a detailed point cloud with an average point spacing of <0.~~002m~~002 m from which GCPs could be accurately identified~~.~~ (Figure 1, Section 2.1). These GCPs represented immobile objects that were present during the recording, and which persisted following the clean-up operation (e.g. lamp-posts and wall corners). Individual point clouds were joined using *CloudCompare* v2.6.1 (2015), resulting in an internal error (RMS) of 0.~~04m~~04 m. This point cloud was rectified to real-world co-ordinates through comparison with control point measurements (n = 12) obtained by a Leica GS14 GNSS system. This resulted in an additional three-dimensional error of 0.~~06m~~06 m.

2.2 Initial Camera ~~Motion and Calibration~~Model

Due to the lack of available navigation data for the UAV, its starting position was modelled using an *a-priori* assumption about its approximate location [X_{est}, Y_{est}, Z_{est}]. This was based on a visual assessment of the objects within view of the camera. 20,000 co-ordinate solutions were randomly generated (X_{est} ± 7.5m; Y_{est} ± 7.5m; Z_{est} ± 5m) resulting in 8.9 discrete locations per m^3~~.~~ (Figure 1, Section 2.2). For each of these potential starting positions, a distorted camera model was generated in MATLAB 2016a (cf. Messerli and Grinsted, 2015). For each camera model, the radial distortion coefficients and image centre parameters that define the camera lens were fixed based on the manufacturer's specification (DJI, 2015). The focal length, and view direction (yaw, pitch and roll) were however free parameters and allowed to vary accordingly. These were optimised to minimise the square projection error of ~~the~~pre-determined GCPs using a modified Levenberg–Marquardt algorithm (Fletcher, 1971). The optimal solution was subsequently defined as the master camera model, which was used as the basis for future projective transformations.

~~Figure 1. An example of georectification and projection of GCP positions (red dots) following optimisation of the distorted camera model alongside the location of actual GCP positions (blue dots).~~

~~Following optimisation of the UAVs starting location, prominent features and GCPs were tracked iteratively between subsequent frames~~2.3 Updated Camera Model

Following generation of the master camera model for the first frame of the video, an updated camera model solution based on updated GCP co-ordinates was generated for each subsequent frame (Messerli and Grinsted, 2015). This enabled UAV movement and changes in view direction to be accounted for. The updated camera model was obtained by randomly generating 1000 new camera positions proximal to the co-ordinates of the optimised camera model for the previous frame (X ± 0.25 m; Y ± 0.25 m; Z ± 0.25 m). These camera co-ordinates were then fixed whilst view direction was perturbed. The optimum camera model for each specific frame was produced by minimising the difference between the actual and projected GCP co-ordinates. In order for this to be achieved, GCPs were defined and tracked iteratively between each frame using the Kande-Lucas-Tomasi (KLT) algorithm (Shi and Tomasi, 1994). Every tenth frame, the position of existing GCPs were manually checked and their location manually updated when changes in illumination conditions resulted in poor tracking performance. Additional GCPs were also manually added to account for changes in the camera viewshed (Figure 1, Section 2.3). This ensured that sufficient GCPs were visible throughout the video and that they were still accurately focussed on the object in question. All GCPs were level with the water surface, non-mobile, and clearly visible within the laser scan generated point cloud.

2.4 Transformation accuracy and apparent movement of GCPs

Every n^{th} and $n + 9^{th}$ frame, where n equals the start of the tracking sequence, the start and finish positions of the successfully tracked ~~features were stored in pixel units creating virtual velocity vectors representing motion during the previous 0.4s of video. These virtual velocity vectors were then corrected for background image displacement so that stationary objects yield zero or negligible velocity values. This was achieved using an approach analogous to the Vector Correction Method (Fujita and Kunita, 2011). This required the generation of an optimised camera model solution based on updated GCP co-ordinates for each~~GCPs were stored in pixel units representing motion during the previous 0.4 s of video. The start and finish positions of the GCPs (px) are converted to real-world coordinates $[N_T, E_T]$ ~~frame (Messerli and Grinsted, 2015). This was achieved by randomly generating 1000 new positions proximal to the co-ordinates of the optimised model for the previous frame (X ± 0.25m; Y ± 0.25m; Z ± 0.25m). These co-ordinates were then fixed whilst view direction was perturbed. The optimum model was produced by minimising the difference between the actual and projected GCP co-ordinates. Once camera movement is accounted for, the corrected virtual velocity vectors are converted to real-world start and finish co-ordinates giving~~ ~~$[X_n, Y_n]$ and $[X_{n+9}, Y_{n+9}]$ respectively. This was achieved through projection of the 2-D image pixel co-ordinates~~ using a two-dimensional transformation (Fujita and Kunita, 2011; Fujita et al., 1998), based on the optimised camera models specific to n^{th} and $n + 9^{th}$ frame (Messerli and Grinsted, 2015). ~~During this process, features were only tracked if they lie within the central 90% of the image. This was necessary to minimise the potential for residual distortion effects to bias measurements, as these were most likely to persist close to the image boundaries (Detert and Weitbrecht, 2015). This process enables the calculation of 2-D velocities~~ ~~$[u, v]$ following application of a conversion factor k to account for the number of tracked frames I and seconds per frame F:~~

~~$[\Delta X, \Delta Y] = [X_{n+9}, Y_{n+9}] - [X_n, Y_n]$ (1)~~

~~$k = \frac{1}{(F\ I)}$ (2)~~

~~$[u, v] = [\Delta X, \Delta Y][k]$ (3)~~

The degree to which the geo-rectification process is a success is assessed by comparing how the co-ordinates of the surveyed GCPs $[N, E]$ compare to the projected GCP locations$[N_T, E_T]$. The residuals $[r, s]$ represent the absolute positional error of the GCPs and provide a direct measure of the accuracy of the geometric transformation from pixel units into geographical co-ordinates~~,~~ (Figure 1, Section 2.4), given by the Euclidean distance between the actual and projected locations R_{EN} (Detert and Weitbrecht, 2015):

$$[r, s] = [N_T, E_T] - [N, E] \quad (\text{~~4~~}1)$$

$$R_{EN} = (r^2 + s^2)^{0.5} \quad (\text{~~5~~}2)$$

The degree to which the projection of the GCPs varies over time is assessed by examining the relative changes in the GCP projection locations (m) between the beginning and end of the feature tracking process:

$$[u_{EN}, v_{EN}] = [r_{n+9} - r_n), (s_{n+9} - s_n)] \quad (\text{~~6~~}3)$$

$$U_{EN} = (u_{EN}^2 + v_{EN}^2)^{0.5} \quad (\text{~~7~~}4)$$

2-D natural neighbour interpolation of the GCP errors is performed, giving spatially distributed estimates of R_{EN} and U_{EN}~~.~~ (Figure 1, Section 2.4).

2.5 Surface Velocity Calculation

As with the GCPs, between the n^{th} and $n + 9^{th}$ frame, surface water features are defined and tracked using the KLT algorithm, with their start and finish positions being stored in pixel units. During this process, features were only tracked if they were within the central 90% of the image. This was necessary to minimise the potential for residual distortion effects to bias measurements, as these were most likely to persist close to the image boundaries (Detert and Weitbrecht, 2015). The start and finish positions (px) of selected surface water features are converted to real-world start and finish co-ordinates i.e. $[X_n, Y_n]$ and $[X_{n+9}, Y_{n+9}]$ respectively. This is again achieved through two-dimensional transformation (Fujita and Kunita, 2011; Fujita et al., 1998), based on the optimised camera models specific to n^{th} and $n + 9^{th}$ frame (Messerli and Grinsted, 2015). This method is analogous to the Vector Correction Method (Fujita and Kunita, 2011) whereby stationary objects yield zero or negligible velocity values with the movement of surface water velocity vectors being corrected for background image displacement. This process enables the calculation of 2-D velocities $[u, v]$ following application of a conversion factor k to account for the number of tracked frames I and seconds per frame F:

$$[\Delta X, \Delta Y] = \left[X_{n+9}, Y_{n+9,}\right] - [X_n, Y_n\ ] \qquad (5)$$

$$k = \frac{1}{(F\ \ I)} \qquad (6)$$

$$[u, v] = [\Delta X, \Delta Y][k] \qquad (7)$$

From which the velocity magnitude is obtained:

$$\mathrm{U} = \sqrt{u^2 + v^2} \qquad (8)$$

Velocity [U] measurements in areas defined as having poor transformation accuracy (i.e. ~~≥ 1m~~R_{EN} ≥ 1 m), or significant apparent movement of the GCPs between frames (i.e. U_{EN} ≥ 0.~~3m~~3 m) are removed prior to analysis, in addition to tracked features exhibiting minimal displacement (i.e. U ≤ 0.~~3m~~3 m). This resulted in 48% of the original ~~velocity vectors~~surface water features being eliminated~~. Data was not subject to any additional filtering.~~ (Figure 1, Section 2.5).

3. Results

3.1 Camera Motion

Using the 20,000 potential solutions, the optimised master camera model was selected based on the minimum square projection error of the GCPs (RMSE). ~~In this instance, the~~ The minimum RMSE of the 20,000 solutions was 11.~~4px~~4 px (n = 8). Optimisation of the initial camera model took 25-min (3.2 GHz CPU, 8GB RAM), and accounted for 29% of the total processing time. Following ~~the~~ perturbation of geographical and orientation parameters for each frame, the flight path of the UAV was successfully modelled~~.~~ (Figure 1, Section 2.3). Cumulative Euclidean distance travelled by the UAV over the 140 frames was 13.~~2m (2.5m~~2 m (mean velocity = 2.5 m s^{-1}) whilst the camera rotated on the y-axis by 28~~°.~~° (Table 1). During the video the RMSE of the optimised camera did not exceed 12.~~9px~~9 px with a mean μ of 9.~~6px~~6 px and a standard deviation σ of 1.~~3px~~3 px.

Table 1. Optimised parameters of the distorted camera models

3.2 Positional Accuracy

Analysis indicates that the precision of the geometric projection R_{EN} remains relatively stable throughout the video (Figure 2a). However the number of GCPs does exert some influence on the associated R_{EN} value. The minimum R_{EN} value of 0.~~4m~~4 m is observed at 0.~~8s~~8 s when 6 GCPs are within shot. With the removal of GCPs that are difficult to resolve, located close to the upper edge of the frame, R_{EN} naturally decreases. The maximum R_{EN} value is 0.~~76m~~76 m which occurs at 1.~~6s~~6 s (13 GCPs). This provides an indication of the minimum spatial scale over which measurements should be averaged and reported. Significant spatial variability in R_{EN} values are observed with median individual GCP R_{EN} values ranging from 0.27 – 1.~~0m~~0 m (Figure 2b). However, the interquartile range of R_{EN} for each GCP is relatively small, with a median value of 0.~~15m~~15 m Furthermore, due to the lack of correlation between geolocation errors and the distance of the GCP from the camera source, we eliminate the potential for significant errors being a function of reduced pixel density per unit area as GCP distance increases (Figure 2b). These findings indicate that the geo-registration errors are relatively stable and occur as a result of persistent residual distortion effects following image correction, especially close to the image boundaries, due to the specified transformation parameters being sub-optimal.

Figure 2. Box plots showing how projection residuals R_{EN} (m) of all GCPs vary with: a) time; and b) distance from the UAV camera. Dot within circle = median; box = 25th and 75th percentiles; whiskers = extremes, open circle = outliers. Line = Number of GCPs/Distance of GCP from image source (m).

Whilst accurate geometric projection is essential for observed velocities to be assigned an appropriate spatial reference, the precision of the transformation over time is of greatest importance~~ (cf. Eq. 7).~~. Unacceptable apparent ground velocities as a result of unstable transformation over time would undermine the value of tracking surface features. This error U_{EN} is quantified by computing the relative movement of reference features across each tracking interval. Unaccounted for movement generally decreases over time following the maximum U_{EN} of 0.~~28m~~28 m at 1.~~2s~~2 s through to the minimum of 0.~~05m~~05 m at 2.~~4s~~4 s (Figure 3a). Median U_{EN} values continue to be < 0.~~15m~~15 m throughout the sequence until the final frame when median U_{EN} increases to 0.26m. Unlike the spatial variability of R_{EN} values, U_{EN} values for specific GCPs are observed to be relatively consistent (Figure 3b). The median of the 15 GCPs ranges from 0.05 - 0.~~13m~~13 m with no apparent relationship between the distance of the GCP and U_{EN}. These findings illustrate the relative spatial and temporal stability of the geometric transformation. Occasionally however the apparent velocity of fixed targets, and therefore associated error, is significant (i.e. > 0.~~3m~~3 m). In these instances, features tracked within areas of unaccounted for movement are identified and filtered from subsequent analysis~~.~~ (Figure 1, Section 2.4).

Figure 3. Box plots showing how the apparent movement U_{EN} (m) of all GCPs varies with: a) time; and b) distance from the UAV camera. Dot within circle = median; box = 25th and 75th percentiles; whiskers = extremes, open circle = outliers. Line = Number of GCPs/Distance of GCP from image source (m).

3.3 Feature tracking & velocity estimation

Following the analysis of the 5.~~2s~~2 s video, and the filtering of features tracked from within inaccurately projected regions of the image, a total of 2644 velocity vectors were compiled within a ~~624m^2~~624 m^2 area of Alyth Burn and the surrounding inundated landscape~~.~~ (Figure 4). This results in an average of 4.2 measurements m^{-2} at a rate of 508 measurements s^{-1}. Analysis of these vectors provides an insight into the complexity of interactions between flow, sediment load and debris during flash floods. The bridge in the video (which was ultimately destroyed) was recorded in the imagery as being blocked by coarse woody debris. Due to the turbulent vortices generated by this blockage, surface velocities upstream of the bridge are calculated to be minimal (0.3 – 0.4 m s^{-1}). This blockage reduced conveyance of the flood waters with a proportion of channel flow becoming diverted into the adjacent street where surface velocities exceeded 1.~~2m~~2 m s^{-1}~~.~~ (Figure 4). Similar breaches of the ~~river's~~river defences upstream of the camera frame result in the routing of flood waters along the adjacent street. This routing produces velocities in the region of 0.9m s^{-1} before these waters are mixed with those diverted from the main channel at the bridge within the camera shot. Further along the road, flow is disrupted by a partially submerged vehicle. This again results in the visible deflection of flow. In the main channel, immediately downstream of the bridge, large-scale turbulent structures as a result of secondary circulation are detected with surface velocities progressively increasing to a maximum of 2.~~14m~~14 m s^{-1}~~.~~ (Figure 4). The uncertainty attached to all calculated velocities is relatively low with a spatial average across the area of ± 0.15 m s^{-1}. Little difference in observed in the uncertainty attached to out-of-bank velocities (± 0.~~15m~~15 m s^{-1}), and within-channel velocities (± 0.~~16m~~16 m s^{-1}), illustrating the consistency of the approach.

Figure 4. Images showing (a) velocity magnitude and (b) standard deviation of measurements calculated by tracking optically visual surface features. Zoomed in views of velocity vectors are provided in (c) and (d), which correspond with the boxes labelled 1 and 2 respectively in (a).

4. Discussion

4.1 Adoption of feature tracking approach

Application of feature tracking in open channels is dominated by methods operating in the Eulerian frame of reference (e.g. ~~Large-Scale Particle Image Velocimetry).~~LSPIV). These methods have been widely successful in the characterisation of instantaneous and time-averaged velocities for the determination of flood discharges, with deviations from acoustically derived measurements of < 10% (~~Dramais et al., 2011;~~Jodeau et al., 2008; Muste et al., 2008; Dramais et al., 2011). Measurements made in the ~~Lagragian~~Lagrangian frame of reference (e.g. ~~Large-Scale Particle Tracking Velocimetry (~~LSPTV~~)),~~), where the path of individual particles are assessed, have been less widely adopted for monitoring high magnitude events. This is despite LSPTV replicating hydraulics accurately with improved performance close to boundaries and in areas experiencing high velocity gradients (Admiraal et al., 2004). Enhanced spatial resolution of measurements may also be possible with lower seeding densities (Detert and Weitbrecht, 2015). Our implementation of the KLT algorithm has demonstrated its potential to generate large volumes of temporally consistent data at a distance of up to ~~50m~~50 m. However, feature tracking from non-stationary platforms poses additional challenges in accounting for errors related to sensor movement and orientation. These challenges, which must be addressed for this approach to be beneficial for monitoring flood flows, are discussed in the following sections.

4.2 Transformation errors

Transformation from pixel to world co-ordinates is one of the greatest challenges in generating accurate velocity estimates, even when measurements are conducted in controlled conditions from sensors of known, fixed locations (Lewis and Rhoads, 2015). Specific error associated with rectification can be controlled by ensuring the camera lens is: i) orthogonal to the water surface (e.g. Lewis and Rhoads, 2015); ii) corrected for distortion (e.g. Le Boursicaud et al., 2015); and iii) accurately calibrated using stable GCPs throughout the field-of-view (e.g. Dramais et al., 2011). Unfortunately it is not always possible to maintain the camera lens orthogonal to the water surface whilst capturing flow processes at the scale of interest, which often necessitates oblique image capture. Such oblique image capture may pose methodological difficulties due to far-field objects being poorly resolved relative to those in near-field. Secondly, lens distortion must be removed prior to the implementation of traditional plan-to-plan perspective projection (Le Boursicaud et al., 2015). This can be achieved based on the manufacturer's specifications (e.g. Detert and Weitbrecht, 2015), or through manual calibration (e.g. Tauro et al., 2015a); however residual distortion may persist close to image boundaries. Finally, following internal camera calibration, the success of the transformation depends on the 3-D distribution of GCPs. Distribution of at least four GCPs are required for a two-dimensional transformation (Fujita et al., 1998; Fujita and Kunita, 2011~~; Fujita et al., 1998~~), or minimum six GCPs distributed across the region of interest for a 3D plan-to-plan perspective projection (Jodeau et al., 2008; Muste et al., 2008). For accurate transformation, elevation errors can be minimised by ensuring GCPs are similar to or located parallel to the water surface elevation (Jodeau et al., 2008; Fujita and Kunita, 2011~~; Jodeau et al., 2008~~). However, an implicit assumption of this approach is that the planar free surface is horizontal and that free surface undulations are negligible across the frame. Due to the often negligible water surface slopes across the area of interest, errors are typically assumed to be insignificant (Hauet et al., 2008), with previous research indicating that water level errors of ±0.~~3m~~3 m result in velocity deviations of < ±5% (Le Boursicaud et al., 2015). A second source of elevation error may be induced by local water level variability as a result of standing waves created by hydraulic jumps, or obstacles. However, previous research ~~(Dramais et al., 2011)~~(e.g. Dramais et al., 2011) has demonstrated that local variability of up to ~~1m~~1 m may still have an insignificant impact on stream-wise velocity measurements when images are collected perpendicular to flow~~. Due to the responsive nature of this Alyth survey to the July rainfall and flood event, the distribution of GCPs was not pre-determined, so despite a total of 15 linear structures within the urban landscape that intersected the water surface being identified as GCPs, spatial coverage is incomplete and availability is temporally variable. While rapid response deployment during floods may therefore introduce errors in the projection that would otherwise be accounted for in planned deployments, the majority of surveys at high discharge will naturally be 'unplanned' and the result of rapid field deployment. Despite this, and the technical challenges of flying surveys during flood periods, the relatively stable transformations achieved throughout the duration of the July 2015 Alyth video presented here demonstrate the utility of the approach~~.

4.3 Accounting for movement

In addition to oblique image capture, camera motion can greatly diminish the precision of any calibration and transformation process. In the case of monitoring fluvial flash floods from UAV platforms, camera motion is inevitable (Tauro et al., 2015a; Tauro et al., 2015b)~~, and this movement should be corrected for on a frame-by-frame basis utilising~~, and this movement should be corrected for on a frame-by-frame basis. This may be achieved through the utilisation of on-board GPS systems (e.g. Bolognesi et al., 2016), or fixed reference points ~~(Lewis and Rhoads, 2015).~~(e.g. Lewis and Rhoads, 2015). In the approach reported on here, we adopt a methodology to account for these uncertainties and their impacts on subsequent velocity measurements whereby fixed control points are manually selected and automatically tracked between frames using the KLT algorithm. ~~This~~Automatic tracking of GCPs is enabled by the distinct image textures of the water surface and the built environment, enabling the precision of the rectification process to be quantified and uncertainty in velocity measurements to be established. Whilst this procedure requires some supervision, in future deployments, purpose built GCPs will be installed across the area of interest with distinct optical characteristics so that (semi-)automatic registration would be possible. However, in areas where naturally existing GCP features do not exist, or where installation of purpose-built GCPs would be problematic, a different approach would be required. Therefore, future research should seek to assess the potential for on-board GPS systems, ranging tools (e.g. lasers) and calibrated cameras to enable UAVs to be utilised. This will also open up the possibility for real-time capture of hydraulic properties of flow.

Due to the responsive nature of this survey of the July 2015 Alyth flood event, the distribution of GCPs was not pre-determined, so despite a total of 15 linear structures within the urban landscape that intersected the water surface being identified as GCPs, spatial coverage is incomplete and availability is temporally variable. While rapid response deployment of UAVs during floods may therefore introduce errors in the projection that would otherwise be accounted for in planned deployments, the majority of surveys at high discharge will naturally be ‘unplanned’ and the result of rapid field deployment. Despite this, and the technical challenges of flying surveys during periods of heavy rainfall associated with floods, the relatively stable transformations achieved throughout the duration of the July 2015 Alyth video presented here demonstrate the utility of the approach.

5 Conclusions

UAVs have the potential to capture information about dynamics at the earth’s surface in ~~dangerous~~hazardous and previously inaccessible locations. ~~Through image acquisition of flash flood events and subsequent object-based analysis, highly dynamic~~Highly transient and oft-immeasurable hydraulic phenomenon may be quantified at previously unattainable spatial and temporal resolutions~~.~~ using image acquisition of flash floods and subsequent object-based analysis. The potential for this approach to provide valuable information about the hydraulic conditions present during dynamic, high-energy flash floods has until now not been explored.

~~In this~~This paper ~~we adopt~~adopts a novel approach, utilising the KLT algorithm to track features present on the water surface which are related to the free-surface velocity. Following the successful tracking of features, a method analogous to the Vector Correction Method has enabled accurate geometric rectification of velocity vectors. We subsequently explored uncertainties associated with the rectification process induced by unsteady camera movements. The maximum geolocation error is 1.~~0m~~0 m, which provides an indication of the minimum spatial scale over which measurements should be averaged and reported. Significant spatial variability in geo-registration error values are observed with median individual GCP error values ranging from 0.27 – 1.~~0m~~0 m. Our analysis eliminates the potential for significant errors being a function of reduced pixel density per unit area as GCP distance increases. Geo-registration errors are relatively stable and occur as a result of persistent residual distortion effects following image correction, especially close to the image boundaries, due to the specified transformation parameters being sub-optimal. Future approaches should seek to ~~calibrate~~use a camera with minimal lens distortion, for which the internal properties of the camera are calibrated, rather than adopting manufacturers lens specifications. The apparent ground velocities of the 15 GCPs ranges from 0.05 - 0.~~13m~~13 m with no apparent relationship between the distance of the GCP and observed ground velocity. These findings illustrate the relative spatial and temporal stability of the geometric transformation.

The application of this approach to assess the hydraulic conditions present in Alyth Burn during a 1:200 year flash flood (Perth & Kinross Council et al., 2015) resulted in the generation of an average 4.2 measurements m^{-2} at a rate of 508 measurements s^{-1}. Analysis of these vectors provided a rare insight into the complexity of channel-overbank interactions during flash floods. The uncertainty attached to the calculated velocities is relatively low with a spatial average across the area of ± 0.15 m s^{-1}. Within-channel and over-bank uncertainty in velocity estimates is comparable.

Comprehensive and innovative monitoring programmes (e.g. Ip et al., 2006; Quevauviller et al., 2012; Smith et al., 2014) have previously improved understanding of transient, rate limiting processes and catchment dynamics during extreme flash floods (Zanon et al., 2010), Similarly, we anticipate that this methodology will be of great use in quantifying highly transient flood flows within ungauged rivers across a wide range of fluvial environments.

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Tables

Optimised Parameter	Frame number	
	1	140
X (m)	324566.9	324565.8
Y (m)	748589.7	748591.3
Z (m)	15.2	16.4
Yaw (radians)	0.33	-0.14
Pitch (radians)	0.61	0.67
Roll (radians)	0.02	0.08
RMSE (px)	11.4	8.3

Table 1. Optimised parameters of the distorted camera models

Figures

~~Note: Figure captions are in main body of text~~

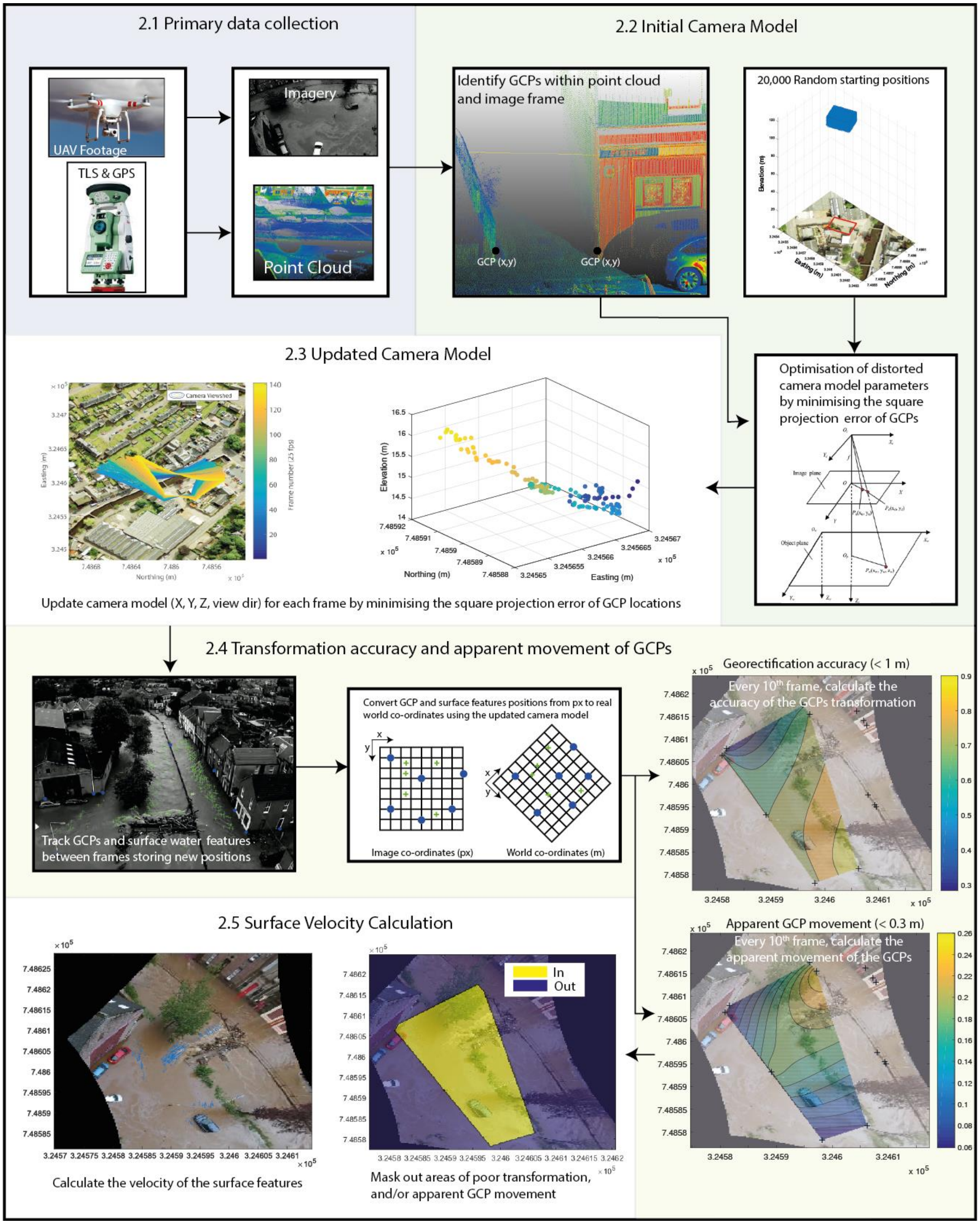

Figure 1. A schematic of the proposed methodology for tracking surface water features from UAVs and their conversion to velocities.

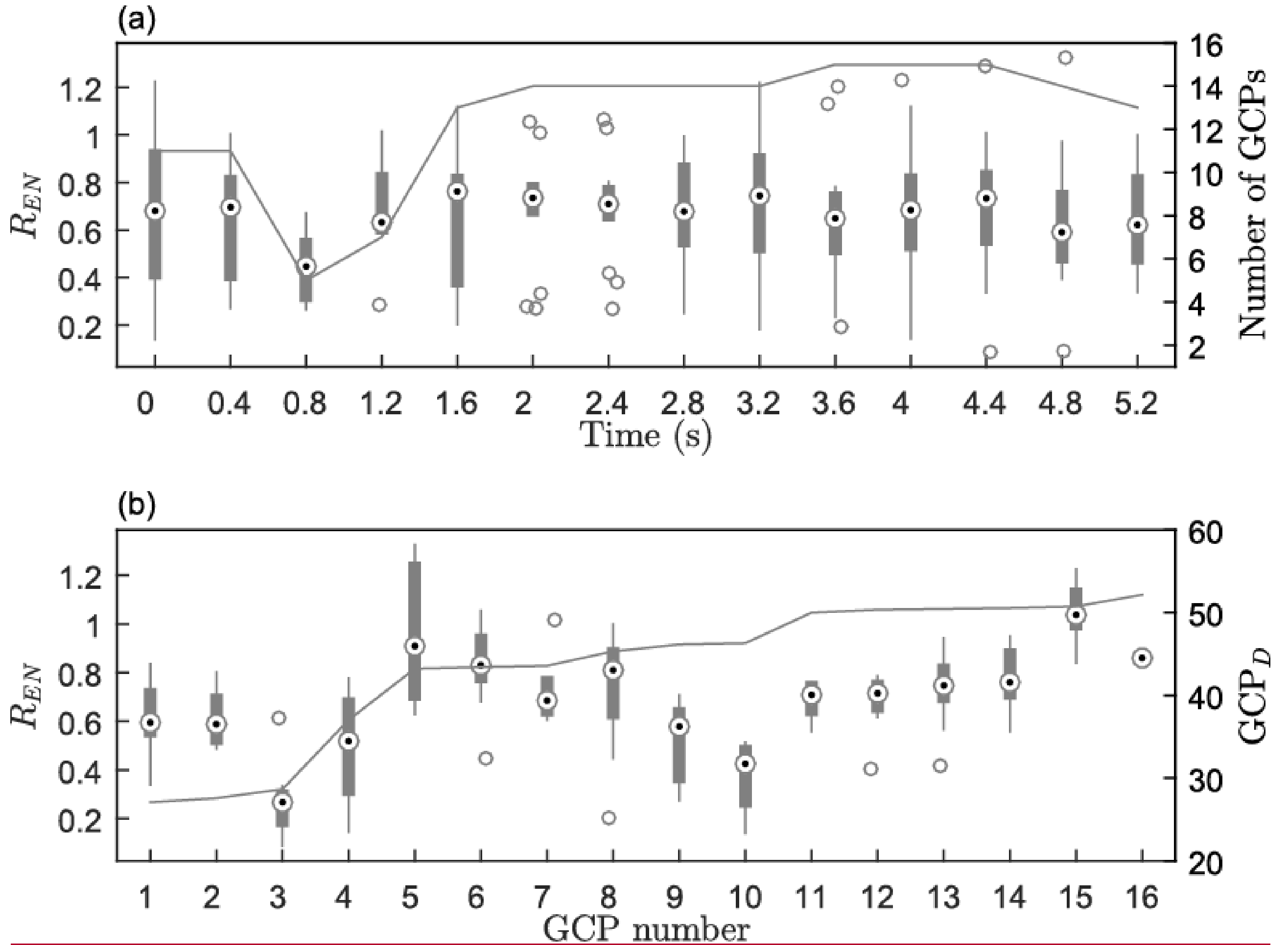

Figure 2. Box plots showing how projection residuals R_{EN} (m) of all GCPs vary with: a) time; and b) distance from the UAV camera. Dot within circle = median; box = 25th and 75th percentiles; whiskers = extremes, open circle = outliers. Line = Number of GCPs/Distance of GCP from image source (m).

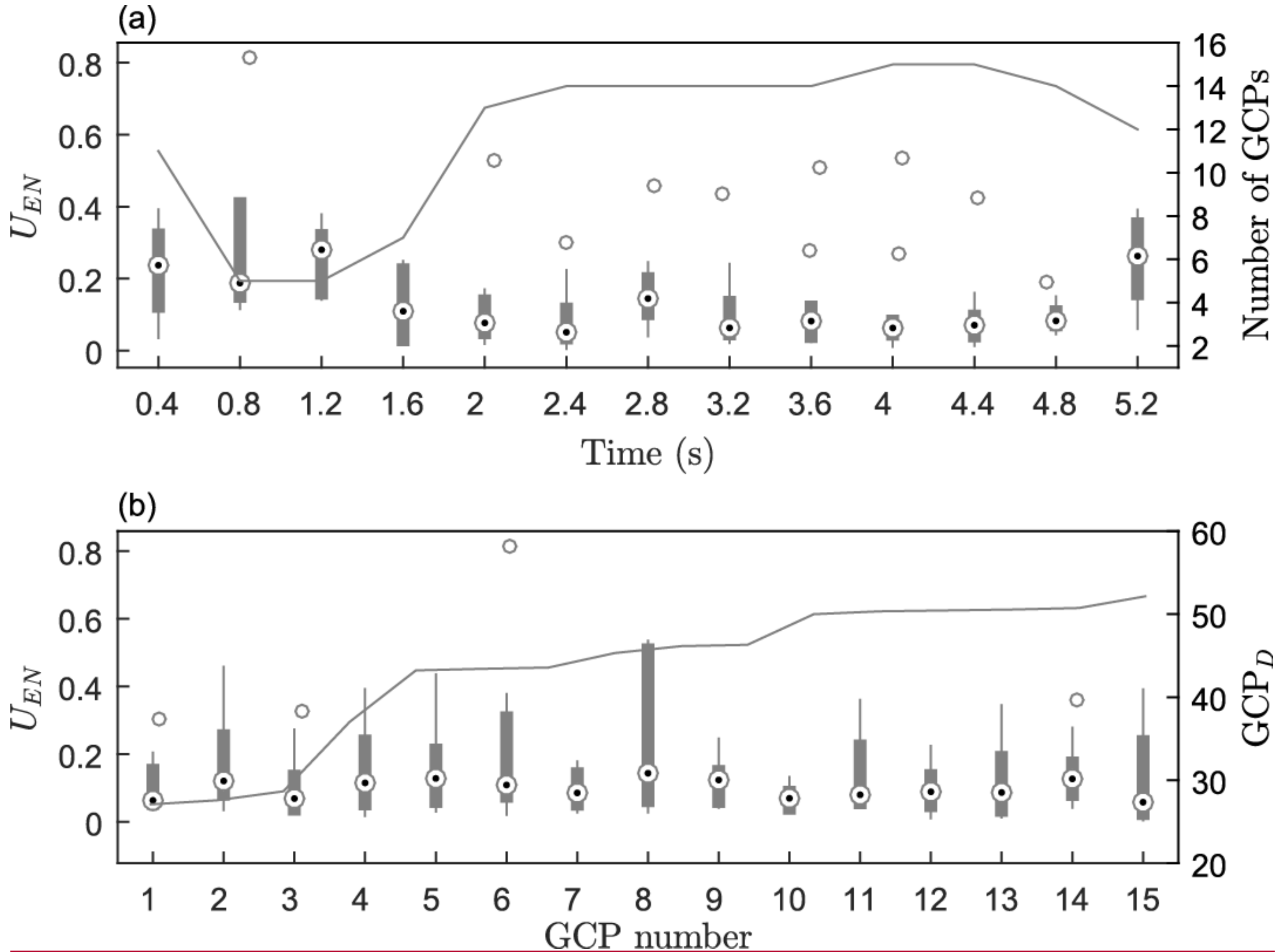

Figure 3. Box plots showing how the apparent movement U_{EN} (m) of all GCPs varies with: a) time; and b) distance from the UAV camera. Dot within circle = median; box = 25th and 75th percentiles; whiskers = extremes, open circle = outliers. Line = Number of GCPs/Distance of GCP from image source (m).

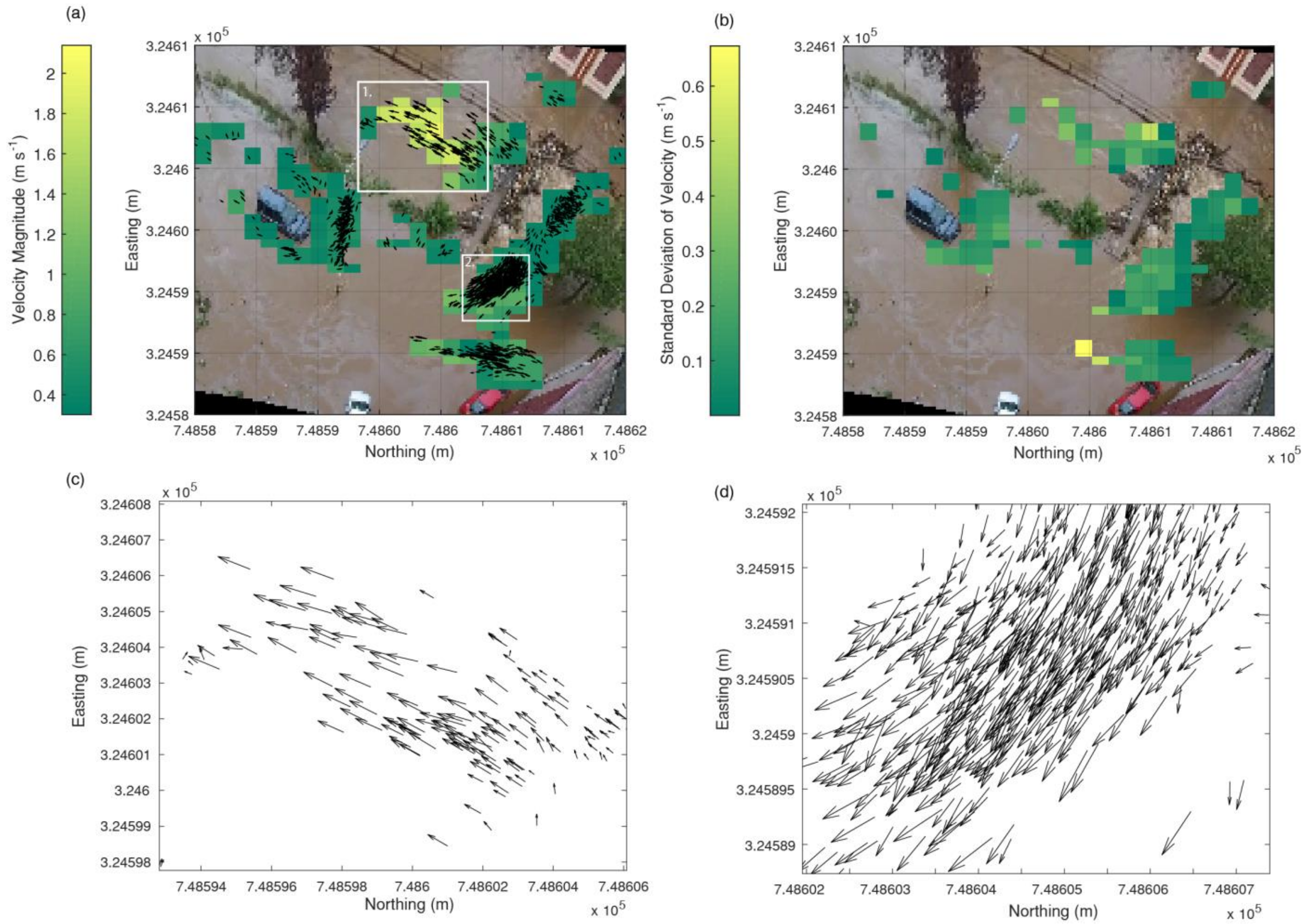

Figure 4. Images showing (a) velocity magnitude and (b) standard deviation of measurements calculated by tracking optically visual surface features. Zoomed in views of velocity vectors are provided in (c) and (d), which correspond with the boxes labelled 1 and 2 respectively in (a).