A low-altitude remote sensing approach to monitoring groundwater-surface water interaction using large-scale particle image velocimetry

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Eight months ago, I could not imagine myself at this point. Through the rain of wrenches, I would like to dedicate this thesis to the following people. To the friends and colleagues who have relentlessly reminded me that I belong here, you are the reason I am still here. To my parents and brother, who have been my cheerleaders from literal day one and who have raised me to feel free to take a different path from the other kids and then made that path possible. I would like to offer a special thanks to Pat Fennelly, who was always enthusiastically up for countless impromptu nighttime field visits. I would also like to thank the computer scientists, Rakesh Rana and Avinash Kommineni for helping me decipher the sometimes finicky PIV software. Finally, I would like to thank my advisor, Dr. Chris Lowry, who encouraged me take the reins on this research, gave me the opportunity to fly a drone, allowed me to disagree at times, and gave high regard to my ideas and opinions. The feeling of undeserved respect is by far my greatest motivator and it is why I am here, at this point, that I could not imagine eight months ago.
Abstract

Large-scale particle image velocimetry (LSPIV) is a relatively new method developed for the remote measurement of surface water velocity from video. The technique uses pattern tracking software that performs cross-correlation analysis on video image-pairs to measure the displacement of pixels over time. Research using this technique has quickly moved from mapping surface velocity patterns to gauging stream discharge; yet, even with promising results, the method has not progressed beyond this application. The research presented here is a proof-of-concept to further advance this technology to quantify groundwater-surface water interaction through differential stream gauging. This study employed the use of commercially available imaging technology, smartphone, GoPro, and drones, to film multiple cross-sections along two streams in western-NY. Accurate discharge results (<10%) from LSPIV analysis were obtained for streams exhibiting homogenous steady flow, uniform bathymetry, and well-defined banks, where particle tracer density is distributed, and glare minimal. Additionally, the error was consistently negative relative to the true value. Drones yield the most accurate and precise discharge results as compared to ground-based systems; however, ground-based LSPIV has the potential to yield highly accurate results under ideal stream conditions. LSPIV was able to correctly measure a groundwater gain over an 8 to 10 km reach scale of Elton Creek in Delevan, NY. Error was established according to different conditions of data collection, giving a range of values between which the true discharge could fall. If the error is smaller than the absolute value of differential discharge, then it can be determined whether that stream reach is gaining or losing. The longer the stretch of stream, or reach scale, the larger the magnitude of groundwater contribution, and thus the more quantitative this method becomes.
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Chapter 1: Introduction

1.1 Groundwater-surface water interaction

Groundwater and surface water are often treated as two distinct resources, but in reality, they are a single resource with changes to the hydraulic properties of one affecting the properties of the other (Sophocleous, 2002; Winter et al., 1998). Surface water (streams) and groundwater meet and interact at the groundwater-surface water interface, across which a transfer of water can occur (fig 1.1) (Sophocleous, 2002; Winter et al., 1998). This transfer not only affects the magnitude of a stream’s discharge, but also has important implications concerning water supply, water quality, and ecosystem health (Findlay et al., 1993; Gu et al., 1998; Lowry et al., 2011; McLachlan et al., 2017).

Figure 1.1) Figure modified from Winter et al., 1998 illustrating how the position of the water table influences exchange at the groundwater – surface water interface (in red) A&C) Configuration of the water table that influences groundwater discharge and surface water recharge, respectively. B&D) Hydraulic head equipotentials for a gaining and losing stream, respectively.
Groundwater and surface water flow across the groundwater - surface water interface depending on the position of the water table. Where the water table is above the stream stage, groundwater will discharge into the stream and it will be considered a gaining stream (fig. 1.1). Conversely, if the water table is below the stream stage, groundwater will be recharged into the subsurface and it will be considered a losing stream (fig 1.1) (Sophocleous, 2002; Winter et al., 1998). The contribution or loss of groundwater as a result of these processes must be accounted for in the mass balance computation when determining water budget and sustainable yield for a watershed (Ruehl et al., 2006; Winter et al., 1998).

Determining the spatial variation of groundwater discharge and recharge along a stream reach helps researchers understand other processes related to the direction of groundwater flow (Sophocleous, 2002; Winter et al., 1998). This sheds light on the location and timing of the exchange of nutrients and contaminants, their concentration, and where they may end up (McLachlan et al., 2017; Poulsen et al., 2015).

The groundwater gradient can be significantly influenced by external sources or sinks, such as rainfall and residential/commercial pumping (Sophocleous, 2002; Winter et al., 1998). For example, regions of heavy groundwater extraction, such as widespread farmland irrigation, can cause a drop in elevation of the water table that is deepest around the well and expands radially over time (fig 1.2) (Barlowe and Leake, 2012). This conical depression can grow laterally for miles and come in contact with streams along the way (Sophocleous, 2002). A gaining stream may become a losing stream if the cone of depression reaches the river (fig 1.2) (Barlowe and Leake, 2012; Sophocleous, 2002; Winter et al., 1998). This can lead to stream depletion, an effect that can be exacerbated by dry climate where groundwater recharge is
scarce and water supply for industrial or irrigation purposes rely heavily on groundwater (Sophocleous, 2002; Winter et al., 1998). The depletion of a stream, whether by extreme weather, groundwater extraction, or a combination of the two, could have severe impact on groundwater dependent ecosystems (GDE) (Huntington et al., 2016; Winter et al., 1998). The discharge of water across the groundwater - surface water interface determines the resiliency of GDEs, such as high elevation meadows, to persist through the dry season (Lowry et al., 2011). Discharging groundwater can also have a regulating effect on the temperature of the stream, where sensitive biota would otherwise experience detrimental diurnal variations caused by solar radiation (Gu et al., 1998). In light of the extreme weather that is expected as a result of the predicted future climate, it is more important than ever for hydrogeologists to understand the sensitivity of stream systems and their habitats (Barron et al., 2012; Klove et al., 2014; Lowry et al., 2011; Stewart et al., 2005).
1.2 Stream Gauging and groundwater discharge

The importance of groundwater - surface water exchange on the factors mentioned above has led agencies such as the USGS to regularly monitor this interaction. Detecting and measuring this exchange is not a straightforward process as discharging groundwater mixes with surface water, while recharging surface water is lost into the subsurface, making direct measurement difficult (Winter et al., 1998). As a result, numerous methods have been developed to make both direct and indirect measurements of groundwater - surface water interaction (Buchanan & Somers, 1969; Kilpatrick and Cobb, 1985; Rosenberry et al., 2008; Zamora, 2008).

The key for indirect methods of quantifying groundwater - surface water interaction is the quantification of stream discharge, specifically differential stream discharge. By measuring discharge at multiple locations along a stream reach, a water balance equation can be used to quantify the exchange of groundwater and surface water continuously over a reach scale (fig 1.3) (Lowry et al. (2007). If there is no precipitation, runoff, or other tributaries contributing to the flow between these two locations, it can be assumed that any discrepancy between discharge values reflects the positive or negative groundwater

![Figure 1.3] The groundwater contribution for the stream reach between the two cross sections (red lines) is determined by subtracting the discharge upstream ($SW_\text{in}$) from the discharge downstream ($SW_\text{out}$).
contribution. In every case, groundwater-surface water exchange is quantified using the same simple mass balance calculation:

\[ SW_{in} + GW_{in} = SW_{out} \]  \hspace{1cm} Eq 1.

Where \( SW_{in} \) is the discharge of the surface water coming into a stream reach and \( SW_{out} \) is the discharge of the surface water leaving the stream reach. The difference between \( SW_{in} \) and \( SW_{out} \) represents the groundwater that is discharging into the stream (+GW\(_{in}\)) or surface water recharging to the aquifer (-GW\(_{in}\)). Therefore, each method aims to quantify the discharge at an upstream location (\( SW_{in} \)) and discharge at a downstream location (\( SW_{out} \)).

Measuring discharge of surface water, or stream gauging, has traditionally been performed using an acoustic Doppler velocimeter (ADV), which measures the average water velocity at discrete points along a stream profile (fig 1.4) (Buchanan and Somers, 1969; USGS,

Figure 1.4) Left: Figure modified from USGS, 2016, illustrating the discretization of a stream profile. Discharge is measured for each subsection and then integrated across the width. Right: A handheld flow meter used for this method of measuring discharge.
These velocities are then multiplied by the area over which the flow is assumed to be representative to determine average stream discharge for that interval (fig 1.4) (Buchanan and Somers, 1969; USGS, 2016). These point discharge measurements are then integrated across the length of the profile to attain the total discharge (Buchanan and Somers, 1969; USGS, 2016). For deeper and more rapid flows, discharge must be measured using an acoustic Doppler current profiler (ADCP), which is typically mounted on a boat (USGS, 2016).

Other methods to measure groundwater - surface water interaction have been developed in order to address small to large-scale problems. Seepage meters and mini-piezometers provide measurements of groundwater discharge at fine-scales (1 m²) (Rosenberry et al., 2008; Zamora, 2008). These two methods, however, do not yield total groundwater recharge/discharge between two cross-sections of a stream (stream reach) and are classified as point measurements. Environmental, solute, and heat tracer methods, which involve measuring concentrations of each along a stream reach, all provide spatially integrated measurements of groundwater interaction where conditions may be too turbulent or dangerous for traditional stream gauging techniques (Kilpatrick and Cobb, 1985). Tracer methods are also inexpensive and could be a viable alternative to traditional stream gauging techniques; however, the injection of groundwater tracers is federally regulated, the stringency of which varies from state to state, leading to delays in deployment (Holmbeck-Pelham et al., 2000).

All of these methods have been developed to fill a specific niche in quantifying groundwater - surface water interaction on large to fine-scales; however, they are all
performed manually in the field. Because of this, none are suitable for difficult-to-access locations and especially not for dangerous high flow rivers or rapid-onset flood events, the discharge of which would be valuable for stage-discharge characterization and flood forecasting (Baer, 2018; Bonacci, 1983). Moreover, methods in surface hydrology are field intensive, requiring long hours in the field and greater expense. With scientific funding more competitive than ever, this does not bode well for long-term monitoring of large-scale watersheds.

1.3 Outlook on long-term monitoring of large-scale watersheds

There are currently 10,130 USGS gauging stations in the U.S. that cost anywhere from $13,000 to more than $30,000 annually to maintain and operate (USGS, 2017a; Koenig, personal comm., 2018). That is an annual cost of ~$182,000,000. For the 2018 fiscal year, the USGS budget was cut by 15% (AGI, 2017), and again another 7% for the 2019 fiscal year (USGS, 2018). To compensate for lack of funding the USGS will likely cut down on the frequency of field visits and may choose to decommission a portion of their gauging stations. In order to maintain the same level of monitoring of groundwater - surface water interaction, the USGS and other agencies must invest in alternative, time-saving, cost effective methods for the long-term monitoring of large-scale watersheds. Finding a solution to this problem is part of the motivation for this research.
1.4 Research Objectives

The purpose of this research is to evaluate a novel and potentially time/cost-saving method of a low-altitude remote sensing approach to monitor groundwater – surface water interaction through differential stream gauging. Large-scale particle image velocimetry (LSPIV) is a technique that uses pattern tracking technology to quantify surface velocity of flows from video imagery (Fujita et al., 1998; Muste et al., 2010; Muste et al., 2004). This technique has already been used in a number of hydrologic studies aiming to map surface flow fields in relation to stream morphology, and has also been used to quantify stream discharge (Creutin et al., 2003; Harpold et al., 2006; Hauet et al., 2009; Le Coz et al., 2010; Sutarto, 2015). The purpose for this research is to extend the application of LSPIV toward the detection and quantification of groundwater discharge, which has not been done before, as well as to establish a consistent workflow that is easily replicable and capable of gathering data quickly over a larger-scale.

Video imagery of stream flow was captured at multiple field sites, in accordance with already established guidelines for acquiring sufficient quality data for accurate stream flow quantification (Engel, 2017). Video imagery was taken from banks and bridges using a Samsung Galaxy S5 smart phone and a GoPro Hero3. In addition to ground-based camera setups, video imagery was taken by drone for aerial LSPIV analysis (fig 1.5). The benefit of aerial LSPIV with drones is to achieve a high angle relative to the stream for video collection in order to reduce glare, as well as to gather data rapidly and potentially unsupervised over large-scales. All cameras and specifications can be viewed in table 2.1 within chapter 2.
One of the main tools of this research is a standard smartphone. A tool that is prolific in modern society, including with the students at the University at Buffalo (UB). This presents an opportunity to explore the possibility of crowdsourcing data for LSPIV analyses. This will be done through CrowdHydrology, a platform developed at UB for transfer of crowdsourced data from the public to researchers through social media. The degree of participation of UB students and visitors as well as the quality of the data will be evaluated. Not only is the benefit of crowdsourced data simply the potential for collecting high spatiotemporal resolution data at virtually no cost, but also to increasing public awareness of scientific monitoring efforts and improving the rapport between the public and scientists (Bonney et al., 2014; Church et al., 2018; English et al., 2018; Silvertown, 2009).
1.5 Monitoring stream flow using particle image velocimetry

Particle image velocimetry (PIV) is an image processing technique developed in the field of fluid mechanics to quantify instantaneous velocity of seeded fluids in a lab setting (Adrian, 1984; Adrian, 1991; Adrian, 2005). The algorithm behind PIV is a cross-correlation analysis to determine the displacement of pixel patterns between image-pairs from a video of a flow surface (fig 1.6) (Adrian, 1991; Fujita et al., 1998; Muste et al., 2010). The PIV software performs this cross-correlation on selected interrogation areas (IAs) and then calculates velocity vector fields based on displacement and the frame rate of the video (fig 1.6) (Adrian, 1991; Muste et al., 2010).

![Image](image.jpg)

Figure 1.6) Conceptualization of LSPIV cross-correlation algorithm from Muste et al. (2010). The grey geometric shapes represent natural or seeded tracers in a river, such as bubbles or leaves.

In its early stages, this technique was confined to centimeter-scale lab experiments due to the lack of commercially available cameras capable of sufficient resolution (Harpold et al., 2006). The application of large-scale PIV (LSPIV), toward hydrologic studies, has been made possible as a result of advancement in camera resolution and field of view (FOV) (Fujita et al., 1998; Grant, 1997; Harpold et al., 2006). Recent research has used LSPIV to quantify surface
velocity of flows and floods, but also to investigate other flow characteristics such as turbulence patterns (Le Coz et al., 2010; Sutarto, 2015) and temporal changes in flow velocity as a function of river erosion (Hauet et al., 2009).

The surface velocity fields derived from LSPIV have been used to compute stream discharge (Creutin et al., 2003; Genc et al., 2015; Harpold et al., 2006). Creuten et al., 2003, using a rating curve based on historical data from a USGS gauging station, determined that even with a higher degree of variance in higher flow conditions, LSPIV derived discharge results were within 4% of true flow of the Iowa River based on this stage-discharge relationship. Harpold et al, 2006 found that at high flow conditions, LSPIV derived discharge error could be up to 25% due to the vertical component of waveforms and eddies that are often present in these conditions. The author found, however, that discharge results for lower-flow conditions were within 5% of true flow. In a study of flash floods, Le Coz et al, 2010 obtained imagery with a UAV, and during lower flow achieved LSPIV results within 10%. Periods of high flow still yielded errors within 20%, but the authors found that unsteady flow conditions could cause deviation of up to 80%. The results of previous studies over the last 15 years show promising results for stream gauging with LSPIV, yet the application of this method as an alternate technique to differential stream gauging has yet to be explored.

Exploring this technique for differential stream gauging, which is the aim of this research, could be a step toward an alternate to the traditional methods. Compared to the other methods of quantifying stream discharge, LSPIV is low-cost (Creutin et al., 2003; Harpold et al., 2006). It is possible to take sufficient quality video on readily available smartphones or digital cameras (Caltrans, 2017; Le Coz et al., 2016). Time in the field could be cut down
significantly as LSPIV would remove the need to enter water, as flow across the profile would be captured simultaneously by remote video footage. There is also potential for this method to become a way to perform differential stream gauging in remote and dangerous flood environments, presenting an opportunity to evaluate LSPIV for its accuracy and replicability for future studies.

1.6 LSPIV methodology

The LSPIV process can be divided into (1) data collection, (2) pre-processing, and (3) post-processing (fig 1.7). (1) After a stream reach is selected as a field site, the stream must be outfitted with georeferenced targets that will be used to rectify the imagery during post-processing (Fujita et al., 1998). Once targets are in place, at least 30 seconds of video imagery

**LSPIV Workflow**

Data Collection

Site Selection → Site Preparation → Image Acquisition

Pre-Processing

Frame Dissection → Image Enhancement → PIV Analysis

Post-Processing

Vector Validation → Image Rectification → Calculate Discharge

Figure 1.7) The general workflow for calculating discharge through LSPIV analysis.
is collected. (2) Using LSPIV software, the video is broken down into its individual image frames, the imagery is enhanced using different algorithms, such as high pass filtering, and then interrogation areas are selected at which point the software performs the PIV analysis (Fujita et al., 1998; Muste et al., 2010; Muste et al., 2004). (3) Once the analysis is finished, the vector field is validated by omitting outliers and interpolating areas of poor vector resolution. The imagery is then orthorectified based on the position of the georeferenced targets that were installed in the field to yield true surface velocity values. Finally, these surface velocity values, along with supplemental knowledge of stream bathymetry are multiplied to determine stream discharge.

Free and open-source software has been developed in order to process video files for LSPIV analysis, including PIVlab, Fudaa-LSPIV, RIVeR toolbox, PTVlab, and applications for smartphones (Brevis et al., 2011; Le Coz et al., 2014; Luthi et al., 2014; Patalano and Garcia, 2016; Patalano et al., 2017; Thielicke and Stamhuis, 2014; Tsubaki, 2015). The image processing workflow involves, first, breaking down the video into its individual frames (Patalano and Garcia, 2016; Patalano et al., 2017). The program then quantifies the displacement of pixels (particles) or groups of pixels (patterns) between each image pair. The frame rate of the video allows for the program to determine elapsed time between frames and pixel displacement to yield velocity (Adrian, 1991; Fujita et al., 1998; Muste et al., 2010). These results, however, are in pixel space so they must be converted to real (metric) space using georeferenced points (GRPs) implemented in the field (Fujita et al., 1998; Thielicke and Stamhuis, 2014).
The accuracy of the results of the LSPIV analysis are dependent on the camera technology, the manner in which data was collected, and the environmental conditions. Previous studies have determined that in order to prevent decorrelation of pixels, the frame rate of the camera must be at least 15 fps, and in order to achieve a sufficient number of image pairs at this frame rate, a duration of at least 60 to 90 seconds will yield the most accurate results (Engel, 2017). To optimize the video quality and minimize the error associated with poor illumination, lack of traceable particles/pixels, and oblique camera angle, prior studies have aimed to determine the ideal setting for the acquisition of data (Engel, 2017). These guidelines, in general state: (1) The closer the point of view (POV) angle of the camera is to 90° to the river surface the better, but oblique angles are acceptable above 15° (fig 1.8). (2) The platform must be as stable as possible. (3) At least four fixed ground reference points (GRPS), such as flags, must be present along the banks. (4) The entire width of the stream transect and the GRPs must be captured in the video field of view (FOV) (fig 1.8). (5) Preferentially avoid areas of uneven or turbulent surface flow as well as bright reflections and shadows. (6) Traceable particles must be present.

Figure 1.8) Left: Visual representation of camera FOV. Right: Visual representation of the camera POV, as the angle of the line-of-sight of the camera incident to the surface of the stream.
Fulfilling these parameters can be difficult from the ground, especially for wide rivers. Even from bridges or ladders, it is difficult to achieve high enough angles to capture the entire width of a stream. As a result, LSPIV studies have begun using drones as a platform for mounted cameras (Blois et al., 2015; Chan et al., 2016; Fujita et al., 2016; Pagano et al., 2014; Tauro et al., 2016a; Tauro et al., 2016b; Thumser et al., 2017).

1.7 Drones as an LSPIV platform

The use of drones for research was historically limited to government and military operations (Cho, 2017). As technology advanced, drones became lighter, smaller, more efficient, and less expensive (fig 1.9) (Cho, 2017). This allowed them to become available to the public, primarily marketed for recreational use (Cho, 2017); however, drones have presented researchers with a new platform from which to collect data. Drone based studies range from mapping geomorphic features, such as drainage networks, erosion, and land-use (Eltner et al., 2015; Rippin et al., 2015), to the generation of digital elevation models via photogrammetry.
Other non-conventional studies are using drones mounted with magnetometers to detect anomalies associated with abandoned oil wells (Adamson, 2016). For hazard monitoring, drones provide a platform for acquiring field data remotely, without putting researchers in harm’s way. The benefits of combining LSPIV and drones as an alternate monitoring method of stream gauging are not limited to being faster and less expensive, but also its ability to capture and process video footage of rapid-onset flooding. This is something that is virtually impossible to accomplish using the other methods of stream gauging, most of which require researchers to enter the water. Additionally, drones can move at speeds around 30 mph, making it possible to quickly perform unsupervised data collection at multiple transects along a stream reach without moving from (DJI, n.d).

The ideal settings for LSPIV video capture are difficult to achieve by a researcher on the ground, even with use of a ladder, but a drone can more easily achieve these recommended setting, as they can fly hundreds of feet in the air, allowing them to capture the entire width of a stream while maintaining near 90° angles. Drones also make it possible to maneuver into positions that reduce the amount of glare, which can be difficult with limited ground access. Despite these benefits, pairing LSPIV with drones has only been explored within the last few years (Blois et al., 2015; Chan et al., 2016; Fujita et al., 2016; Pagano et al., 2014; Perks, 2016; Tauro et al., 2015; Tauro et al., 2016a; Tauro et al., 2016b; Thumser et al., 2017).

Previous studies have found that aerial LSPIV is capable of yielding surface velocities comparable with results from ground-based LSPIV configurations with sufficient seeding and illumination conditions (Tauro et al., 2015). Studies employing aerial LSPIV have also
successfully quantified discharge within 10% of the true flow (Fujita and Kunita, 2011). In drone-based LSPIV, measures must be taken to mitigate additional error sources (Tauro et al., 2016a; Tauro et al., 2016b). For example, instability of the platform (e.g. vibration, wavering, inaccurate GPS) and greater distance from the stream surface can lead to larger error (Tauro et al., 2016a). The presence of highly visible and homogenously distributed tracers will help improve accuracy.

1.8 Crowdsourcing data

While UAVs present a tool to quickly acquire data over large scales by the researchers themselves, there is another emerging method for acquiring spatially distributed data, by the public. With the advancement of technology making communication across the country rapid and easy, so has the rise of citizen science as a recognized technique for data collection, relying on the public to provide the data. The potential of citizen science is to provide spatially and temporally dense data simply by having hundreds of eyes in the field at any given time (Church et al., 2018; Silvertown, 2009). This tactic has been used for centuries; for example, the National Audubon Society has been running an annual Christmas Bird Count to understand patterns in bird species using teams of volunteers since 1900 (Audubon, n.d.; Silvertown, 2009). This campaign has reported tens of millions of birds across the country in most recent years (LeBaron, 2017; Silvertown, 2009). Now with advancement in communication technology (i.e. internet and smartphones), more researchers are adopting this citizen science as a serious research methodology (Bonney, 2014; Silvertown, 2009). Another driver of this data collection method is that with the uncertainty in scientific funding, researchers are looking to citizen
scientists as a free resource (English et al., 2018; Silvertown, 2009). Perhaps more importantly, citizen science campaigns lead to improved rapport between scientists and the public, raising awareness of environmental problems and understanding of the scientific efforts to monitor/mitigate them (Bonney et al., 2014; Church et al., 2018; English et al., 2018; Silvertown, 2009).

LSPIV studies have been no exception to the emergence of citizen science. In this modern age, more and more people own advanced digital imaging technology that can fit in their pocket: smartphones (Fahringer et al., 2015). These smartphones can take sufficient quality video for LSPIV processing. At least one study has successfully used crowd-sourced data to quantify surface velocity of a flash flood by applying LSPIV processing to a YouTube video (Le Boursicaud et al., 2016). Around the world, organizations have begun large-scale citizen science initiatives aiming to rapidly acquire real-time flood stage data at a high spatiotemporal resolution (Le Coz et al., 2016). RiskScape, an initiative through the New Zealand national institute (NIWA), constructed flood stage maps for the cities of Christchurch in 2014 and Dunedin in 2015 from crowdsourced photographs (Le Coz et al., 2016). Both Flood Chasers, through the National University of Cordoba in Argentina, and FloodScale, through the National Agency for Research, in France aimed to quantify surface velocity of flash floods using LSPIV techniques (Le Coz et al., 2016). Both projects, however, experienced issues with lack of participation and poor video quality. The success of these initiatives is highly dependent on how effectively they are broadcast to the public as well as the clarity of the instructions (Le Coz et al., 2016). Without proper communication, the number of responses will be limited and without proper instruction the quality of the data submitted will be poor, rendering it unusable.
These issues, however, can be mitigated with better broadcasting tactics, procedural instructions, and by providing training programs (Le Coz et al., 2016).

1.9 Field Sites

Two streams were chosen for LSPIV analysis, Elton and Ellicott Creeks in western NY (fig. 1.9). These locations were selected as a result their accessibility, their monitoring history, and their low-flow conditions. Elton Creek, a 3rd order perennial stream in Delevan, NY (fig. 1.9), has been studied by UB researchers for the better part of a decade (Blersch, 2016; Haugland et al., 2012; Malzone et al., 2014; Malzone and Lowry, 2012; Malzone, 2015; Malzone et al., 2016a; Malzone and Lowry, 2015; Malzone et al., 2016b; Thomas et al., 2011). Previous studies have indicated that this stream, containing series of glacially influenced pool and riffle sequences, has a net gain of groundwater along the stream reach of interest (Malzone and Lowry, 2015; Malzone et al., 2016b). Data was collected at three locations along Ellicott Creek, which cuts through the UB campus (fig. 1.10). Ellicott Creek was selected because it possesses a USGS gauging station, providing continuous discharge information to compare with LSPIV results. Additionally, the presence of an on-campus walking path along the stream provided a location in which to implement the citizen science campaign. Lower-order streams were chosen for this study due to their shallow flow conditions and narrow channels, allowing for direct measurement using a hand-held flow meter as well as relatively close-up video capture that can maintain the entire stream width. Higher and faster flowing streams tend to be large and contain more areas of turbulence leading to a greater chance for decorrelation of pixels during LSPIV analysis.
1.10 Results and future research

The results of this research consist of a series of ground-based and aerial LSPIV surface velocity datasets for multiple cross-sections along Ellicott and Elton Creeks, taken at different times during the spring. These velocity maps reflect periods of relatively high and low flow between 1 and 9 m$^3$/s. Each velocity dataset was used in the computation of discharge. Flow meter datasets were collected concurrently with video imagery, so that calculated discharge from LSPIV analysis could be compared with benchmark values. The flow meters were also used to measure surface velocity and average velocity in order to establish true surface to average velocity relationships for each stream. Additionally, a
statistical approach to evaluating the success and accuracy of LSPIV for future use is presented.

Monitoring groundwater-surface water interaction at a reach scale is important for hydrologic monitoring for water availability and quality. Having accurate measures of groundwater-surface water interaction at reach scales will improve the accuracy of groundwater models, whether the goal is gauging water availability for residential and commercial use, monitoring contaminant plumes, or predicting GDE response to climate change. The workflow established for this research will support the development and application of LSPIV in other studies seeking to optically measure streamflow and/or groundwater discharge. The success of this method has important implications toward the speed and expense at which long-term, large-scale monitoring efforts can be executed. With the uncertainty of future funding, agencies such as the USGS face the risk of budget cuts, impacting their ability to continue monitoring of sensitive watersheds. This technique has the potential to be a time-saving, cost-effective, method of performing large-scale, long-term monitoring of watersheds.

In the scope of geohazard research, this technique can allow for remote capture of flood discharge where direct measurement is unsafe or impossible. Because floods usually occur rapidly, can be wide-spread, are often too dangerous to manually gauge, flood flow and discharge remains an elusive property. Drone-based LSPIV could make this measure possible so hydrologists can begin understanding flood-discharge relationship and recurrence intervals. Future applications of the LSPIV technique may cross into other fields where researchers seek to quantify flow velocity of landslides or debris flow events. Perhaps discharge can be extended to quantify debris volume or flow viscosity. In time,
further development of this technology may allow it to become remotely automated and could lead to integration with early warning systems.

By exploring the capabilities of LSPIV to accurately quantify surface water velocity, the groundwork may be laid for more development toward a standardized methodology that utilizes drones to rapidly collect field data, and perhaps even an automated system that yield immediate discharge values. Ultimately, the impact of this study is to encourage the use of LSPIV as an inexpensive, time-saving alternative to large-scale, long-term monitoring of watersheds. As the use of citizen science is on the rise across many fields, this research also aims to push LSPIV research to keep pace with this emerging field.
Chapter 2: Methods

The objective of this research is to determine if large-scale particle image velocimetry (LSPIV) is a viable alternative to differential stream gauging in order to monitor groundwater-surface water interaction. To do this, LSPIV analyses was performed at a number of cross-sections along two streams to quantify discharge. The traditional method with a flow meter was also employed to provide benchmark data against which to compare the LSPIV results. With a quantification of the error and uncertainty associated with LSPIV-derived discharge values, the viability of LSPIV-based stream gauging can be determined. The longer-term goal of this research is to establish a workflow for LSPIV-based stream gauging without the support of a flow meter.

The generalized workflow for quantifying stream discharge using LSPIV involves (1) data collection or image acquisition (fig 2.1), (2) pre-image processing to calculate a vector field, and (3) post-image processing to rectify surface velocities and use cross-section bathymetry to calculate discharge (fig 2.4). This workflow is repeated at multiple cross-sections at which point the difference between adjacent discharge values is considered the positive or negative groundwater contribution for that stream reach.

![Data Collection Workflow](image)

Figure 2.1) Data collection workflow, involving site selection, preparation of the site with georeferenced targets, and image acquisition of stream flow.
2.1 Selecting a stream cross-section

When selecting Elton and Ellicott Creek, the primary concern was accessibility, but not all streams are suitable for LSPIV analysis so a number of other conditions, based on suggestions from previous studies were considered (Creutin et al., 2003; Harpold et al., 2006; Le Coz et al., 2010; Muste et al., 2010). LSPIV processing for discharge quantification is most effective over sections of streams that experience laminar flow and minimal turbulence. Turbulence can cause strange flow patterns that do not reflect the directional velocity of the river and also obscures floating tracer particles. Large rocks and other objects that stick out above the surface will also obscure flow velocity.

The presence and density of natural tracer particles was also considered. Natural tracers, such as bubbles, sticks, and ice were present at all sites, but could not be guaranteed on a day to day basis. The lack of these particles was mitigated by adding artificial tracers. In this case, light-colored biodegradable mulch and/or popcorn was added upstream of the region of interest (ROI). During data collection, video was taken with and without artificial seeding to assess how well LSPIV can measure surface velocity with minimal or no floating tracer particles.

Stream width must be considered when conducting LSPIV and specifications of a particular cameras field of view (FOV) need to be taken into account. The stream widths at Ellicott and Elton Creek are narrow enough for the cameras to capture the whole width of the stream as well as georeferenced targets within a FOV. The Sheridan Drive profile along Ellicott Creek was too wide for the smartphone FOV, but not for the GoPro®️, which had to be mounted on an extension rod to capture both banks even with its fish eye lens. The drone was also able
fly higher to capture both banks, but low hanging tree canopy had to be avoided. Additionally, the further from the stream, the lower the resolution becomes when attempting to capture small particles on the surface.

In terms of accessibility, there must be vantage points in which ground-based and drone-based configurations can capture the entire width of a stream at a high angle of incidence. Bridges are an ideal vantage point, but steep banks can also provide a high enough angle for ground-based video capture. Drone based video platforms allow for flexibility in specifying the angle of incidence.

It is also necessary to select a stream crossing where stream bathymetry can be measured, because video recordings only produce surface velocity, which then must be combined with a given stream cross-sectional area to calculate discharge. The stream crossings for this study were no more than 20-meters across and no more than 1-meter deep.

If the purpose of the project is to quantify groundwater contribution, all other sources of inflow must be avoided. In other words, to quantify groundwater discharge for a stream reach, there must not be any tributaries that connect up with the stream within that reach. However, since this is a proof-of-concept study, it did not matter if the differential gain was due to a joining tributary, as long as LSPIV could correctly detect a gain.

2.2 Preparing the stream

Regions of laminar flow containing plenty of tracers are ideal for LSPIV analysis, yet before anyone can go to a stream with a camera and take a video with intent to analyze surface
velocity, a number of georeferenced points (GRP) must be identified. In order for the flow velocity measured with LSPIV to be useful, the imagery has to be georeferenced, otherwise, values would be given in pixel space and not real (metric) space. This is also necessary to account for any distortion generated by the camera POV angle or camera lens incident to the stream. In order for the LSPIV software to mitigate these issues, GRPs were implemented along the banks of Ellicott and Elton Creeks with measured distances between them. An example of one of these targets as well as the general configuration of targets can be viewed in figure 2.2. The GRPs were constructed out of PVC pipe and spray-painted bright orange for ease of visibility. 4-ft rebar were attached to the ~1-foot pipe targets and inserted into the ground to

Figure 2.2) Inset: Georeference point (GRP). Right: Configuration of targets at Ellicott Creek – Sheridan. Yellow lines indicate where distance was measured between targets. Between GRPs 1 and 4 is the cross-section used to determine discharge with both LSPIV and a flow meter.
ensure the permanence of the targets no matter the stream conditions. GRPs were placed so that at least four could be contained within the FOV of each camera, the minimum number that allow imagery to be georeferenced. The distances were measured between all combinations of targets. Due to accessibility of vantage points, varying stream widths, and other factors like tree canopy, four to six targets were implemented at each field site. With six targets, a larger reach scale could be attained while also allowing cameras with smaller scale FOV to contain at least four targets.

2.3 Flow meter measurements

In order to verify the results of the LSPIV analysis, discharge measurements were also acquired through the traditional method using a Sontek FlowTracker ADV (Buchanan and Somers, 1969; USGS, 2016). These measurements were taken simultaneously with video imagery so that results from both reflect the same stream stage and flow conditions. These measurements served as the benchmark values for discharge, against which to compare the results of the LSPIV analysis. With a Sontek Flowtracker, average velocity and depth were measured at discrete points along each stream cross-section (fig. 2.3). The flow meter then integrates these velocities across the
length of the cross-section. Due to friction along the base of a stream, there is a vertical velocity gradient present in the stream water column, where flow at the surface is higher than flow at the base (fig 2.4). The FlowTracker is set at about 60% of the depth of the water column to measure average velocity, according to the log-profile computation.

Since LSPIV analysis only quantifies surface velocity, a correction factor has to be applied to obtain the average velocity from LSPIV according to this vertical gradient. This correction factor is a ratio of average velocity to surface velocity, and changes with the relative friction of the bed. To reduce error associated with using an assumed correction factor, surface velocities were also measured with the FlowTracker and compared with the FlowTracker’s average velocity measurements. For this study, up to 25 paired average and surface velocities per stream cross-section were measured, the average of which would be the correction factor applied to the LSPIV results.

After LSPIV surface velocities are corrected to yield average velocity, these velocities are again integrated across the length of the cross-section, with depths obtained with the FlowTracker, to yield total stream discharge. The comparison between the LSPIV and FlowTracker results is only possible when the cross-sections generated in the LSPIV software is
superimposed over the same transect gauged with the FlowTracker. See section 2.6 for further discussion.

2.4 LSPIV data collection

To capture video, multiple camera platforms were used including a smartphone, GoPro®, drone, and thermal camera, all of which possess a frame per second (fps) rate of 30. Camera platform and video specifications can be viewed in table 2.1. Videos were taken for at least one minute from each of these platforms in order to have a sufficient number of frame-pairs for LSPIV analysis. To ensure pixel trajectories were not affected by camera movements, the ground-based platforms were kept as stable as possible using a tripod. The UAV possessed a gimbal, which mitigated high frequency vibrations, but was still susceptible to low frequency motion from wind.

<table>
<thead>
<tr>
<th>Platform/Camera</th>
<th>Frame rate (FPS)</th>
<th>Resolution</th>
<th>Focal Length</th>
</tr>
</thead>
<tbody>
<tr>
<td>Samsung Galaxy S5</td>
<td>30</td>
<td>1920 x 1080</td>
<td>31 mm</td>
</tr>
<tr>
<td>GoPro® Hero 3</td>
<td>30</td>
<td>1920 x 1080</td>
<td>17.2 mm</td>
</tr>
<tr>
<td>Drone (DJI Mavic)</td>
<td>30</td>
<td>3840 x 2160</td>
<td>26 mm</td>
</tr>
<tr>
<td>FLIR Thermacam™ SC640</td>
<td>30</td>
<td>640 x 480</td>
<td>300 mm</td>
</tr>
</tbody>
</table>

In accordance with previous studies, a number of conditions were met in the field to help ensure quality video data. These conditions consisted of only filming areas of laminar flow, where no stationary objects obscure the stream surface, filming at high angles to reduce image distortion, and filming primarily when the sun was low in the sky. Image quality is highly sensitive to sun glare, diminishing the visibility of flow tracers. To help mitigate glare, polarizing lenses were used. An example of the effect the polarizing lens had on the imagery can be seen in figure 2.5. As a potential alternative to the problem of glare, thermal imagery was taken in
an attempt to extract comparable surface velocities by tracking patterns in thermal variation. Problems were encountered with the thermal camera, partially due to the low resolution and FOV (table 2.1) unable to capture both banks of the stream. The main problem, however, was the inability to track thermal patterns due to incident reflection of sunlight on waveforms. Floating ice was clearly visible in thermal imagery, but was a rare occurrence in this case.

Filming was performed from the ground as well as from the air with a drone-mounted camera. Video was taken as close to 90° orthogonal to stream surface as possible to reduce distortion in the imagery. The GoPro® camera was able to take near-90° angle along at the Sheridan Drive profile of Ellicott Creek, where filming could be done from the bridge. This location was too wide for the smartphone. The drone-mounted camera, was also able to achieve a high angle over the stream. Filming with the smartphone took place from a variety of vantage points, including steep banks, ladders, and bridges.

Figure 2.5) Images of Ellicott Creek near Sheridan Drive taken right after one another. The left picture was taken without a polarizing lens while the right picture was taken with the polarizing lens.
Video of the streams were taken both parallel and perpendicular to the direction of flow. It should not matter how the camera is oriented relative to the direction of flow as long as both banks of the stream are contained within the video. The banks serve two purposes within the video: (1) to provide a stationary object with a relative velocity of zero against which the LSPIV software can properly label flow vectors, and (2) location to install georeferenced targets. The camera was angled so that the entire width of the stream profile was within the video frame at an angle as close to 90 degrees to the stream surface as possible (fig. 2.6). To achieve this high angle in the ground-based configuration, cameras were elevated using ladders, bridges, and extension rods.

Figure 2.6) Left: Drone filming along Elton Creek. Top right: Camera POV from the drone in the left image. Bottom Right: footbridge from which ground-based imagery was collected along Ellicott Creek in Amherst State Park.
2.5 Citizen Science Campaign

LSPIV is a relatively inexpensive technique that requires no more than a modern camera and a georeferenced location. In this day and age, most people own advanced digital imaging technology in their phones. This presents the opportunity to evaluate the possibility of crowdsourcing stream flow video for LSPIV analyses. Along the Amherst Bike Path, adjacent to Ellicott Creek at a location on the University at Buffalo north campus, a sign was installed with instructions for passersby to record and upload video of the stream to social media via CrowdHydrology. CrowdHydrology is a platform developed for the broadcasting of citizen science campaigns and transfer of data (fig. 2.7) (Lowry and Fienen, 2012). The sign provides instruction on how to capture the video and upload it to CrowdHydrology sites, as well as a camera mount to place the phone so that all video is consistent and captures the appropriate part of the stream. The data uploaded to social media will be processed in the same way described in section 2.6 and 2.7. The purpose of this part of the research is to

Figure 2.7) CrowdHydrology sign with instruction on how to take a video of streamflow and upload to social media for LSPIV analysis. The red cut-out provides a mount for the citizen scientist’s phone camera. The mount allows for consistency in the video POV.
evaluate if crowdsourcing is a plausible method for gathering LSPIV data. The benefit of crowdsourcing is to improve the spatial and temporal resolution of stream discharge data, which could be very successful in high traffic areas, including tourist locations such as National Parks and Forests.

2.6 Data Processing

Video imagery was processed using the Matlab toolbox, PIVlab and the Matlab-built standalone program, RIVeR (Rectification of Image Velocity Results) (fig 2.8). PIVlab computes the vector field for a stream flow video (Thielicke and Stamhuis, 2014), while RIVeR converts the results to metric space by orthorectification using the GRPs installed along the stream banks (Patalano et al., 2017). PIVlab can be downloaded from the Mathworks file exchange site and requires a MATLAB license with the image processing and application compiler toolboxes (MathWorks, 2018). RIVeR can be downloaded directly from the authors' website (RIVER, 2017).

Figure 2.8) The two Matlab-based LSPIV softwares used in this study. PIVlab calculates the vector displacement field while RIVeR rectifies the PIV result.
A more in-depth instruction for using PIVlab and RIVeR for image processing can be found in the appendix. The image processing can be broken down into pre- and post-processing (fig 2.9). The image pre-processing consists of breaking down the stream flow video into individual frames in the form of jpeg images.

![Diagram](image.png)

**Pre-processing**
- Frame Dissection
- Image Enhancement
- PIV Analysis

**Post-Processing**
- Vector Validation
- Image Rectification
- Calculate Discharge

Figure 2.9) Pre- and post-processing workflows for LSPIV analysis. Pre-processing sets up the video and dissected images for PIV analysis, while post-processing validates and rectifies the PIV result.

PIVlab provides four built-in image enhancement algorithms: Contrast-limited adaptive histogram equalization (CLAHE), highpass filtering, intensity capping, and weiner2 denoise filtering. Generally, particles floating on the surface of a stream will have a higher reflectivity than water, which absorbs more light. In greyscale, pixels in an image will represent a certain number value between 0 and 255, black and white respectively. The closer to 255, the higher the degree of reflectance of the particle and will appear lighter than the water, which will plot closer to 0. Image enhancement works to create more contrast between tracer particles and the stream water based on their respective degree of reflectance.
The CLAHE image enhancement algorithm is a type of histogram equalization (HE). HE stretches the frequency distribution of greyscale values over a larger range of values to create more contrast between the highest and lowest reflectivity pixels in an image (Campbell and Wynne, 2011). Contrast Limited Adaptive Histogram Equalization (AHE) takes it a step further and creates multiple histograms for equally sized non-overlapping portions of an image to enhance them individually (Reza, 2004).

High pass filtering produces sharper boundaries between features by emphasizing the components of an image where there is a high frequency of pixel value variation (i.e. feature boundaries) by using various convolution matrices to calculate a new pixel value based on the values of the neighboring pixels (Campbell and Wynne, 2011). If there is a sudden change in pixel value, the filter will create a larger localized contrast. By this same method, within a feature where pixel value variation is low frequency, there is little contrast, thus emphasizing boundaries between features. A comparison of the effects of CLAHE and high-pass filtering can be viewed in figure A.5 of the Appendix.

Weiner2 denoise is a low pass filter that reduces noise in an image by estimating the mean square error from another a noiseless image. This technique did not seem to have any effect on the images in this study. Intensity capping puts a limit on the pixel values for the brightest regions of an image, which could theoretically be beneficial for areas of glare, but had very little effect on the images in this study.

After frames are dissected and enhanced, PIVlab uses a cross-correlation technique for tracking pattern displacement between image pairs. PIVlab provides two correlation algorithms, direct cross-correlation (DCC) and fast fourier transform (FFT) to quantify the
velocity map. The differences between these algorithms are described further in Thielicke and Stamhuis (2014). The cross-correlation technique used for processing imagery for this research is a fast fourier transform (FFT), which generated a vector field for each image pair. Once PIVlab has finished calculating the vector field for all frame pairs, they must be validated, meaning outliers and velocities that contradict the direction of flow are omitted. When data is omitted, PIVlab will automatically interpolate areas of missing data, based on the surrounding values. Finally, all frames are averaged to produce a characteristic velocity vector map for the stream.

The next step, image rectification, is performed in RIVEr. RIVEr uses the PIV result from PIVlab and the georeferenced targets to orthorectify the results, converting them into metric space. The results of this rectification are displayed in m/s. A cross-section can then be drawn across the stream at which point RIVEr will open a new window and display the velocity profile for that cross section and the corresponding data table. The velocities given are surface velocities, so they must be corrected based on the measured or assumed surface-average velocity correction factor to yield the results as average velocities.

RIVEr also offers a built-in tool for computing discharge for this velocity profile. It is the USGS Areacomp2 program, but attached to the RIVEr application. Areacomp2 fits the LSPIV-drawn profile to inputted cross-section length and depth data that was collected by the flow meter in the field. If the true cross-section length does not match the LSPIV drawn cross-section, the data is interpolated to the edges, not scaled to the edges. This presented a problem for this research. Often times the cross-section length computed in RIVEr was a meter or two short of the true cross-section length as measured in the field. This caused RIVEr to
interpolate the velocities to the edge, which underestimated flow and also was not spatially accurate. So instead, the length of the RIVeR derived cross-section was scaled so that it matched the true length as well as the corresponding depths. Then discharge was calculated by hand with the corrected bin areas and LSPIV-derived average velocities.

2.7 Quantifying groundwater-surface water interaction

According to the mass balance equations described in section 1.2, in the absence of any other water sources, such as rain or connecting tributaries, groundwater discharge can be quantified as the difference in discharge between an upstream and downstream transect of a stream reach. Discharge upstream is subtracted from discharge downstream from both LSPIV and the flow meter to quantify either a positive or negative groundwater contribution. In this thesis, the differential discharge calculated from the flow meter will be considered the true value of groundwater discharge. The accuracy of the LSPIV results are evaluated in terms of relative percent error, or the percent value that the results are off from the true value. One-to-one plots were constructed from these values for visual assessment of accuracy.

The more accurate the LSPIV results, the more closely they should match the flow meter results; however, it is the precision of the results that will tell whether LSPIV can be used as a standalone method to quantify groundwater discharge. Since groundwater discharge into surface water is measured as a differential between two surface discharge measurements, the error uncertainty is compounded, making it possible for the LSPIV result to yield a false positive or negative value, especially if the true groundwater contribution is small. The more precise the results, the smaller the range of uncertainty in the differential. High-precision results with
low uncertainty will prove that this low-altitude remote sensing technique is a reliable and quantitative technique to measure groundwater discharge. That being said, larger uncertainties may even prove useful for a more qualitative measure of where streams are gaining or losing as long as the groundwater contribution is large. The margin of error can also be mitigating by increasing the scale of the analysis. That is, increase the distance between stream cross-sections, and the groundwater contribution will become larger relative to the error.

2.8 Error and uncertainty analysis for future studies

2.8.1 Root Mean Square Error (RMSE)

The aim of this research is to move toward making this method an alternative to the traditional method of stream gauging, which is field-intensive, time consuming, and becoming too expensive with the continued lack of funding. By using benchmark values measured by the FlowTracker, the results of the LSPIV analysis can be evaluated for their root mean square error (RMSE), which gives a static range around the observed LSPIV value in which the true value may fall. The equation for RMSE is given as:

$$RMSE = \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}$$

Where \(\hat{y}_i\) is the expected value or the FlowTracker value in this study, \(y_i\) is the observed value or the LSPIV value in this study, and \(n\) is the total number of measurements. This method is based on the number of measurements and the average magnitude they tend to deviate from the expected value. The RMSE is for the individual discharge measurements, but the error
propagates when the upstream discharge is subtracted from the downstream discharge. The equation for compounding error is:

\[\delta Q = \sqrt{\delta a^2 + \delta b^2}\]

Where \(\delta a\) is the error one of the LSPIV-derived discharge values and \(\delta b\) is the error on the other LSPIV-derived discharge value. Both errors are likely to be the same, unless separate RMSE analyses are performed under various conditions, such as for the individual stream cross-sections and/or for variant data collection techniques.

The LSPIV technique to quantify groundwater discharge will be successful if the compounded error is smaller than the differential discharge value. For example, if the differential discharge is quantified as +10.0 m\(^3\)/s groundwater contribution, and the error is ±1.0 m\(^3\)/s, then the researcher can expect the true discharge to fall between 9.0 and 11.0 m\(^3\)/s with fairly good accuracy. If the differential is quantified as 0.5 m\(^3\)/s with the same error, the researcher can expect the true discharge to fall within -0.5 and 1.5 m\(^3\)/s. This time, because the differential is smaller than the error, there is a possibility that the stream could actually be losing and LSPIV results show a false positive.

2.8.2 t-based 95% confidence interval

In addition to the commonly used RMSE statistical analysis, another method of evaluating the results was explored in terms of percent error. RMSE is a static value and would lead to the implication of higher accuracy at higher flow conditions, which may not be the case. If LSPIV is capable of giving accurate results at low-flow conditions, larger deviation of results at high-flow conditions may lead to a large error, which would make LSPIV unfavorable for low-
flow conditions. For these reasons, error was also analyzed in terms of the ratio of the deviation from the expected. RMSE analysis also assumes a large (>30) sample size, which was not the case for this research.

Due to the small sample size, a t-based confidence interval was used to analyze the 95% confidence interval for the mean error of the data. What this means is the uncertainty calculated by this test will be a range at which one can be 95% confident the true value will deviate from the expected. The equation for the t-based confidence interval is:

\[ \mu \pm t \frac{\sigma}{\sqrt{N}} \]

Where \( \mu \) is the mean error, which is a ratio in this study, \( t \) is the t-statistic as determined from the two-tailed t-distribution table, \( \sigma \) is the standard deviation of the sample, and \( N \) is the number of values in the sample. If the mean relative error for a dataset is -0.10 and the uncertainty is ±0.05, then the researcher can be 95% confident that the LSPIV result is underestimated by about -10% on average with an uncertainty ranging between -5% and -15%.

The use of this technique is based on the assumption that the greater the discharge magnitude the more accurate the results, but in fact, it has been argued that streams with greater flow are more likely to exhibit larger error in LSPIV results.

Because this error is a unit-less ratio as opposed to a static value of discharge, the compounding error formula used for RMSE cannot be applied in this state. The uncertainty is given as a ratio and must be used to scale the raw LSPIV results by using the range of ratios as correction factors (CF) to give the range in units of \( m^3/s \) instead. Because the uncertainty is a
percentage of the whole, the range for greater discharge results will be larger than for lesser
discharge results. Just like with RMSE, if the uncertainty in units of m³/s is smaller than the
groundwater contribution, LSPIV will be successful. The accuracy of the LSPIV result will also be
improved with a larger groundwater contribution. Once in this state of m³/s, then the
compounding error formula given in section 2.8.1 can be used for the recalculated differential
discharge results.
Chapter 3: Results & Discussion

3.1 Depth-Averaged Velocity Relationship

Friction along the substrate causes a vertical velocity gradient in stream columns, so a correction factor is needed to adjust surface velocity to represent the vertically averaged stream velocity needed to calculate stream discharge. Initially, a standard correction factor (CF) of 0.8 was assumed for the ratio between surface and average velocity. This value was based on literature of the velocity gradient for shallow streams with rough substrates (Herschy, 2009). After preliminary results revealed that discharge was underestimated from all LSPIV platforms, this correction factor was re-evaluated. In order to determine the specific surface – average velocity relationship for Ellicott and Elton Creeks, surface velocity was measured with the flow meter in addition to the standard mean velocity measured within the water column at a depth 60% below the stream surface (Herschy, 2009).

3.1.1 Surface – Average Velocity Relationship for Ellicott Creek

The surface-average velocity relationship was considered at Ellicott Creek at Amherst State Park (fig 3.1). Two separate datasets taken at different flow conditions and gave a CF of 0.89 at the time of high flow, and 0.76 at the time of low flow (fig 3.1). These results are consistent with literature, but these two datasets are likely not enough to fully constrain the relationship between stream stage and CF for average velocity (fig. 3.2). The surface-average velocity relationship was not directly measured at the Sheridan Drive cross-section and so LSPIV velocities were scaled in accordance with the stage corresponding correction factor value from
Figure 3.1) The top bar graph displays the ratio of average velocity ($V_a$) to surface velocity ($V_s$) for each corresponding bin on the depth profile graph for the Amherst State Park cross-section of Ellicott Creek. All data was collected using a flow meter. On the depth graph, the white dots indicate the location where average velocity measurements were taken, while the red dots indicate surface velocity measurements. The red dashed line indicates the average ratio or correction factor for the time at which measurements were made.
Amherst State Park. The two values, although limited, may imply a variation in this surface-average velocity ratio with stage at Ellicott Creek (fig 3.2).

While data from Ellicott Creek reflect temporal changes in the surface-average velocity ratio, data from Elton Creek was taken on the same day from four cross-sections, reflecting how the surface-average velocity ratio varies spatially. Results seemed to show little spatial variance, which all fell close to 0.80 (figures 3.3 – 3.4). This limited spatial variation supports the use of a common correction factor for nearby locations along Elton Creek.

Figure 3.2) Scatterplots of Correction factor vs depth (left) and correction factor vs discharge (right). It is apparent that more data is needed to make any statement about the relationship between the correction factor of a stream and its flow or depth.
3.1.2 Surface – Average Velocity Relationship for Elton Creek

Figure 3.3) Top graphs: Ratio \( \frac{V_a}{V_s} \) graph for cross-sections 1 and 2 of Elton Creek. Bottom graph shows corresponding depth data for the two profiles.
Figure 3.4) Top graphs: Ratio Va/Vs graph for cross-sections 3 and 4 of Elton Creek. Bottom graph shows corresponding depth data for the two profiles.
3.2 LSPIV Discharge Results

Results of the LSPIV analysis are listed in table 3.1, in order of increasing relative error. LSPIV analysis consistently underestimates discharge compared to the true values as measured by the flow meter (table 3.1, fig 3.5). This underestimation varies from <10% to >70% depending on the video collection platform and site conditions. One LSPIV result overestimated the discharge, but within 1% of the true value measured along cross-section 4 of Elton Creek. This large variation is a result of the dynamic environment in which this study was performed. Stream flow and weather conditions varied across sampling periods. Additionally, fundamental differences in the manner of data collection also contributed to this variation. The first three columns of table 3.1 reflect these dynamic factors that influenced the results. Peeling back each layer reveals patterns in what works, and what does not work.

3.2.1 Camera platform

The platform from which video is collected has a significant effect on the accuracy of the results. Table 3.1 and figure 3.5, are color coated by platform: drone, smartphone, and GoPro®. A qualitative assessment of these colored coated rows shows drone results are skewed toward the top of the table, meaning they generally yield more accurate results. Smartphone and GoPro® platforms do have the potential to yield highly accurate results, with error below 15% (table 3.1), but seem to be more varied (figs 3.5). It should be noted that thermal imagery proved to be unusable in part due to poor camera resolution and small field of view. More importantly, waveforms in the stream caused the thermal camera to detect incident sunlight rather than thermal flow patterns. Ice floating in the stream during winter sampling using the
thermal camera was correctly detected but was not reliable. Future work using thermal imagery may be of interest for LSPIV analysis, especially as they can be mounted to drones, but improving this platform is out of the scope of this research.

Table 3.1) All results of LSPIV analysis listed by platform and stream site. The (u) in the platform column indicates results from unseeded experiments. The ratio column gives the factor of error for each result compared to the benchmark values. Results that were within 20% of the benchmark

<table>
<thead>
<tr>
<th>#</th>
<th>Platform</th>
<th>Site</th>
<th>Date; Time (2018)</th>
<th>LSPIV Q (m³/s)</th>
<th>FlowTracker Q (m³/s)</th>
<th>Ratio: LSPIV/FlowTracker</th>
<th>% Relative Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Drone</td>
<td>Ellicott</td>
<td>4/30; 19:30</td>
<td>3.39</td>
<td>3.57</td>
<td>0.95</td>
<td>-4.86</td>
</tr>
<tr>
<td>2</td>
<td>-</td>
<td>-</td>
<td>4/30; 17:30</td>
<td>3.41</td>
<td>3.64</td>
<td>0.94</td>
<td>-6.28</td>
</tr>
<tr>
<td>3</td>
<td>-</td>
<td>-</td>
<td>4/30; 19:30</td>
<td>3.29</td>
<td>3.57</td>
<td>0.92</td>
<td>-7.83</td>
</tr>
<tr>
<td>4</td>
<td>-</td>
<td>-</td>
<td>2/28; 11:30</td>
<td>2.27</td>
<td>3.51</td>
<td>0.65</td>
<td>-35.48</td>
</tr>
<tr>
<td>5</td>
<td>-</td>
<td>-</td>
<td>2/28; 10:30</td>
<td>3.22</td>
<td>3.79</td>
<td>0.85</td>
<td>-15.27</td>
</tr>
<tr>
<td>6</td>
<td>-</td>
<td>Elton</td>
<td>4/27; 18:30</td>
<td>3.97</td>
<td>3.94</td>
<td>1.01</td>
<td>0.63</td>
</tr>
<tr>
<td>7</td>
<td>-</td>
<td>-</td>
<td>4/27; 13:00</td>
<td>1.18</td>
<td>1.40</td>
<td>0.84</td>
<td>-16.10</td>
</tr>
<tr>
<td>8</td>
<td>-</td>
<td>-</td>
<td>4/27; 16:30</td>
<td>1.18</td>
<td>1.56</td>
<td>0.75</td>
<td>-24.55</td>
</tr>
<tr>
<td>9</td>
<td>-</td>
<td>-</td>
<td>4/27; 15:00</td>
<td>0.54</td>
<td>1.48</td>
<td>0.36</td>
<td>-63.51</td>
</tr>
<tr>
<td>10</td>
<td>Drone (u)</td>
<td>Ellicott</td>
<td>4/30; 17:30</td>
<td>3.14</td>
<td>3.64</td>
<td>0.86</td>
<td>-13.75</td>
</tr>
<tr>
<td>11</td>
<td>-</td>
<td>Elton</td>
<td>4/27; 13:00</td>
<td>0.71</td>
<td>1.40</td>
<td>0.51</td>
<td>-49.10</td>
</tr>
<tr>
<td>12</td>
<td>-</td>
<td>-</td>
<td>4/27; 16:30</td>
<td>0.71</td>
<td>1.56</td>
<td>0.46</td>
<td>-54.12</td>
</tr>
<tr>
<td>13</td>
<td>-</td>
<td>-</td>
<td>4/27; 18:30</td>
<td>1.66</td>
<td>3.94</td>
<td>0.42</td>
<td>-57.97</td>
</tr>
<tr>
<td>14</td>
<td>-</td>
<td>-</td>
<td>4/27; 15:00</td>
<td>0.33</td>
<td>1.48</td>
<td>0.22</td>
<td>-77.94</td>
</tr>
<tr>
<td>15</td>
<td>Ground</td>
<td>Ellicott</td>
<td>4/02; 17:30</td>
<td>7.36</td>
<td>8.18</td>
<td>0.90</td>
<td>-10.00</td>
</tr>
<tr>
<td>16</td>
<td>-</td>
<td>-</td>
<td>4/02; 17:30</td>
<td>7.31</td>
<td>8.18</td>
<td>0.89</td>
<td>-10.57</td>
</tr>
<tr>
<td>17</td>
<td>-</td>
<td>-</td>
<td>4/24; 18:30</td>
<td>2.74</td>
<td>3.24</td>
<td>0.84</td>
<td>-15.63</td>
</tr>
<tr>
<td>18</td>
<td>-</td>
<td>-</td>
<td>2/28; 11:30</td>
<td>2.06</td>
<td>3.51</td>
<td>0.59</td>
<td>-41.29</td>
</tr>
<tr>
<td>19</td>
<td>-</td>
<td>-</td>
<td>2/28; 10:30</td>
<td>1.56</td>
<td>3.51</td>
<td>0.44</td>
<td>-55.65</td>
</tr>
<tr>
<td>20</td>
<td>-</td>
<td>-</td>
<td>2/28; 10:30</td>
<td>1.14</td>
<td>3.80</td>
<td>0.30</td>
<td>-70.10</td>
</tr>
<tr>
<td>21</td>
<td>-</td>
<td>-</td>
<td>2/28; 10:30</td>
<td>0.56</td>
<td>3.80</td>
<td>0.15</td>
<td>-85.35</td>
</tr>
<tr>
<td>22</td>
<td>-</td>
<td>Elton</td>
<td>4/27; 13:00</td>
<td>0.90</td>
<td>1.30</td>
<td>0.64</td>
<td>-35.70</td>
</tr>
<tr>
<td>23</td>
<td>-</td>
<td>-</td>
<td>4/27; 18:30</td>
<td>1.58</td>
<td>3.94</td>
<td>0.40</td>
<td>-59.85</td>
</tr>
<tr>
<td>24</td>
<td>-</td>
<td>-</td>
<td>4/27; 15:00</td>
<td>0.50</td>
<td>1.48</td>
<td>0.34</td>
<td>-66.22</td>
</tr>
<tr>
<td>25</td>
<td>-</td>
<td>-</td>
<td>4/27; 16:30</td>
<td>0.45</td>
<td>1.56</td>
<td>0.29</td>
<td>-70.81</td>
</tr>
<tr>
<td>26</td>
<td>Ground (u)</td>
<td>Ellicott</td>
<td>4/24; 17:30</td>
<td>1.25</td>
<td>3.79</td>
<td>0.33</td>
<td>-66.93</td>
</tr>
<tr>
<td>27</td>
<td>-</td>
<td>Elton</td>
<td>4/27; 13:00</td>
<td>0.76</td>
<td>1.40</td>
<td>0.54</td>
<td>-45.63</td>
</tr>
<tr>
<td>28</td>
<td>-</td>
<td>-</td>
<td>4/27; 18:30</td>
<td>1.42</td>
<td>3.94</td>
<td>0.36</td>
<td>-63.92</td>
</tr>
<tr>
<td>29</td>
<td>-</td>
<td>-</td>
<td>4/27; 16:30</td>
<td>0.50</td>
<td>1.56</td>
<td>0.32</td>
<td>-67.96</td>
</tr>
<tr>
<td>30</td>
<td>-</td>
<td>-</td>
<td>4/27; 15:00</td>
<td>0.0394</td>
<td>1.48</td>
<td>0.03</td>
<td>-97.34</td>
</tr>
</tbody>
</table>
Figure 3.5) A one-to-one plot for all results, representing the ratio between the LSPIV results and the benchmark values as measured by the FlowTracker. The blue line is the 1-to-1 line, meaning a 1-to-1 ratio between the two variables. The closer these data points fall to this line, the more accurate the results. Due to the extreme variations in environmental conditions and data collection platforms, there appears to be a weak 1-to-1 relationship with a large RMSE denoted by the error bars.
The consistency of drone results as compared to the variability of smartphone/GoPro® results is primarily a result of the camera point of view (POV) angle. High angle POV reduces distortion of the imagery. With the drone, a consistent angle, orthogonal to the stream surface was achieved at every stream location. The ground-based camera platforms were highly dependent on location, where availability of vantage points was limited.

Bright glare completely obscured stream tracers at some sites (fig 3.6). Resultant vector maps for images from this study containing bright glare would yield regions of relatively low velocity coinciding with the locations of glare (fig 3.6). Data from the first day in the field showed relatively higher error in the results for Ellicott Creek, especially for ground-based platforms. This was because data was collected at midday, and so subsequent data was collected in the evenings. With limited vantage points, glare may be unavoidable even when filming in the evening and with a polarizing lens. Drones, however, can maneuver into positions that avoid reflected light.

3.2.2 Site conditions

The most accurate discharge results calculated in this study show that the most ideal streams for LSPIV analysis exhibit homogenous flow as a result of uniform bathymetry and well-defined banks. In table 3.1, under the site column, certain sites consistently fall lower on the table, reflecting larger error. This can also be seen in figure 3.7. Results from Elton Creek cross-sections P1, P3, and P4, plot relatively close to the 1-to-1 line relative to cross-section P2, which showed poor results from all platforms.
Figure 3.6) Left: Images taken on 2/28/18 around 11 am. It is difficult to distinguish the tracer particles from the glittering reflections after high pass filtering. Right: The velocity magnitude map shows a ‘V’ shaped pattern in green that coincides with the two brighter sections of glare in the middle of the stream (top left).
Figure 3.7) LSPIV discharge results for Elton Creek from both drone and smartphone data collection platforms. It can be seen that cross-section profiles 1, 3, and 4 plot relatively close to the 1-to-1 line compared to cross-section profile 2. Results from cross-section profile 4 exhibit the most highly accurate results of all cross-sections.
The PIVlab results shown in figure 3.8 show why discharge was so greatly underestimated for the second cross-section of Elton Creek. First and foremost, the stream bathymetry data shows a shallow shelf approaching the left side of the bank, while its location along a broad curve in the stream caused the majority of flow to hug the right side (fig. 3.8). This also caused natural and seeded tracers to be absent from the shallow part of the flow, since tracers tend to converge into faster flow regimes (see flow vectors, fig 3.8).

Figure 3.8) The second profile (P2) along Elton Creek overlain with the PIV result showing higher velocity to the right side of the stream. The cross section bathymetry aligned below shows the asymmetry in depth of the channel.
Ellicott Creek, on the other hand exhibits homogenous flow, uniform bathymetry, and well-defined banks, yielding results in good agreement with flow meter values (fig 3.9). In comparing the bed roughness of the four cross-sections of Elton Creek, the more uniform the depth along the transect and the more defined the banks, the more accurate the results of LSPIV analyses (fig 3.11, 3.12). Large cobbles and boulders in Elton Creek at the base of the second and third cross-section induced regions of more turbulent flow, eddies, and stagnant pools where tracers would sometimes become trapped or from which would be absent. Comparatively, the first and fourth cross-section of Elton Creek had a uniform depth and more accurate results than the second and third cross-section (figs 3.11, 3.12). Note, that with a higher stage, the relative variability of the base should reduce and thus flow will become less turbulent. For individual streams, there may be a minimum stage that LSPIV will be successful.
Figure 3.10) LSPIV discharge results for Ellicott Creek from both drone and smartphone data collection platforms. Drone results plot closest to the 1-to-1 line more often, but smartphone and GoPro are capable of yielding accurate results at both low and higher flow.
Shallow areas should also be avoided due to the apparent effect on LSPIV results by substrate patterns in clear water. This was only noticed with drone video, as the substrate was not visible in the low-angle ground-based video. The fourth cross-section of Elton Creek gave the most accurate discharge results, but the only condition that sets it apart from the first cross-section is the opacity of the water (fig. 3.9, 3.10). Even with a gimbal, the drone experienced low frequency motion while correcting for wind. This combined with visibility of rock patterns on the substrate caused false motion of an otherwise stationary feature. These patterns may have obscured the visibility of tracers leading to lower estimated velocity vectors and discharge for the other three cross-sections. The opacity of the fourth cross-section made for a better contrast with tracer particles during LSPIV analysis and lead to the highest accuracy result within 1% of the true flow (figs 3.7, 3.12).
Figure 3.11) Cross-sections 1 and 2 of Elton Creek with their relative errors. The difference in bathymetry can be clearly seen in the depth profile. The images also show how shallow the left edge of cross-section 2 becomes as compared to the well-defined banks of cross-section 1.
Figure 3.12) Cross-sections 3 and 4 of Elton Creek and their relative error. Profile three has a slightly more variable depth profile as compared to profile 4. Profile 4 also exhibits high opacity, creating more contrast between tracers.
3.2.3 Stream tracers: seeded vs unseeded

Both drone- and ground-based platforms saw error at less than 15% when tracers were abundant and evenly distributed (table 3.1). Along Ellicott, for example, when tracers were not present or distributed, results were underestimated by up to 55%, but that error was reduced to 10% when tracers were present. The effect of tracers can be seen in figure 3.5 for Elton Creek where all results where tracers were not artificially introduced (hollow markers), have a larger error than their seeded counterparts (solid markers). Seeded and unseeded results are comparable for Ellicott Creek, as seen in figure 3.8, as a result of the natural tendency of this stream to have highly visible and distributed natural bubble tracers. The bubbles seemed to be sourced from a riffle sequence upstream of the foot bridge. An upstream riffle sequence may be another beneficial condition to look out for when selecting a stream for LSPIV analysis. In table 3.1, results 2, 5, 6, and 7 are the only unseeded results to fall within 15% of the true flow, all along Ellicott Creek, which had abundant natural tracers on those days.

The presence of tracer particles, whether seeded or natural, have the most significant effect on the accuracy of the LSPIV results, improving results by an average of 30%. For drone-based imagery alone, tracers reduced error by about 60%, and for ground-based platforms by about 20%. This is of particular importance for the ground-based platforms because it implies that there is more sensitivity to the presence of tracers than the negative effect of low-angle distortion. The Amherst State Park cross-section, which fulfills the above mentioned conditions for an ideal LSPIV site, including natural tracer presence, but can only be filmed at a 30° angle with ground-based cameras saw results below 20% error. The larger error associated with the
data collection on 2/28/2018, results can be attributed to glare as it was the middle of the day and it proved to obscure tracers even with the polarizing lens.

3.3 Citizen Science

With a long Buffalo winter raging well into April, there was unfortunately not a sufficient number of streamflow videos as requested by the CrowdHydrology sign to perform an LSPIV analysis. However, the limited number of videos that were posted to social media revealed a few flaws in instruction and implementation. For example, some video taken on windy days had a great deal of vibration, showing either a need to stabilize the sign post, or instruct citizen scientists to hold the sign steady while filming. In another video, the citizen scientists were running back and forth in front of the sign throughout the video marking a clear misunderstanding of the project as a result of limited descriptive information of what the video would be used for or the ideal conditions of the stream flow data.

3.4 RMSE analysis continued

As a result of variability in site characteristics and monitoring platforms used during this research, accuracy of the results varied greatly. Because of these inherent differences in site conditions and data collection, the uncertainty should not be evaluated by averaging the variance of all results. To reflect these inherent differences in data collection, the results were divided into groups based on the platform and seeding conditions for the streams, each of which were separately analyzed for RMSE (table 3.2). For all analyses conditions were assumed to be for ideal cross-sections as defined in the above sections. Consequently, cross-section 2 of Elton creek was omitted as it is deemed a non-ideal stream reach, as well as data collected on
2/28/2018 as errors were made in the field, including leaving a tagline up, which obscured flow across and due to uncorrected fish eye from the GoPro. These results and their corresponding error bars can be viewed in figure 3.13.

Table 3.2 RMSE values for all results and the four groupings based on platform and tracer conditions. The values for the four grouping are based on the assumption that streams are of the ideal conditions described above.

<table>
<thead>
<tr>
<th>Platforms</th>
<th>RMSE (m³/s)</th>
<th>Conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>1.42</td>
<td>All results regardless of platform or site condition</td>
</tr>
<tr>
<td>Drone</td>
<td>0.53</td>
<td>Video of both Elton and Ellicott Creeks, taken from a drone. Ideal stream has relatively homogenous flow and abundant tracers.</td>
</tr>
<tr>
<td>Drone (unseeded)</td>
<td>1.46</td>
<td>Identical video and stream conditions as above, without artificial seeding.</td>
</tr>
<tr>
<td>Ground</td>
<td>1.67</td>
<td>Video of Elton and Ellicott Creeks from ground-based platforms. Ideal stream has relatively homogenous flow and abundant tracers.</td>
</tr>
<tr>
<td>Ground (unseeded)</td>
<td>1.89</td>
<td>Identical video and stream conditions as above, without artificial seeding.</td>
</tr>
</tbody>
</table>

Figure 3.13) One-to-one plots for the four groupings defined in table 3.2 with corresponding RMSE bars. Drone data under seeded conditions yield the smallest error compared to the other groupings.
Because LSPIV results are consistently underestimating the true value, a mean of -10% could under these conditions could be used to scale the results up. However, even with promising results, the uncertainty as determined through a t-test analysis implies that any LSPIV result under these conditions, could be anywhere from -3% to -18%. The magnitude of the uncertainty is in part due to the small sample size, and would surely reduce with more data.

The mean error and the uncertainty associated with drone results under conditions where tracers are not artificially added is much larger (table 3.2). This information is directed toward researchers who hope to use this method for entirely non-intrusive and rapid data collection or where the introduction of tracers is prohibited. Referencing figures 3.10 and table 3.1, unseeded results for higher flow conditions at Ellicott Creek have more accurate results. It was observed at Ellicott Creek that when flow is higher, there is an abundance of bubbles floating along the surface. Perhaps this is the case with many streams, implying that for unseeded LSPIV analysis, data collection should only be done along streams of higher flow, or where researchers know natural tracers are present in abundance.
For researchers that hope to use this method, but do not own or have access to drone, there is still potential, but extra care and effort must be taken in site selection. Primarily, the site must have a good vantage point. The higher the angle between the camera and the stream the better, but individual results appear to imply that the presence of tracers and lack of glare are more important than having a near-90° angle. The mean error for ground-based LSPIV (smartphone and GoPro®) is much larger, but less variable with an uncertainty of ± 21%, as compared to the ± 31% uncertainty for unseeded drone LSPIV. A fairly similar mean was reported for unseeded ground-based results, but a higher uncertainty. These results are disconcerting, but considering all the cross-section conditions (fig 3.9, 3.11, 3.12) of study, some were more appropriate than others.

Looking at individual results, Amherst State Park was the best site for ground-based LSPIV (table 3.1). Ground-based platforms yielded results within 20% and as low as 10% error. This location provided a good vantage point achieved from a foot bridge (fig 3.14). The angle is still relatively low, but the stream is narrow enough and straight enough to fit in the smartphone field of view, possessed well-defined banks, and homogenous flow to yield higher

Figure 3.14) Imagery taken via smartphone from the Amherst State Park. Well distributed natural bubble tracers can be seen on the stream surface. The stream also has good opacity, homogenous flow, and well defined banks.
accuracy results as long as natural tracers were present (fig 3.14). By selecting more sites with appropriate vantage points and tracer conditions, the uncertainty of ground-based results will be reduced. In comparing the three sites based on their uncertainty, Amherst State Park has the lowest mean error and uncertainty, while the Sheridan Drive cross-section has a high mean error and uncertainty.

It should be noted that for this study, average velocity was computed from LSPIV-derived surface velocities using measured velocity profile correction factors (fig 3.1, 3.3, 3.4), which eliminated the uncertainty that would be introduced by the assumed value of 0.8. One of the goals for this method, however, is to develop it as an alternative to flow meter stream gauging in which this correction factor would not be directly measured and must be assumed. Using a generalized correction factor would introduce uncertainty that propagates through in the computation of error uncertainty for the final product, and thus must be considered. When setting up a stream for long-term monitoring with LSPIV, it is recommended that stream gauging for average and surface velocity be done at the start to evaluate a characteristic ratio between the two for the particular stream or stream reach.

3.5 Differential Discharge

The primary objective of this research has been to extend the application of LSPIV to the quantification of groundwater – surface water interaction. Using the results from both Elton and Ellicott Creeks, the goal is to determine whether LSPIV successfully detected and measured the groundwater contribution over these reach scales. Because differential discharge is a residual, it is the uncertainty, which reflects the precision of the method, that will allow for
quantitative measure of groundwater contribution; therefore, a supplementary goal of this research is to present a statistical approach to estimating accuracy of the differential discharge result for future studies that employ LSPIV without prior knowledge of true flow from flow meter gauging.

3.5.1 Elton Creek

According to the flow meter results shown in the left column labeled FT in table 3.3, Elton Creek is gaining between all four cross-sections (figure 3.15). This gain is at a very small rate (<10% change) between the first three cross-sections. Between cross-sections 3 and 4, the gain increases by greater than 150%.

<table>
<thead>
<tr>
<th>Elton Creek cross-sections (Reach distance)</th>
<th>Cross-section 1 (0 km)</th>
<th>Cross-section 2 (0.5 km)</th>
<th>Cross-section 3 (2 km)</th>
<th>Cross-section 4 (10 km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>FT</td>
<td>LSPIV</td>
<td>FT</td>
<td>LSPIV</td>
<td>FT</td>
</tr>
<tr>
<td>Discharge (Q) (m$^3$/s)</td>
<td>1.40</td>
<td>1.18</td>
<td>1.48</td>
<td>0.54</td>
</tr>
<tr>
<td>Diff. Q (m$^3$/s) (1-2-3-4)</td>
<td>+0.08</td>
<td>-0.64</td>
<td>+0.08</td>
<td>+0.64*</td>
</tr>
</tbody>
</table>

LSPIV results also reported an increase across the entire stream reach except for cross-section 2. LSPIV results erroneously yield a negative net groundwater contribution between cross-sections 1 and 2 at -0.64 m$^3$/s (table 3.4) as compared to the true value of +0.08 m$^3$/s (table 3.3). This is due to the poor conditions of cross-section 2 as described in section 3.2.2 and does not give a clear understanding of LSPIV accuracy. LSPIV appears to correctly yield a positive groundwater contribution between 2 and 3 (table 3.4), but overestimates the
contribution by 24 times the true value of +5% (table 3.3), again due to the large error associated with the poor conditions of cross-section 2 and should excluded from analysis.

Differential discharge results between the remaining cross-sections can be viewed in table 3.4 and figure 3.15. After propagating the RMSE for drone-based discharge (table 3.2), the compounded RMSE for the differential discharge results came out to be ±0.75 m$^3$/s (fig 3.16).

Figure 3.15) Aerial view of Elton Creek in Delevan, NY and the four cross-sections (red markers) over a 10 km stream reach. Blow out photo shows cross-sections 1 through 3 over a 2 km stream reach. Percent gain in flow is indicated between each adjacent profile according to the FlowTracker results.
Table 3.4) Differential discharge for cross-sections 1, 3, and 4 of Elton Creek from the Flow Tracker and LSPIV omitting cross-section 2. Relative error (%) from true values is also given, as well as the reach distance. scale between the corresponding cross-sections.

<table>
<thead>
<tr>
<th>Elton Creek 4/27</th>
<th>Flow Tracker Differential (m$^3$/s)</th>
<th>LSPIV Differential (m$^3$/s)</th>
<th>Relative Error (%)</th>
<th>Reach Scale (km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CS 1-3</td>
<td>+0.16</td>
<td>0</td>
<td>-100%</td>
<td>2</td>
</tr>
<tr>
<td>CS 3-4</td>
<td>+2.38</td>
<td>+2.79</td>
<td>+17%</td>
<td>8</td>
</tr>
<tr>
<td>CS 1-4</td>
<td>+2.54</td>
<td>+2.79</td>
<td>+10%</td>
<td>10</td>
</tr>
</tbody>
</table>

Figure 3.16) LSPIV differential results against FlowTracker results. Each point corresponds to the reach of the same color in table 3.4. The differential RMSE was determined by propagating the RMSE for Drone-based discharge measurements listed in table 3.2.
Although results plot close to the 1-to-1 line, the groundwater contribution between cross-sections 1 and 3 is so small that LSPIV reported no change in flow compared to the true +0.16 m$^3$/s gain measured with the FlowTracker (table 3.4). RMSE indicates that on average, LSPIV results could deviate in either direction by ±0.75 m$^3$/s. This means that the groundwater contribution has to be greater than ±0.75 m$^3$/s in order for LSPIV to correctly report a positive or negative groundwater contribution. Thus the differential between cross-sections 1 and 3 is too small of a change for LSPIV to be able to accurately whether the reach between cross-section 1 and 3 is gaining or losing. The true groundwater contribution between cross-sections 3 and 4 is +2.38 m$^3$/s (table 3.4). The differential LSPIV comparatively is +2.79 m$^3$/s, just a +17% relative error (table 3.4). This value is much greater than the RMSE, which shows that groundwater contribution can be definitively determined at this reach scale using LSPIV. The reach scale between 3 and 4 is about 8 km (fig. 3.15). By expanding the stream reach even further to 10 km between cross-sections 1 and 4, it is shown that the accuracy of this measure improves with a relative error for the LSPIV result at only +10% (table 3.4, figure 3.16). Since RMSE is static, this means that the greater the change in flow, the smaller the error is relative to the total value and the more accurate differential LSPIV becomes. This may imply that LSPIV will only be successful for longer stream reach scales and greater discharge/recharge magnitude; however, even lesser flow change can be qualitatively measured as a net positive or negative, as long as the differential is greater than the RMSE of 0.75 m$^3$/s.
3.5.2 Ellicott Creek

Ellicott Creek contained two cross-sections at Amherst State Park and along Sheridan Drive, a 2 km stream reach (fig 3.17). Discharge results at each cross-section revealed a potential for <10% relative error, especially in the latest datasets. Differential discharge results were evaluated from an early dataset (2/28/18) and from the last dataset collected (4/30/18) (table 3.5; figure 3.18). FlowTracker results from the first dataset give a true net gain of +0.28 m³/s compared to LSPIV which yields a gain of +0.95 m³/s, a +239% relative error.

Table 3.5) FlowTracker and LSPIV differential discharge results for the 2/28/18 and 4/30/18 datasets collected for Ellicott Creek. The relative error and reach scale for each dataset is also included.

<table>
<thead>
<tr>
<th>Ellicott Creek Amherst – Sheridan Dr</th>
<th>Flow Tracker Differential (m³/s)</th>
<th>LSPIV Differential (m³/s)</th>
<th>Relative Error (%)</th>
<th>Reach Scale (km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2/28/18</td>
<td>+0.28</td>
<td>+0.95</td>
<td>+239%</td>
<td>2</td>
</tr>
<tr>
<td>4/30/18</td>
<td>+0.07</td>
<td>+0.12</td>
<td>+71%</td>
<td>2</td>
</tr>
</tbody>
</table>

Figure 3.17) Aerial view of Ellicott Creek. The Amherst State Park and Sheridan Dr. cross-sections are indicated by the arrows in relation to the UB north campus. The reach between these two cross-sections is ~2 km.
Figure 3.18) Differential discharge results for the two datasets. The relatively large error associated with the 2/28/18 dataset is likely due to non-ideal conditions of data collection, namely reflections as a result of filming at midday, mulch as tracers instead of popcorn, and the fact that a tagline was left up across the stream.

This large relative error is likely due to the non-ideal stream conditions associated with this first dataset, including filming at midday when reflections were at their most severe and the use of mulch as a tracer, which was much less visible than popcorn used later. This caused the discharge at Amherst State Park to be greatly underestimated, leading to the seemingly large increase between that point and Sheridan Drive. The LSPIV result is greater than the RMSE value, which should at least give a positive indication of gain or loss. Results from the 4/30/18 dataset, on the other hand, are more accurate with the true FlowTracker results showing a gain.
of +0.07 m$^3$/s, compared to the +0.12 m$^3$/s gain from LSPIV. Individual discharge results from this dataset were at only a -8% and -6% relative error for Amherst State Park and Sheridan Drive respectively, but because the change in flow is small compared to the total discharge at each cross-sections, the LSPIV differential (+0.07 vs +0.12 m$^3$/s) still shows a +71% relative error. However, for LSPIV to measure a value this close at such a small true change in flow is very promising. The RMSE value, however, is larger than the LSPIV result, and would imply that it could not be determined from LSPIV alone if this reach is gaining or losing for this dataset. More data is needed to understand if this reach scale along Ellicott Creek is appropriate for LSPIV analysis.

Considering the results from both streams, LSPIV is capable of both qualitative and quantitative measurements of differential discharge. The three most important considerations to achieve in order to successfully use LSPIV to monitor groundwater-surface water interaction are 1) the surface velocity to average velocity ratio. If the correction factor cannot be established, the uncertainty of an estimated correction factor must propagate through to the final result. 2) the platform and conditions of the stream cross-sections, in terms of ideal flow, channel geometry, and tracer presence, to ensure accurate and precise discharge measurements, which will result in lower uncertainty. 3) An appropriate reach scale must be selected. This will be different for different streams and is based on how rapidly a stream is gaining or losing over a distance. Along Elton Creek, LSPIV was able to detect groundwater discharge over 8 km at a discharge rate of about 0.3 m$^3$/s per km. Along Ellicott Creek, LSPIV was able to detect groundwater discharge over a 2 km reach scale at a discharge rate of about
0.10 m³/s per km. The larger the magnitude of contribution and reach scale, the more accurate
this method becomes.

3.6 t-based 95% Confidence Interval

RMSE analysis is based on the assumption of large (>30) sample sizes that are normally
distributed. With only 30 data points total and fewer when broken down into the subgroups,
more data is needed to obtain a more accurate evaluation of RMSE. As more data was
collected and processed using LSPIV analysis, the discharge results improved. As was seen at
Ellicott Creek, discharge results were oftentimes within 10% of the true flow even at relatively
small magnitudes. LSPIV results for streams with greater magnitude flow rates would also yield
discharge values within 20% of the true flow. RMSE, however, is static and would favor large
magnitude discharge and differential volumes over the smaller magnitudes, even though there
seemed to be similar relative percent error at small and large flow rates. Additionally, LSPIV
seemed to underestimate true discharge the majority of the time, something that RMSE cannot
take into account, as it only uses the absolute value of the residuals to calculate error. For
these reasons, another statistical method was also explored, the t-based confidence interval.

The t-based confidence interval is a statistical method developed to use with small
datasets (<30), and determines a range of values within which the researcher can be 95%
confident that the true mean will fall. The goal using this method is to prevent the favoring of
larger magnitude discharge and differential discharge as well as to take into account the
consistent underestimation of discharge by LSPIV. This is achieved by evaluating the evaluating
the mean relative error, a unitless residual given as a factor or percent. So a mean relative
error of -0.10 or -10%, would imply that the measured discharge is, on average, -10% of the true discharge value. Using this as opposed to the mean static discharge residual used to compute RMSE allows the error to scale with the magnitude of discharge. For example, this mean relative error will be $0.1 \text{ m}^3/\text{s}$ for a discharge of $1 \text{ m}^3/\text{s}$ versus $10 \text{ m}^3/\text{s}$ for a discharge of $100 \text{ m}^3/\text{s}$. The 95% confidence interval is the error associated with the mean relative error within which the researcher can be 95% confident the true mean relative error falls. So $-0.10 \pm 0.08$ would imply that the measured discharge is, on average, -10% of the true discharge plus or minus 8%. Using the same sub-categories defined in section 3.4, the mean relative error and confidence intervals for each are listed in table 3.6.

Table 3.6) Mean Relative Error and 95% confidence interval for the four subcategories defined in section

<table>
<thead>
<tr>
<th>Platforms</th>
<th>Mean Relative Error</th>
<th>95% Confidence interval</th>
<th>Conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drone</td>
<td>-0.10</td>
<td>±0.08</td>
<td>Video of both Elton and Ellicott Creeks, taken from a drone. Ideal stream has relatively homogenous flow and abundant tracers.</td>
</tr>
<tr>
<td>Drone (unseeded)</td>
<td>-0.36</td>
<td>±0.31</td>
<td>Identical video and stream conditions as above, without artificial seeding.</td>
</tr>
<tr>
<td>Ground</td>
<td>-0.46</td>
<td>±0.21</td>
<td>Video of Elton and Ellicott Creeks from ground-based platforms. Ideal stream has relatively homogenous flow and abundant tracers.</td>
</tr>
<tr>
<td>Ground (unseeded)</td>
<td>-0.44</td>
<td>±0.23</td>
<td>Identical video and stream conditions as above, without artificial seeding.</td>
</tr>
</tbody>
</table>
The reasoning for using this statistical method is because it is meant for evaluating small datasets (<30) such as the four subcategories. RMSE assumes a normally distributed larger sample size (>30). Looking at the data distribution in figure 3.14, it does not necessarily seem that lower magnitude discharge results in greater error for the LSPIV results. The RMSE is a static value for all points regardless of discharge magnitude and thus favors greater discharge. Oftentimes greater discharge is marked by more turbulent flow and could possible result in greater error not reflected by the RMSE. Using relative error as opposed to static error given in m³/s allows for the error to scale with the magnitude (figure 3.19).

![Figure 3.19](image)

Figure 3.19) For 95% confidence interval for LSPIV results from drone imagery under seeded conditions: Plot portraying the trend of the 95% confidence interval (yellow shaded) with LSPIV scaled according to the mean relative error against hypothetical raw LSPIV measured values (blue line) between 0 and 5 m³/s. Because 95% confidence interval range is a factor of the original value, it increases with greater discharge.
To illustrate how to interpret the error based on this method, the following analysis focuses only on the LSPIV results derived from drone imagery under seeded conditions, since these collection conditions yield the most accurate results. These LSPIV results after scaling according to the mean relative error and this new error analysis can be viewed in table 3.7 and figure 3.20.

Table 3.7) LSPIV results only from the drone-imagery datasets under seeded conditions. The new ratios between this value and the FlowTracker benchmark values are given, as well as the unique 95% confidence interval for each cross-section, based on the magnitude of the LSPIV results.

<table>
<thead>
<tr>
<th>#</th>
<th>Site</th>
<th>Date ; Time (2018)</th>
<th>Raw LSPIV Q (m³/s)</th>
<th>Scaled LSPIV Q (m³/s)</th>
<th>FlowTracker Q (m³/s)</th>
<th>Ratio: LSPIV/FlowTracker</th>
<th>95% Confidence Interval (m³/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Ellicott</td>
<td>4/30 ; 19:30</td>
<td>3.39</td>
<td>3.78</td>
<td>3.57</td>
<td>1.06</td>
<td>(3.48 – 4.14)</td>
</tr>
<tr>
<td>2</td>
<td>-</td>
<td>4/30 ; 17:30</td>
<td>3.41</td>
<td>3.81</td>
<td>3.64</td>
<td>1.05</td>
<td>(3.50 – 4.17)</td>
</tr>
<tr>
<td>3</td>
<td>-</td>
<td>4/30 ; 19:30</td>
<td>3.29</td>
<td>3.67</td>
<td>3.57</td>
<td>1.03</td>
<td>(3.38 – 4.02)</td>
</tr>
<tr>
<td>4</td>
<td>-</td>
<td>2/28 ; 11:30</td>
<td>2.27</td>
<td>2.54</td>
<td>3.51</td>
<td>0.72</td>
<td>(2.34 – 2.79)</td>
</tr>
<tr>
<td>5</td>
<td>-</td>
<td>2/28 ; 10:30</td>
<td>3.22</td>
<td>3.60</td>
<td>3.79</td>
<td>0.95</td>
<td>(3.32 – 3.95)</td>
</tr>
<tr>
<td>6</td>
<td>Elton</td>
<td>4/27 ; 18:30</td>
<td>3.97</td>
<td>4.43</td>
<td>3.94</td>
<td>1.12</td>
<td>(4.08 – 4.85)</td>
</tr>
<tr>
<td>7</td>
<td>-</td>
<td>4/27 ; 13:00</td>
<td>1.18</td>
<td>1.33</td>
<td>1.40</td>
<td>0.95</td>
<td>(1.21 – 1.44)</td>
</tr>
<tr>
<td>8</td>
<td>-</td>
<td>4/27 ; 16:30</td>
<td>1.18</td>
<td>1.33</td>
<td>1.56</td>
<td>0.85</td>
<td>(1.21 – 1.44)</td>
</tr>
</tbody>
</table>

Figure 3.20) The scaled LSPIV values against the FlowTracker benchmark results. The error bars reflect the unique 95% confidence intervals for each discharge value.
It can be seen that the smaller discharge values have a smaller error, which is intended to reflect the mean relative error given as a percentage of the whole. Although half of the points do not have error ranges that overlap with the true values, error bars do appear to follow the trend compared to the RMSE bars, which shows that using the mean relative error may be more appropriate for statistically evaluating LSPIV results than using the RMSE.

Differential discharge results using the scaled LSPIV values can be viewed in table 3.8 and figure 3.21. Compared to differential discharge using the raw LSPIV values, the relative error has increased, overestimating the true differential. For discharge at individual cross-sections, LSPIV underestimates the true value and if this underestimation is more at the upstream location, this will result in a greater differential. Unfortunately, this overestimation increases when the discharge values are scaled according to the -0.10 mean relative error, because it will boost the larger downstream value more than the lesser upstream.

Table 3.8) Differential discharge for cross-sections 1, 3, and 4 of Elton Creek from the Flow Tracker and LSPIV omitting cross-section 2. Relative error (%) from true values is also given, as well as the reach distance. scale between the corresponding cross-sections.

<table>
<thead>
<tr>
<th>Elton Creek 4/27</th>
<th>Flow Tracker Differential (m³/s)</th>
<th>LSPIV Differential (m³/s)</th>
<th>Relative Error (%)</th>
<th>Reach Scale (km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CS 1-3</td>
<td>+0.16</td>
<td>0</td>
<td>-100%</td>
<td>2</td>
</tr>
<tr>
<td>CS 3-4</td>
<td>+2.38</td>
<td>+3.11</td>
<td>+30%</td>
<td>8</td>
</tr>
<tr>
<td>CS 1-4</td>
<td>+2.54</td>
<td>+3.11</td>
<td>+22%</td>
<td>10</td>
</tr>
</tbody>
</table>
As seen in the left plot of figure 3.21, the 95% confidence interval gives a smaller error range compared to the RMSE, especially for the small differential discharge value. However, the two methods still agree that the true differential result between cross-section 1 and 3 is too small compared to the uncertainty of LSPIV to obtain a definitive measure of groundwater contribution. The smaller error range compared to the RMSE makes it possible for smaller differentials to be less ambiguous and more conclusive with the error being less likely to span over negative and positive values. The fact that the 95% confidence interval does not overlap with the true values for the two larger differentials does not necessarily mean that this analysis method is a failure, but more an indication that more data is needed in order to improve the mean relative error estimate and confidence interval range. The error associated with the differential discharge is more a matter of precision than accuracy. If the raw LSPIV results are
off by a consistent relative error, then the uncertainty should be less, thus improving the accuracy of the differential.

The results from Ellicott Creek can be viewed in table 3.9 and figure 3.22. Again, the 95% confidence interval is smaller compared to the RMSE. The differential discharge result from the 2/28/18 dataset has a large relative error and the confidence interval does not overlap with the true differential value. This is again due to the non-ideal filming conditions mentioned previously in section 3.5.2. Even though the result from 4/30/18 is still very close to the true

Table 3.9) FlowTracker and LSPIV differential discharge results for the 2/28/18 and 4/30/18 datasets collected for Ellicott Creek. The relative error and reach scale for each dataset is also included.

<table>
<thead>
<tr>
<th>Ellicott Creek Amherst – Sheridan Dr</th>
<th>Flow Tracker Differential (m³/s)</th>
<th>LSPIV Differential (m³/s)</th>
<th>Relative Error (%)</th>
<th>Reach Scale (km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2/28/18</td>
<td>+0.28</td>
<td>+1.06</td>
<td>+277%</td>
<td>2</td>
</tr>
<tr>
<td>4/30/18</td>
<td>+0.07</td>
<td>-0.13</td>
<td>+88%</td>
<td>2</td>
</tr>
</tbody>
</table>

Figure 3.22 ) Differential discharge and 95% confidence interval around the scaled LSPIV values compared to differential discharge with RMSE around the raw LSPIV values (same plot as figure 3.17) for Ellicott Creek. Colors correspond to the date of the data from table 3.5.
value and has a smaller error range, it would still be ambiguous whether groundwater is discharging or surface water is recharging because the error spans over negative and positive differential values. Obtaining more results like the one from 4/30 to be used in the computation of error will cause this range to diminish, allowing even small changes to be accurately detected.

Results of the RMSE analysis appropriately give large uncertainty ranges due to the small sample datasets, but this error does not change with the magnitude of stream discharge and thus favors streams with greater discharge. This does not reflect the apparent trend that the relative error is fairly consistent between individual discharge results. It also ignores the fact that streams with greater discharge are oftentimes exhibiting turbulent flow, which will yield less accurate LSPIV results. Although the t-based confidence interval analysis was able to reflect this trend, it did not give accurate error ranges when compared to the true value, which is likely also due to the small sample sizes. The t-based 95% confidence interval was used because of the small datasets (<30), but with larger, normally distributed, datasets other statistical methods, including RMSE could be performed using the ratio of relative error rather than the residuals relative to the FlowTracker values.
Chapter 4: Conclusions

Low-altitude remote sensing is an emerging field born out of the advancement of commercially available imaging and drone technology. These advancements have helped spur development of new techniques for monitoring surface features and processes. The advancement of imaging technology has allowed for the application of particle image velocimetry (PIV) to larger scale flow features like streams. By tracking particles/pixels in short video clips, large-scale particle image velocimetry (LSPIV) has been successfully used to map surface velocity in rivers. Only within the last few years have researchers attempted to extend this technology to the computation of stream discharge. Even with promising results, there have not yet been any studies extending the technology even further toward differential stream gauging for the purpose of monitoring groundwater-surface water interaction.

Monitoring groundwater-surface water interaction is an important endeavor, as it helps hydrogeologists understand groundwater flow paths for water budgets and contaminant transportation, as well as the resiliency of groundwater dependent ecosystems to a changing climate. Current methods of monitoring groundwater-surface water interaction are field intensive, requiring intrusive data collection that often puts the researcher into the stream, which can be impossible in remote settings or during dangerous high flow conditions. Additionally, with decreasing funding for hydrologic monitoring, it is likely agencies, such as the USGS will reduce the number of field visits as well as decommission gauging stations. In searching for alternative methods, it has been demonstrated that LSPIV is capable of accurately estimating stream discharge with minimal time in the field. The logical next step would be to
use LSPIV based measurements to detect and measure groundwater-surface water interaction through differential stream gauging.

The research presented here is a proof-of-concept that LSPIV is a viable approach to measuring and monitoring groundwater-surface water interaction, rapidly over various reach scales. Using ground-based and drone-based camera platforms to collect stream flow data from various cross sections along two WNY streams, this study determined that it is possible to both qualitatively and quantitatively determine the groundwater contribution over a stream reach using LSPIV. The accuracy of the differential discharge results is dependent on the precision of the LSPIV-derived discharge calculation between two or more stream cross sections. Thus, this study also identifies the ideal data collection conditions for accurate and precise LSPIV analysis. The results are then analyzed to report the uncertainty one can expect when collecting data in these conditions.

Two streams were selected in WNY to serve as the study sites. Since LSPIV analysis yields only surface velocities, it was imperative to determine the surface-average velocity relationship of the streams. Stream discharge is quantified using the stream’s average velocity across the profile multiplied by the stream cross-sectional area, which is directly measured using the traditional flow meter method. The flow meter was used to measure velocity at the surface. This way, the appropriate correction factor to apply to the LSPIV-derived surface velocities to yield average velocity, could be determined using the ratio between surface and average velocity. Results imply that there could possibly be a temporal variation in surface-average velocity ratio, with stream stage. Spatially along a single stream, results support there is little spatial variation in this ratio, at least within 10 kilometers. Constructing a surface-
average velocity relationship for all streams or stream cross sections reduces the uncertainty associated with an assumed correction factor based on literature-recommended values. It is, therefore, recommended that a surface-average velocity relationship is first established for each site where the objective is long-term monitoring. Surface-average velocity relationships defined in this study supports previous literature with correction factors falling between 0.75 and 0.9 and thus, researchers who hope to perform rapid LSPIV analysis for short term monitoring may be able to use an assumed value effectively, as long as the uncertainty propagates through to the final product.

These results provided a better understanding of the ideal stream conditions for accurate and precise LSPIV analysis, and what should be considered when selecting a stream for study. Most importantly, the stream should exhibit homogenous flow across the profile. This is usually achieved when the stream reach has a relatively even depth and there are no large rocks close to or above the surface. A stream reach along a meander bend should not be selected as flow would be skewed to one side of the profile. Ideal stream cross sections should also have fairly defined banks, meaning there is not significant shallowing as one approaches either edge of the stream. The stream width should be narrow enough to fit within the FOV of the camera or cameras being used. While the GoPro camera is capable of a larger FOV, there must be a correction for the lens curvature. The program used in this study, GoPro Studio, cuts off a portion of each edge of the video after the correction so there should be a significant area within the FOV beyond the bank and georeferenced targets.

Equally important for accurate and precise LSPIV analysis is the presence of tracers. Results show that tracers had a more significant effect on results than low angle camera point
of views (POV). If there is no intent to artificially seed the stream, there must be highly visible natural tracers with good dispersal. Bubbles were the most visible, evenly distributed, and consistent natural tracer compared to sticks, leaves, and any other floating object. Bubbles seemed to be more abundant during high flow and usually followed areas of surface turbulence such as rapids in riffle sequences. With this in mind, it may be prudent to locate a site a short way downstream of a riffle sequence. Good artificial tracers are light in color. Using artificial tracers, it was found that popcorn was more visible and effective than mulch tracers. Abundant tracers are ever more important if stream water has high clarity. This is more of an issue for drone-based imagery that can see to the bottom of shallow, slow moving streams. Patterns on the stationary substrate combined with the low frequency motion of the drone can produce false motion and velocity vectors. The presence of more tracers could potentially obscure these rock patterns and yield truer flow vectors.

Another thing to consider when selecting a stream is the presence of effective vantage points for ground-based data collection. Low angle camera POV introduces more distortion in the video. Low angle POV data can still yield accurate velocity results with adequate presence of tracers, but for best results should be greater than 30°. It is best to locate a stream cross-section where bridges or steep banks are present, from which there is an unobstructed view of the river. It does not matter the orientation of flow with respect to the camera, meaning flow does not have to be flowing toward or away from the camera POV, as long as the view is clear and at a high enough angle relative to the stream surface. If one has access to a drone, it is recommended over ground-based platforms, as results from this study show the drone platform, due to its ability to achieve high angles, yields the most accurate results.
Related to camera angle is the presence of glare. Glare can completely obscure tracers and confound LSPIV results. It is difficult to avoid glare during the day, so it is recommended to film in the morning or evening when the sun is low in the sky. Even at these times, reflection of the sky can be bright. Polarizing lenses are quite effective at diminishing glare and revealing tracers. If LSPIV must be done during the day, a polarizing lens is vital to reduce error. Drones are capable of reducing or eliminating glare when maneuvered in a position that avoids incident sunlight.

The results of this study reveal that drone-based LSPIV analysis under seeded conditions are most accurate with an RMSE uncertainty of 0.53 m$^3$/s, compared to ground-based LSPIV analysis. Ground-based LSPIV analysis has the potential to yield highly accurate results under the same seeding conditions, but gives a much higher RMSE of 1.67 m$^3$/s due to the poor precision associated with much more variable camera angles achieved at each cross-section. These conditions still show a lower uncertainty than both drone- and ground-based platforms under unseeded conditions. The lack of artificial seeding caused a significant increase in the uncertainty of the results. The issue with using RMSE is that it does not reflect the apparent trend that many of the results appeared to have a similar relative mean error regardless of magnitude. So it would favor greater discharge rates, even though this often coincides with turbulent flow, which reduces LSPIV accuracy. RMSE is also meant to be used with large datasets (>30). For these reasons, uncertainty was also evaluated using relative error rather than the residuals from the FlowTracker values. Similar conclusions can be made from this 95% confidence interval analysis with drone-based results under seeded conditions yielding a mean relative error of -0.10 ± 0.08 compared to the ground-based 95% confidence interval of -0.46 ±
Using these ranges of relative error to scale the raw LSPIV results eliminated the favoring of greater discharge.

Differential discharge results of this study prove that it is possible to correctly detect a positive or negative groundwater contribution over a reach scale. In this study, the reach scale over which LSPIV correctly detected a net gain for Elton Creek was about 8 km between the 3rd and 4th profile. The detected gain by LSPIV was overestimated about 1.2 times the true value between these two profiles. Extending this reach even further between Elton Creek profiles 1 and 4, which was a scale of about 10 km, results in a more accurate and quantitative measure of the amount gained. At this larger reach scale between profile 1 and 4, LSPIV estimated a gain only 1.1 times the true value.

It is the magnitude of the gain or loss between two cross-sections rather than the distance that will influence the reach-scale over which LSPIV will be most accurate and quantitative. This will depend on many factors, including the geographic location, climate, and groundwater flow paths. So for a river that experiences a high rate of groundwater discharge or surface water recharge over a smaller distance, the reach-scale at which LSPIV can accurately predict a gain or loss will be smaller and provide higher resolution data. Between the two profiles of Ellicott Creek, was only a +0.07 m³/s gain in flow over a reach scale of about 2 km. Although LSPIV correctly estimate a positive increase at +0.12 m³/s of the flow, the uncertainty as defined in this study for these data collection conditions would imply there was a chance that the results could have actually indicated a loss, making it impossible to definitively say whether this reach is gaining or losing. Simply, when the gain is smaller than the uncertainty, it
cannot be a conclusive measure of gain or loss. Ellicott Creek has shown a larger magnitude
gain, however, when the stage is higher, potentially making it possible to detect groundwater
contribution during higher flow periods. These later datasets did also appear to yield more and
more accurate results, as the authors improved data collection technique according to the ideal
conditions spelled out in chapter 3.

Future Work:

This study has shown that LSPIV is capable of detecting and measuring groundwater-
surface water interaction comparable to measurements made using the standard and accepted
method of differential stream gauging with a flow meter. The next step is determining an
accurate measure of uncertainty for the LSPIV results, which is vital for correctly evaluating
whether LSPIV can be used on its own at a quantitative and/or qualitative standard. The large
uncertainties of these results are in part due to the small sample sizes. With more datasets and
larger sample sizes, this uncertainty is expected to decrease. More work must be done
following the same method outlined in this study for evaluating error and uncertainty using
benchmark values of discharge. By following these strict guidelines for site selection and data
collection, the precision of LSPIV results will surely improve as will the uncertainty.

As this uncertainty is minimized with additional data and analysis, LSPIV will become
capable of improved quantitative measures of groundwater-surface water interaction over
smaller reach scales. Even with the large uncertainty determined by this study, groundwater
contribution can still be qualitatively determined over various reach scales as gaining or losing,
depending on the magnitude of the change in flow being smaller than the uncertainty. The greater the change in flow between one stream cross-section and the next, the more accurate the LSPIV measure of change becomes.

Because cross-sectional area changes with stream stage, there is a need to develop a system that would allow stream stage and cross-sectional area to be determined within the video used for LSPIV analysis. By establishing a relationship between stage and cross-sectional area, there would be no need to measure bathymetry with a flow meter every time. A more advanced method could be drone-based bathymetric photogrammetry. Obtaining this bathymetry data would allow for unsupervised data collection. Perhaps a permanent camera can be installed at several stream sites set up with the stage monitoring system that can be operated remotely at any time. Or a small unmanned aerial system (sUAS) where data can be rapidly collected by drones at several profiles over a large reach scale. Crowdsourced data through citizen science initiative will also see benefit from a system like this. As more videos are uploaded via the Amherst Bike Path stream flow sign, the effectiveness of crowdsourcing LSPIV data will be determined.

Despite uncertainty, LSPIV successfully detected a groundwater contribution over a reach scale of about 8 to 10 km. Considering the number of results that fell within 10%, the uncertainty is expected to decrease as more data is collected in the future. With cuts in funding toward environmental monitoring initiatives, agencies will be looking for new innovative approaches to monitoring groundwater-surface water interaction. This study shows the promise of low-altitude remote sensing techniques to detect a virtually invisible transfer of water across the groundwater-surface water interface. Over the course of this study, data
collection (filming 1-minute videos) took less than 20 minutes, as compared to close to an hour with the flow meter, yet was still capable of yielding comparable results. This research has also taken advantage of the commercial availability of drones, which has numerous implications toward making this method faster, remote, and safer in dangerous flow events. As the first study to test LSPIV as a viable alternative method to differential stream gauging, these results show success and demonstrate an exciting opportunity to become the new standard for long-term large-scale monitoring of groundwater-surface water interaction in ungauged watersheds.
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Appendix: Data Processing in PIVlab and RIVeR

Video imagery was processed using the Matlab toolbox, PIVlab and the Matlab-built standalone program, RIVeR (Rectification of Image Velocity Results) (fig A.1). PIVlab computes the vector field for a stream flow video (Thielicke and Stamhuis, 2014), while RIVeR converts the results to metric space by orthorectification using the GRPs installed along the stream banks (Patalano et al., 2017). PIVlab can be downloaded from the Mathworks file exchange site and requires a MATLAB license with the image processing and application compiler toolboxes (MathWorks, 2018). RIVeR can be downloaded directly from the authors’ website. RIVeR requires the MATLAB runtime environment 9 (Patalano et al., 2017; River, 2017). The latest version of MATLAB that is compatible using runtime environment 9 is R2015b (Engel, 2017; River, 2017). These programs have difficulty reading in files with long path names so it is suggested that source data be kept in folders on the C-drive. Additionally, no folder within the path name should have any spaces, as the programs are unable to read them.

Figure A.1) The two Matlab-based LSPIV softwares used in this study. PIVlab calculates the vector displacement field while RIVeR rectifies the PIV result.
First, the video file must be broken down into its individual frames in RIVEr. Note, if using a GoPro®, a lens correction must be applied to remove the fish eye distortion. For this study, this was done with the software GoPro® Studio.

**File > Extract Images From File**

Select the target video file and select open. A dialog box will appear giving options for the sampling duration and sampling rate (fig A.2). For slow moving streams, a frame per second (FPS) rate of 30 fps, does not allow enough displacement of patterns to occur between image-pairs for LSPIV to accurately track them, thus a smaller sampling rate must be assigned.

![Image extraction dialog box in RIVEr](image.png)

Figure A.2) Image extraction dialog box in RIVEr. Fps refers to the sampling rate. The default value is the frame rate at which the video was taken and would imply every frame would be sampled. The range refers to the segment of the video selected to be broken down.

It has been recommended to have 15-25 pixels of displacement between each image-pair (Engel, 2017). At 30 fps, stream video acquired at the low order streams of this study had around 15-25 pixels of displacement between every 5th to 10th frame. The sampling rate will be larger for fast flowing streams, while lower for slow flowing streams. To determine the correct sampling rate, the frame rate of the video must be divided by the sampling interval, so 30 fps
divided by a sampling interval of 10 is 3 fps. 30 fps divided a sampling interval of 5 is 6 fps. 3 and 6 frame sampling seemed to work well for processing imagery for Ellicott and Elton Creek.

Back to RIVeR,

File > Extract Images From File

Input the selected frame sampling rate as well as the selected duration of the video. The duration selected should be at least 10 seconds but longer durations will provide a better representation of the true stream velocity, especially if tracer particle density is low. For this study, a duration of about 1-minute was selected, which contained the most stable portion of the video as well as the highest tracer density. While selecting the sampling rate and video duration there is an option to view video in grayscale (fig A.2). The grayscale option is not necessary as this refers to how the imagery is displayed to the user. PIVlab automatically processes the imagery in grayscale, but displaying in grayscale can reduce processing time. However, this will most likely make it difficult for the user to identify GRPs. Select the Extract Frames button. As mentioned before, this breaks down the video into jpeg images and are automatically saved in the same folder as the source video.

Switch over to PIVlab

File > New Session

Click on the Load Images button. A new window will appear with load options (fig A.3). First check “sequencing style 1-2, 2-3, 3-4,” which refers to the image-pairs that will be analyzed. Frame 1 will be compared to frame 2, which will also be compared to frame 3, and so on. Select the images and click add. Click import.

Analyses settings > Exclusions (ROI, Mask)
This step allows the user to omit the regions of the video that are not of interest, such as the sky, trees, and distant portion of the river, so that the program is not calculating velocity vectors for those locations. This will greatly reduce the processing time. Click **Select ROI**.

Figure A.3) Load images window in PIVlab. “Sequencing style 1-2,2-3,3-4, ...” is checked. The broken down frames are shown in the bottom left window.

Draw a rectangle that encompasses at least four GRPs, but leave some room on both sides of the intended transect where discharge will be determined (fig A.4).

Click **Draw mask(s) for current frame**. This step allows you to mask the stationary parts of the imagery, the stream banks, within the ROI, again so the program does not calculate vectors for these regions. Left click to generate a polygon around one of the banks and double
click to close it. The polygon edges should be outside of the ROI rectangle. To draw a mask on
the other bank, **Draw mask(s) for current frame** must be selected again. After masks are
drawn, make sure the Apply to frames box displays “1:end” then click **Apply current mask(s) to
frame** ... There will be no noticeable indication by the program that the masks were applied,
but there is a scroll bar at the bottom right that allows one to scroll through the frames and
confirm the mask was applied to all frames. If the video underwent any sort of movement
through the duration of filming, perhaps low frequency motion of a drone, it is a good idea to
use the scroll bar to check if the masks migrate over the river. If this occurs, velocities will be
underestimated, so masks should be redrawn.

Figure A.4) Region of interest (blue dotted line) and masks (red shaded area) denoting flow region to analyze.
Analyses settings > Image pre-processing

PIVlab provides four built-in image enhancement algorithms: Contrast-limited adaptive histogram equalization (CLAHE), highpass filtering, intensity capping, and weiner2 denoise filtering. These techniques work to create more contrast between tracer particles and the background noise. For this study, after testing the results using different combinations of image enhancement algorithms, it was found that high pass filtering yields more accurate results. High pass filtering causes the background to become dark and featureless, while making lighter floating particles even lighter (fig A.5). CLAHE was sensitive to reflections and wave forms and thus did not create enough contrast between the background noise and tracers, but it is up to the user to determine which technique or combination of techniques is most effective for their stream. The intensity capping and weiner2 denoise made no significant change to the image so were not used. The effects of CLAHE and high pass filtering can be previewed by clicking **preview current frame** (fig A.5).
Figure A.5) Top: Effect of CLAHE on one of the image frames. In this case, waveforms and reflections are enhanced, which work to obscure floating tracer particles. Bottom: Effect of high-pass filtering on the same image frame. Here reflections and waveforms are suppressed while the relatively high reflectance mulch is lightened, allowing for tracer particles that follow true flow to be detected by PIV algorithm.
To minimize processing time, videos for this study were processed with the FFT algorithm. Select FFT window deformation. Multiple passes can be performed to minimize loss of information using the FFT method. Three passes have been the standard in previous studies (Engel, 2017). The size of the interrogation area (IA) for each pass depends on the camera resolution, the size of the river, the height from which the video was taken, and the desired resolution of the final vector field. In this study, all imagery was taken from similar heights so for the higher resolution drone imagery, the IAs were set at 256 px, 128 px, and 64 px for the three passes. For the smartphone and GoPro® imagery, the IAs were set at 128 pixels, 64 pixels, and 32 pixels for the three passes. **Input the IA and corresponding step value (half the IA) in the Pass 1 box.** Then input the same step value from pass 1 into the IA for pass 2. The step value will automatically update.

Continue filling in the IA with the previous pass’ step value for the desired number of passes. The IAs will appear on the video image (fig A.6).

Analysis > Analyze!

Click analyze current frame.

This allows you to judge the scale of the vector arrow. If

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*Figure A.6*) Interrogation areas for the three FFT passes in PIVlab. The smallest IA reflects the resolution of the final vector field.
you want to increase or decrease the marker size:

**Plot > Modify plot appearance**

**Under vector scale, you can alter the size and width of the vector.** No other alteration is necessary, but you can change the vector color scheme and colorbar position under the Derived parameters only box.

**Analysis > Analyze!**

**Click analyze all frames.** The time this takes depends on the length and resolution of the video, the processing power of the computer, and the correlation algorithm. The processing time for this study, using FFT took anywhere from 10 to 40 minutes depending on the video resolution and length.

**Post Processing > Vector Validation**

**Check the “display all frames in scatterplot” box and click select velocity limits.** A scatterplot appears of velocity data (fig A.7). This step allows the user to filter out outliers in the data by selecting velocity limits where the data is clustered most densely. Additionally, values that plotted negative relative to the direction of flow, meaning they indicate flow opposite the known direction of flow, were omitted. These values are likely due to motion of the platform or turbulent regions of the stream. **Use the left click and hold to draw a box around the densest portion of the data-cluster.** PIVlab uses the velocity limits to interpolate the omitted data in each frame. The smaller the box, the more vectors must be interpolated. **Click on apply to all frames** and wait to finish. The velocity map for the final frame-pair will appear with
measured velocities in green and interpolated velocities in orange. The next step is to calculate
the average of all the velocity maps for each frame-pair.

Figure A.7) Velocity values displayed as a scatter plot in units of px/frame in the x and y direction. The
densest part of the cluster represents the most frequent velocity values and should be
representative of the true velocity.

Plot > Derive Parameters/Modify Data

Click Calculate mean vectors. This adds the averaged velocity map as the last frame (fig A.8).

Figure A.8) PIV results averaged from all frame results after validation. The orange vectors indicate
that they were averaged from interpolated vectors in over half of the frames following vector
validation. It is better to have more green and less orange.
File > Save > PIVlab session

Switch back to RIVeR

Workflow > Load PIV/PTV Analysis > Load PIVlab/PTVlab session

Workflow > Load Background Image

A dialogue box will appear with an option to select the background image or automatically generate one. **Select automatic**, which will generate an average image from the first 10 images in the working folder. It will appear in the log window when each step is completed.

Workflow > Load CPS Image

**Select the very first image in the folder.** Again, when this action is completed it will appear in the log window.

Workflow > Define CPs > Define in a 2D plane > Define distances (if only 4 CPs)

The cursor will turn into cross-hairs so the user can manually select the GRPs, referred to as control points (CPs) by RIVeR, that were installed in the field earlier. **To select a CP, right click the locations of the CPs in counterclockwise order.** The left click can be used to zoom in, but this can cause the program to freeze or crash so refrain from doing so. After all four control points are selected, a dialogue box will appear asking “Do you want to load lengths between CPs.” If the lengths are listed in a column of an excel spreadsheet, they can be imported after selecting “Yes”. **Otherwise, select “No”** and manually input the lengths between CPs (fig 2.16).
Figure A.9 Control points (GRPs) selected in the RIVeR software. The lengths in real space are measured in the field and entered into the dialog box for the corresponding color.

**Workflow > Define Region of Interest**

This is not the same ROI selected in PIVlab, it does not need to be a rectangle. This is to select the region of the PIV result to be orthorectified, so it should be slightly larger than the ROI selected in PIVlab, and must include some stationary bank as a stationary reference. Left click in a counterclockwise direction to build a polygon around the ROI. Double click to close the polygon. You may have to double click a second time before the ROI is applied (fig 2.17). It should be noted that the imagery is orthorectified in only two dimensions.

**Workflow > Define Time step**

The time step is the elapsed time in milliseconds between successive frames. It can be found in the image extraction text file, which was automatically saved in the working folder or it can be
determined manually. For a 3 fps sampling rate that samples every 10th frame from a 30 fps video files, the frame rate would be 333.3333 milliseconds (ms). A 6 fps sampling rate, which samples every 5th frame of the original video, would thus have shorter elapsed time between frames at 166.6667 ms.

**Workflow > Rectify results**

This will take a few moments, but displays results for every frame pair, which can be navigated through with a slider at the top left of the results window. Move the slider to the very end. The result message will be highlighted green and display the averaged velocity field frame calculated in PIVlab (fig 2.17). This may be the best time to save the RIVeR file.

![Figure A.10) Rectified velocity map derived from the PIV result. Red indicates the highest velocity while blue indicates the lowest velocity. By including the banks in the ROI, the colorbar scales the velocities in reference to the stationary banks so there is a greater contrast between colors.](image)
2.4 Calculating discharge in RIVeR

Workflow > Define Y+ direction

A blue line will appear on the rectified image. Orient the line so that it is parallel to the general direction of flow (fig 2.18). This line indicates the direction of flow. Make sure the slider at the top left of the rectified image is all the way to the right for the averaged velocity field.

Figure A.11) The blue line in the rectified image right, defines the direction of flow to RIVeR before selecting a cross-section.

Cross-Section > Add New > On original image (left)

Left click, hold, and drag a line across the river and double click, in order to get a velocity profile for that transect. For this study, since LSPIV results will be compared with field values, the cross-section drawn was made to match the same transect that was gauged with the flow meter. Name the cross section, then a new window will appear displaying the velocity profile
and data table (fig 2.19). The velocity profile will be either negative or positive depending on which bank the cross-section line is drawn from. It is important to note at this point the station value, which refers to the distance across the profile, in the RIVeR cross-section starts at 0 m from whichever side the cross-section was drawn from. This was often opposite the side that flow meter gauging started from. It is an easy fix, which just requires drawing the cross-section from the other side of the bank and reversing the sign of the velocities.

Figure A.12) Velocity profile and corresponding data table derived from LSPIV velocities.
As was mentioned before, when the profile lengths as measured in the field and by RIVeR are off by a meter or two, the AreaComp2 application does not give accurate discharge measurement. Instead, the data from the table on the cross-section window (fig 2.19) was copied into an excel spreadsheet and scaled so that the depths from the FlowTracker file could be matched with the appropriate station value from the RIVeR data. The velocity results from RIVeR are always given as a set of fifty velocities over the length of the profile. These velocities are multiplied by the measured or assumed depth-averaged velocity correction factor to yield average velocity. The cross-sectional area for each interval multiplied by the LSPIV derived velocity for that interval gives the interval’s discharge. The sum of those values yields the total discharge. Example spreadsheets showing these steps can be viewed in the digital appendix.