Modeling rating curves from close-range remote sensing data
Application of laser and acoustic ranging instruments for capturing stream channel topography
Norris Lam

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Abstract
A rating curve provides a functional relationship between water height (i.e. stage) and discharge at a specified cross-section in a river. Used in combination with a time series of stage, rating curves become one of the central components for generating continuous records of streamflow. Since developing and maintaining rating curves can be time consuming, hydraulic models have shown potential to reduce the effort required for developing rating curves. A central challenge with modeling procedures, however, is the acquisition of accurate stream channel and floodplain topography. From this perspective, this thesis focuses on the real-world application of close-range remote sensing techniques such as laser-based ranging technologies (i.e. Light detection and ranging or LiDAR) or acoustic based ranging technologies (i.e. acoustic Doppler current profiler or ADCP) to capture topographic information for hydraulic modeling applications across various spatial scales. First, a review of the current LiDAR literature was carried out to identify potential ways to take full advantage of these novel data and technologies in the future. This was followed by four interconnected studies whereby: (i) a low-cost custom laser scanning system was designed to capture grain size distributions for a small stream; (ii) synthetically thinned airborne laser scanning (ALS) data was applied in a physically-based hydraulic modelling framework to develop rating curves; (iii) low-resolution national-scale ALS was coupled with ADCP bathymetry to be used in conjunction with a hydraulic model to develop rating curves; and (iv) the impact of measurement uncertainties on generating rating curves with a hydraulic model were investigated. This thesis highlights the potential of close-range remote sensing techniques for capturing accurate stream channel topography and derive from these data, the necessary parameters required for hydraulic modeling applications.

Keywords: laser scanning, acoustic Doppler current profiler, hydraulic modeling, rating curves, Sweden.

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Keywords: laser scanning, acoustic Doppler current profiler, hydraulic modeling, rating curves, Sweden
Sammanfattning


Den här avhandlingen fokuserar på tillämpningen av fjärranalysteknik för avståndsmätning på nära håll, såsom laserbaserade teknik (dvs. Light detection and ranging eller LiDAR) och akustisk baserad teknik (dvs. acoustic Doppler current profiler eller ADCP), för att fånga topografisk information för hydraulisk modellering av vattendrag i olika rumsliga skalor. Först presenteras en litteraturstudie av den nuvarande LiDAR-litteratur för att identifiera potentiella sätt att dra full nytta av dessa nya data och tekniker i framtiden. Detta följs av fyra sammanlänkade studier: (i) tillämpning av ett lågkostnads-laseravsökningssystem för att fånga kornstorleksfördelningar i ett litet vattendrag, (ii) syntetiskt förtonad flygburen laserskanningsdata (ALS) applicerad i en fysiskt baserad hydraulisk modell för att utveckla avbördningskurvor, (iii) lågupplöst ALS från Svensk nationell höjdmodell kopplade med ADCP-batymetri för att ta fram en avbördningskurva med en hydraulisk modell, och (iv) undersökning av effekterna av osäkerheter på måttdata för att generera avbördningskurvor med en hydraulisk modell. Denna avhandling belyser potentialen för fjärranalystekniker för avståndsmätning på nära håll, för att fånga strömfårans exakta topografi och ifrån dessa data härleda de parametrar som krävs för hydrauliska modelleringstillämpningar.
Thesis content

This doctoral thesis consists of a summary text and five papers. The papers will be referred to as Papers I–V in the summary text. The published papers are reprinted with permission from the respective copyright holders.


V. Lam, N., Lyon, S.W., Kean, J.W., Westerberg, I., Beven, K., & Mansanarez, V. Implications of field measurement uncertainties on modeled rating curves. *Manuscript.*
**Author contributions**

I. NL contributed to the early planning of the workshop with SWL and AAH (lead author). NL participated in the workshop and contributed mainly to the paper section entitled ‘advances in hydrology using LiDAR.’ All the authors contributed to the writing of the paper.

II. NM, NLundgren, RR and SWL designed the equipment and experiment. NL participated in the field data collection with NM and NLundgren. NL was responsible for all the data analysis and led the writing of the paper with guidance from SWL. All the authors contributed to the writing of the paper.

III. The experiment was designed by MN and SWL. MN collected the field data. MN and NL completed the hydraulic modeling with assistance from JWK. MR provided the filtering of the LiDAR point clouds. HD and HL helped contextualize the study. NL contributed to the data analysis, hydraulic modeling and writing. All the authors contributed to the writing of the paper.

IV. NL and SWL designed the study. NL collected and processed all the field data and conducted all the hydraulic modeling with guidance from JWK in the early stages. NL analyzed all the results and led the writing of the article with support from SWL. All the authors contributed to the writing of the paper.

V. NL and SWL designed the study with guidance from KB and IW. All the data was collected by NL with assistance from IW on one of the field campaigns. NL conducted all the hydraulic modeling with guidance from JWK in the early stages. NL analyzed the data with guidance from IW, VM and SWL. NL led the writing of the manuscript with support from all the co-authors. All the authors contributed to the writing of the paper.
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Abbreviations and symbols

ADCP – Acoustic Doppler current profiler
ALS – Airborne laser scanning
DGPS – Differential global positioning systems
DTM – Digital terrain model
GPS – Global positioning system
KCS – Krycklan Catchment Study
LiDAR – Light detection and ranging
MC – Monte Carlo
RMSE – Root mean square error
RTK-GPS – Real-time kinematics global positioning systems
SMHI – Swedish Meteorological and Hydrological Institute
TLS – Terrestrial laser scanning
TIN – Triangulated irregular network
TS – Total station

\( D_{84} \) – 84\(^{th}\) percentile of a grain size distribution
\( h \) – Stage
\( n \) – Manning’s \( n \)
\( Q \) – Discharge
\( R \) – Hydraulic radius
\( z_o \) – Roughness height
1 Introduction

Freshwater resources are essential for sustaining all life on earth and this limited resource is currently under threat due to human and climate induced changes (Döll 2009; IPCC 2014). Robust monitoring strategies of fresh water resources are required for assessing the social and ecological impacts of these threats on future water availability (Vörösmarty et al. 2001; Hossain et al. 2011). Since streams are an integral piece of the freshwater cycle, the ability to accurately and consistently monitor the amount of water flowing in streams becomes paramount in hydrology. Reliable streamflow information is important for calibrating hydrologic models (Wi et al. 2015), monitoring pollution and biogeochemical transport (Futter et al. 2010; Laudon et al. 2011; Peterson et al. 2013) and managing flood risks (Stedinger et al. 1993).

Despite the importance of streamflow information, stream discharge is however rarely measured directly. Instead, streamflow is typically determined by converting water depth in the stream (i.e. stage) into discharge through a rating curve (Rantz 1982; Herschy 2009). A rating curve provides a functional relationship between stage and the discharge at a specified cross-section in a river. Rating curves can be (and often are) empirically derived from simultaneous stage-discharge measurements (i.e. gaugings). Even though such empirical methods are considered robust and are the most common methods for developing rating curves, some challenges remain. For example, collecting the required gauging measurements can be costly due to the need for frequent field measurement campaigns for maintaining the rating curve, the measurements can be dangerous or impossible to obtain at high flows, and unsteady flow conditions (i.e. hysteresis effects due to flood wave propagation) have the potential to increase measurement uncertainties. Furthermore, stage-discharge relationships are seldom constant in space or time. For example, overbank flood events can accelerate erosion and sedimentation processes thereby affecting stream channel morphology (Rumsby and Macklin 1994; Nardi and Rinaldi 2014). This, in turn, can lead to increased rating curve uncertainty when not properly accounted for in post flood event monitoring (Westerberg et al. 2011; Juston et al. 2014; McMillan and Westerberg 2015) and, in the worst case, the need to totally re-establish the rating curve (World Meteorological Organization 2010). Looking globally, these challenges for establishing and maintaining rating curves could be exacerbated in regions where climate change effects have increased the frequency of flooding (Milly et al. 2005; Hirsch and Archfield 2015; Mallakpour and Villarini 2015), which has direct consequence for managing water resources as climatic patterns are expected to become more drastic in the future (Park et al. 2011; IPCC 2014). Therefore, methods that can quickly and (potentially more importantly) accurately develop rating curves would be helpful for assessing the relative stability of existing rating curves and streamflow information. Such methods would be beneficial for monitoring potential changes to future water resources across various locations.

One alternative approach to empirical methods for developing or maintain rating curves is to estimate streamflow from flow resistance equations or hydraulic models for a monitored stream reach. Developing rating curves from such modeling methods have been shown useful for extrapolating rating curves beyond available gauging measurements (Lang et al. 2010; Di Baldassarre and Claps 2010), generating rating curves for ephemeral or ungauged streams (Bullard et al. 2007; Clayton and Kean 2010) and investigating the effects of rating curve hysteresis (Petersen-Øverleir 2006; Muste and Lee 2013; Pietroń et al. 2015). In general, such methods require less time and effort, compared to empirical methods, as discharge can be predicted from a smaller number of coupled stage and discharge measurements. However, a
central challenge with hydraulic modeling efforts is the acquisition of accurate stream channel and floodplain topography, which is a cornerstone for these approaches.

Topographic information, along with gauging measurements, are commonly used to quantify flow resistance in submerged river channels. The most common flow resistance equations (e.g. Chezy 1776; Manning 1891) are quite similar in their formulation and share a common reliance on empirical roughness coefficients for determining discharge (Powell 2014). Empirical roughness coefficients (i.e. Manning’s $n$) are implemented in popular hydraulic modeling packages such as HEC-RAS developed by the U.S. Army Corps of Engineers’ River Analysis System and MIKE 11 by the Danish Hydraulic Institute. The use of empirical roughness coefficients in hydraulic models has been openly criticized owing, for example, to the subjectivity with which they are often prescribed (Lane 2005; Ferguson 2010). This debate around the subjectivity has led to the development of alternative methods for quantifying roughness by, for example, explicitly determining flow resistance from geometric measurements of the stream channel topography (Kean and Smith 2005; Lane 2005; Smith et al. 2007). Regardless of the chosen method for quantifying and representing flow resistance, accurate measurements of the stream channel structure are required for constraining any subsequent hydraulically modeled flows (Casas et al. 2006; Legleiter et al. 2011).

In this regard, recent technological advances in close-range remote sensing, such as laser-based ranging technologies (i.e. Light detection and ranging or LiDAR) or acoustic based ranging technologies (i.e. acoustic Doppler current profiler or ADCP), can help provide accurate topographic information for hydraulic modeling applications. These instruments enable repeat and precise collection of three-dimensional information of the Earth’s surface characteristics at various spatial scales. The different ranging techniques (i.e. light or acoustic based) each have their own advantages and limitations, however, both ranging technologies operate based upon a similar principle. Distance to an object is determined by (1) emitting an energy pulse (e.g. light or sound pulse), (2) measuring the round-trip travel time of the reflected signal and (3) taking half the product of the round-trip travel time and the speed of the energy pulse (Gordon 1996; Shan and Toth 2009). The resulting point measurement contains, at a minimum, positional information in three-dimensions for the target object where the collection of measured points is commonly referred to as a point cloud. These technologies have great potential for improving our ability for monitoring and observing changes in riverine environments (Dinehart and Burau 2005; Maxwell and Smith 2007; Hohenthal et al. 2011; Glennie et al. 2013; Harpold et al. 2015) as accurate area measurements can be collected in a relatively short period compared to more traditional manual surveying methods.

From this perspective, and with an eye towards real-world applications, this thesis focuses on the application of close-range remote sensing techniques to acquire stream channel topography and derive from these data, the necessary parameters required for hydraulic modeling applications. More specifically, the objectives of this thesis are:

A. Investigate the potential of close-range remote sensing for capturing stream channel topography at various spatial scales.
B. Evaluate the performance of these topographic data for generating rating curves within a physically-based one-dimensional hydraulic modeling framework.
C. Quantify the potential impact of measurement uncertainties on rating curves developed with a 1-dimensional hydraulic model.
The work presented in Papers I–V address these thesis objectives. An overview showing how the objectives were addressed through Papers I–V is provided in Table 1. Paper I is a review of LiDAR applications in critical zone science and provides the motivation for the endeavor of this thesis. Paper II focuses on developing a custom laser scanner and analysis method for estimating grain size distributions and Manning’s roughness values for a stream channel. Papers III investigates the potential of using synthetically thinned airborne laser scanning (ALS) data for generating rating curves in a 1-dimensional hydraulic modeling framework. Paper IV demonstrates the potential of capturing stream channel topography by coupling ALS data and ADCP bathymetry data for modeling rating curves. Paper V explores the collective effects of input measurement uncertainties on rating curve modeling within a simple Monte Carlo (MC) framework.

<table>
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<tr>
<th>Objectives</th>
<th>Paper</th>
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<tr>
<td>Investigate potential of close-range remote sensing for capturing stream channel topography</td>
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<td>Evaluate performance of close-range remote sensing data for generating rating curves</td>
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Table 1 - Overview of how thesis objectives were addressed with the papers included as part of the thesis.
2 Background

2.1 Manual surveying methods

Stream channel topography is commonly obtained through manual surveys of the river banks and submerged channels. Nowadays, these manual surveys can be acquired with total stations (TS) (Fuller et al. 2003; Nathanson et al. 2012) or high-precision global positioning systems (GPS) (Wheaton et al. 2010; Kean and Smith 2010) or a combination of these methods (Brasington et al. 2000). TS measurement systems resolve distances and angles between the instrument itself and a target. Typically, the target is a prism mounted on a rod of known length, also known as a prism rod. Collecting elevation measurements requires a clear line of sight between the TS and prism rod, which can be a limitation in areas of dense foliage. Topographic information collected from these instruments can be used both as ground-truth data for evaluating other topographic survey data and for improving the spatial positioning of existing topographic data (Paper IV). Manual topographic surveys are often collected as full or partial transects perpendicular to the stream reach and then interpolated as continuous grid surfaces for defining model domains in hydraulic modeling applications. Of course, complete bank-to-bank transects are only possible if the submerged stream can be waded.

While manual surveying techniques are generally precise, they are typically used for collecting low density measurements because of the effort required for covering large areas, hence the collection of transects surveys. However, manually surveying large areas at high measurement densities is definitely possible given enough time and effort. Brasington et al. (2000) demonstrated this by surveying a 200 m by 80 m braided gravel-bed river at point densities between 0.001 and 4.5 points/m² with a real-time kinematics global positioning systems (RTK-GPS) and a TS. The reach was surveyed for two time periods and the field data collection took 7 and 10 days respectively. Although, this study illustrated the possibility of generating precise high-resolution DEMs of the stream channel, it is clear that manually surveying extensive stream and riparian areas is laborious. Reducing the effort required could be addressed through surveying portions of the stream channel and augmenting these data with those acquired from other surveying methods such as LiDAR (Paper III, Paper IV).

2.2 Light detection and ranging (LiDAR)

Laser-based ranging techniques determine distances to objects by emitting laser light pulses and recording the backscattered energy with an optical receiver (Shan and Toth 2009). The return laser pulse can be represented as a discrete return containing only the time of travel and return signal intensity or as a full waveform signal illustrating the spectral signature of the sampled backscattered laser pulse (Glennie et al. 2013). Depending on the method of instrument deployment, laser-based ranging techniques can acquire topographic information (i.e. point clouds) at the landscape scale (> 1000km²) and at spatial resolutions capable of capturing fine-scale features (< 10 cm). LiDAR data are commonly acquired from airborne laser scanners (ALS), terrestrial laser scanners (TLS) and mobile laser scanners (MLS). ALS systems are typically deployed from fixed-wing aircraft and helicopters, and are equipped with a GPS and inertial measurement unit (IMU) to enable the tracking of the orientation and location of the scanner for geometric calibration and georeferencing the individual points. ALS systems have the benefits of being able to cover relatively large geographical areas while collecting elevation
information below the vegetation canopy at measurement point densities that are practically impossible to obtain from traditional surveying methods (Höfle et al. 2009; Legleiter 2012; Glennie et al. 2013). TLS systems are typically mounted on tripods or other fixed locations and fixed targets surveyed with high-resolution GPS are used to georeferenced the LiDAR data into a single coherent point cloud.

TLS has the benefit of collecting high density point clouds that enable the observation of small-scale process such as mapping stream channel topography at the grain scale (Heritage and Hetherington 2007; Hodge et al. 2009; Smith et al. 2012). MLS systems are deployed from moving platforms such as vehicles and boats and are advantageous for collecting point clouds with spatial resolutions similar to TLS but at a greater spatial coverage. The high spatial resolution and coverage of MLS have enabled the 3D mapping of urban areas (Haala et al. 2008), extraction of painted road markings (Guan et al. 2014) and capturing fluvial processes and shallow bathymetry (Kukko et al. 2012; Vaaja et al. 2013). It is clear that advancements in LiDAR technologies have enabled quantification of topographic, vegetative, and hydrological processes at various spatial and temporal scales (Hohenthal et al. 2011; Harpold et al. 2015) not possible with manual surveying methods.

Furthermore, the application of LiDAR based studies are likely to increase given the current trend towards open access LiDAR data and processing tools, such as the OpenTopography initiative (Krishnan et al. 2011). The increase in open access data for research can also be seen in the various national-scale ALS scans on offer. For example, Denmark provides publicly available ALS data at resolutions of about 0.5 points/m² through their online Kortforsyningen portal (https://download.kortforsyningen.dk/) whereas Sweden offers national-scale ALS datasets for academic purposes with a density of about 1 points/m² to 0.5 points/m². As outlined in Paper I, the increased availability of LiDAR data can lead to improved characterization of the earth’s surface. In Papers III and IV of this thesis, this potential is realized, for example, through characterizing stream channel topography for generating rating curves with a hydraulic model.

LiDAR offers exciting potential for capturing high-resolution area-wide elevation information for fluvial applications (Hilldale and Raff 2008; Hodge et al. 2009b; Vaaja et al. 2013); however, typical laser scanning systems that employ infrared laser light (e.g. 1064 nm) generally cannot acquire submerged stream channel topography. This is because of the strong attenuation of infrared light by the water column. Stream channel topography can be obtained from bathymetric LiDAR systems that combine a traditional infrared laser scanner with a supplementary blue-green laser operating at a wavelength of 532 nm. The additional laser is able to penetrate the water column as the wavelength of the blue-green laser pulse is weakly attenuated by the water column. These bathymetric LiDAR systems enable the collection of coherent point clouds of the land and submerged topography. These bathymetric LiDAR systems have proven effective for providing accurate topographic information in hydraulic modeling applications (Guenther et al. 1994; Kinzel et al. 2013; McKean et al. 2014; Mandlburger et al. 2015).

The main challenges with bathymetric LiDAR systems are the corrections required for the laser pulse when it passes through the air–water interface in both the incoming and outgoing directions. These corrections include the change in laser pulse speed when passing through the different medium (i.e. air or water) and distortions due to the refraction of light at the air–water interface. Distortion of the laser pulse due to the refraction of light at the air–water interface results in the laser pulse footprint to be much larger on the submerged ground surface. Because these corrections are required in both the incoming and outgoing directions, improper
representation of the water surface can lead to increased measurement uncertainties (Guenther et al. 2000; Mandlburger et al. 2015). Furthermore, water quality and sediment load can also impact the reflected laser pulse signal strength whereby depth measurements are often limited to between 1 and 2 Secchi depths (Wang and Philpot 2007). The Secchi depth is a water clarity measurement whereby a black and white disc is lowered into the water until it is no longer visible to the human eye (World Meteorological Organization 1994). More recent bathymetric LiDAR systems, such as Hawkeye II (now superseded by Hawkeye III, see Leica Geosystems 2015), have been shown effective for collecting river bathymetry corresponding to five Secchi depths but measurement density was reduced at depths greater than 2.9 m (Bailly et al. 2010). These new bathymetric LiDAR systems show great promise for collecting river bathymetry but data from such systems are not yet widely available.

2.3 Acoustic Doppler current profilers (ADCP)

Acoustic-based ranging techniques operate by emitting acoustic pulses and recording the back scattered signal. Acoustic-based ranging techniques have an advantage over laser-based systems for collecting bathymetry because the instruments are deployed just below the water surface. This means the emitted and backscattered acoustic pulses remain only in the water and corrections for signal refraction are not required. Therefore, acoustic-based ranging instruments are well-suited for capturing bathymetry in various types of water (i.e. lakes, oceans, rivers). Examples of acoustic-based ranging instruments include sonar, echo-sounders and ADCP. Sonar and echo-sounders are commonly used to acquire water depth in lakes and oceans while ADCP are usually deployed in rivers to simultaneously collect water velocity and water depth for the purpose of estimating discharge (Gordon 1996).

ADCP collect water velocity and depth information by emitting multiple acoustic pulses at various audio frequencies and pulse lengths and recording the backscattered signal. Water velocity is determined using acoustic pulses of higher frequency and shorter length. These pulses are typically emitted from several transducers mounted at an angle from nadir and the backscattered energy from suspended particles in the water column is recorded. The phase change due to the Doppler shift in the backscattered pulse is used to determine flow direction and water velocity for various depths cells in the water column. Water depth and the positioning of the ADCP, when mounted to a boat, can be determined by measuring the Doppler shift in lower frequency acoustic pulses of longer length that echo off the river bed, also referred to as bottom-tracking. Bottom-tracking information is obtained from a dedicated transducer mounted at nadir and is typically used to correct for boat velocity when determining absolute water velocities. Bottom-tracking corrections can be biased by particles moving along the streambed, which can lead to increased uncertainty in the discharge measurements when not properly considered (Rennie and Church 2010; Williams et al. 2015). Improving the spatial position of the ADCP boat, particularly for mobile bed conditions, can be achieved with differential global positioning systems (DGPS) or real-time kinematics global positioning systems (RTK-GPS). Additionally, georeferencing the depth measurements allows the coupling of the bathymetry with elevation data obtained from other topographic surveying methods such as LiDAR. From the perspective of hydrometric agencies, ADCP may be one of the most viable options for collecting river bathymetry because application of these instruments are well established and are the preferred measurement technique for various national hydrometric agencies (Mueller and Wagner 2009; SMHI 2014).
2.4 Open-channel flow and hydraulic modeling

The flow of water in open-channels is governed by the forces of gravity and friction. The downhill flow of water is made possible by gravity whereas friction forces dissipate the energy to slow down the flow of water (Wohl 2014). The flow of water in open-channels can be classified according to the change in velocity with respect to time and space. With respect to time, flow is said to be steady when the velocity is constant through time or is unsteady (and varied) when the velocity varies through time. Flow in natural open-channels is typically considered to be varied (gradually or rapidly). With respect to space, flow is said to be uniform when the velocity is constant in the channel or the flow is non-uniform or varied when velocity varies spatially in the channel.

Predicting unsteady non-uniform flow is typically achieved with the Saint-Venant equations that are based on the continuity and momentum equations. However, due to the mathematical complexity of the full Saint-Venant equations, simplified versions of these equations are typically used (Maidment 1992). An example of a simplified version of the Saint-Venant equations for one-dimensional steady non-uniform flow is implemented in the hydraulic model (Kean and Smith 2005; Kean and Smith 2010) used in Papers III, IV and V of this thesis (model is further described in Section 4.4). The equations governing a simple steady, one-dimensional flow conservation of mass ($\frac{\partial Q}{\partial x} = 0$) and momentum is:

$$\frac{1}{2} \frac{\delta (u^2)_{av}}{\delta x} + g \frac{\delta E}{\delta x} + \frac{1}{\rho} \frac{\tau_b}{R} = 0$$

where $(u^2)_{av}$ is the square of the downstream velocity component averaged over the cross section, $x$ is the downstream direction, $g$ is the acceleration of gravity, $E$ is the water surface elevation, $\rho$ is the density of water, $(\tau_b)_{av}$ is the perimeter-averaged shear stress, and $R$ is the hydraulic radius of the cross-sectional area. The streamwise change of velocity is described by the first term of Equation (1); the pressure-gradient changes due to streamwise changes of water-surface elevation is described by the second term, and the resistance contributions is described by the third term. The resistance term can be estimated in a number of ways. For the modeling carried out in this thesis, the roughness of the streambed was estimated as a roughness height ($z_o$). For stream channels where a grain size distribution of the streambed can be obtained, $z_o$ can be approximated by $z_o = 0.1D_{84}$ where $D_{84}$ represents the 84th percentile of a grain size distribution (Whiting and Dietrich 1990).

An alternative to the Saint-Venant equations is the empirically derived Manning’s equation for predicting uniform flows in metric units:

$$V = \frac{2}{R^{\frac{3}{2}} S^{\frac{1}{2}}}$$

where $V$ is the mean channel velocity, $R$ is the hydraulic radius, $S$ is the slope of the energy line (in uniform reaches, equal to the bed and water surface slopes) and $n$ is the coefficient of roughness referred to as Manning’s $n$ (Gordon et al. 2004). This formula, which finds a home in many engineering applications, was derived from experimental data collected on artificial and natural channels and is the most widely used uniform-flow equation for open-channels. Determining the appropriate $n$ values for a given channel can be accomplished by taking measurements of velocity, hydraulic radius and energy slope to solve for $n$ in Equation (2). If these measurements are not available, lookup tables of predefined values (see pages 109–113
in Chow (1959)) can be used. Manning’s roughness coefficient can also be determined as a function of the diameter of the streambed material obtained from a grain size distribution with Strickler (1924):

\[ n = \frac{d^6}{21.1} \]  

(3)

where \( d \) is a grain size diameter in meters with the median grain size typically used (Gordon et al. 2004). Manning’s \( n \) has also been estimated, for example, as a function of the hydraulic radius of the channel using the empirical equation of Limerinos (1970):

\[ n = \frac{0.1129R^\frac{1}{5}}{1.16 + 2.0 \log \left( \frac{R}{D_{84}} \right)} \]  

(4)

where \( R \) is hydraulic radius (m) and \( D_{84} \) is the 84\textsuperscript{th} percentile (m) of the grain size distribution for the reach. With an eye towards hydraulic modeling, Paper II demonstrates the ability of a custom laser scanner for collecting the hydraulic radius and grain size distribution for estimating Manning’s \( n \) with Equations (3) and (4). As such, there are clear opportunities when it comes to combining recent advances in technologies associated with measuring stream channel geometries and the increased accuracy of streamflow measurement techniques with hydraulic modeling approaches.
3 Study sites

Figure 1 – Overview map of Sweden (left) and photographs of the study locations (right) presented in this thesis.

The research in this thesis was carried out in Sweden at four streams of various size (Figure 1). A summary of the site characteristics is provided in Table 2. The smallest stream is about 1 m wide and 0.5 m deep while the largest stream is about 30 m wide and 5 m deep. Papers II and III were carried out at two regularly monitored field sites (i.e. main outlet and Kallkålshöken) within the Krycklan Catchment Study (KCS). Paper IV was carried out at the Röån gauging station and Paper V was carried out at the Nybro gauging station. The water at all four study sites is brown in color due to the high levels of dissolved organic matter (Ekström 2013). As such, the stream bottom is not visible with the naked eye at the study sites for Papers III, IV and V.

Table 2 – Overview of study sites presented in this thesis.

<table>
<thead>
<tr>
<th>Paper</th>
<th>Name and coordinates</th>
<th>Drainage area (km²)</th>
<th>Channel width (m)</th>
<th>Channel depth (m)</th>
<th>Minimum flow (m³/s)</th>
<th>Median flow (m³/s)</th>
<th>Maximum flow (m³/s)</th>
<th>Estimated Dₘₙₐₛ (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>II</td>
<td>Kallkålshöken (64°12’N, 19°46’E)</td>
<td>0.5</td>
<td>1.0</td>
<td>1.0</td>
<td>0.00008</td>
<td>0.402</td>
<td>0.10</td>
<td>0.090</td>
</tr>
<tr>
<td>III</td>
<td>Main outlet KCS (64°12’N, 19°52’E)</td>
<td>67.0</td>
<td>6.5</td>
<td>1.5</td>
<td>3.0</td>
<td>0.3</td>
<td>8.5</td>
<td>0.23</td>
</tr>
<tr>
<td>IV</td>
<td>Röån station (63.64°N, 15.76°E)</td>
<td>584.0</td>
<td>10.0</td>
<td>2.4</td>
<td>1.9</td>
<td>58</td>
<td>15.9</td>
<td>0.98</td>
</tr>
<tr>
<td>V</td>
<td>Nybro station (61.36°N, 15.53°E)</td>
<td>2251.0</td>
<td>30.0</td>
<td>5.3</td>
<td>4.3</td>
<td>2.9</td>
<td>218.9</td>
<td>0.23</td>
</tr>
</tbody>
</table>
3.1 Papers II & III Krycklan Catchment Study (KCS)

The KCS is a 67 km² basin located at approximately 64°12’ N and 19°52’ E in the Svartberget Experimental Forest approximately 50 km northwest of Umeå, Sweden (Laudon et al., 2013). The geology of the KCS is primarily dominated by glacial till and thin soils (Cory et al. 2009). The topography is gently undulating with elevations between 127 and 372 m a.s.l. The catchment is comprised of coniferous forests (88 %), wetlands (8 %), agricultural lands (3 %) and lakes (1 %). At KCS, the stream monitoring network is made up of 15 sub-catchments with areas ranging from 0.03 km² to 67 km². Continuous research in the KCS includes several multidisciplinary research topics related to water quality, hydrology, stream biodiversity and climate effects in the boreal landscape (Bishop et al. 1990; Grabs et al. 2012; Nathanson et al. 2012; Lyon et al. 2012; Tetzlaff et al. 2015).

3.1.1 Kallkälbsäcken outlet

Paper II was carried out at the outlet of the Kallkälbsäcken catchment (often referred to as C7 or dammhuset) within the KCS. This second order stream drains an area of 0.48 km² and the landscape immediately surrounding the study area is dominated by glacial till with mature Norway spruce on thin soils (Cory et al. 2009). A 5 m by 2 m reach area was chosen for the study since this section of stream channel is well defined and consists primarily of pebbles, stones and sand. The stream channel is about 1 m wide and 1 m deep with an average streambed slope of about 4 %. The riparian vegetation along the streambanks consists mainly of mosses, grasses as well as small shrubs and ferns. Moss was observed on the tops of some pebbles and stones within the stream channel (Figure 2e). A 90° V-notch weir maintained in a small heated house is used to monitor the year-round streamflow at the Kallkälbsäcken catchment outlet (Laudon et al. 2011). The median daily streamflow is about 2.4 L/s and the recent minimum and maximum streamflow were 0.08 L/s and 100.20 L/s, respectively.

3.1.2 Main Outlet of KCS

Paper III was carried out at the main drainage outlet of the KCS for a 90-m long stream reach. The study reach was located downstream from a staff gauge installed in a stilling well. The reach topography along the west side of the stream is steep while the east side is relatively flat. The floodplain on both sides of the main stream channel is about 1.5 m above the low flow water level with dense deciduous shrubs and small trees close to the stream. The wetted width of the stream reach is approximately 6.5 m at low flow and 8m at high flow. The streambed consists of sand and gravels, and as such, sand ripples and sand dunes are found along the stream channel profile. The average water surface drop of the surveyed reach is 0.004 m/m and was measured at both high and low flows. Low flow conditions in the autumn is approximately 0.6 m³/s while the peak discharge during the spring flood can exceeding 8 m³/s. For this study, the empirical rating curve was defined as \[ Q = 3.6 \ h^{2.5} \] \[ (r^2 = 0.91) \] based on approximately four years of direct observations collected between 2009 and 2012 (Nathanson et al. 2012).

3.2 Paper IV - Röån gauging station

Paper IV was carried out at the Röån River located in northern Sweden (63.64 °N, 16.76°E). The stream drains an area of 584 km² and the landscape in the catchment consists of rolling hills with a mixture of clay-silt and sandy soils. A 10 m wide and 80 m long reach was chosen
for this study. A small pedestrian bridge is located at the upstream end of the reach and this was used to deploy the surveying equipment used in this study. Backwater effects due to the bridge piers were not observed during the field surveys. The study reach is straight and excessive bank erosion was not observed. The river channel is moderately sloped along both streambanks and the riparian vegetation found on both banks consists mainly of young willow, alder, tall grasses and sedges with stem diameters less than 10 cm. The material of the streambed is composed of gravels and sand, and large roughness elements (e.g. boulders and fallen trees) were not observed in the main stream channel.

The Röån gauging station is located at the downstream end of the study reach and is operated by the Swedish Meteorological and Hydrological Institute (SMHI). The gauging station collects daily average stage with a float and the stage values are converted to flow through the official rating curve. Both the stage measurements and official rating curve were not available for the study. According to SMHI’s online database Vattenwebb (http://vattenwebb.smhi.se/station/), the annual minimum, mean and maximum discharge is 1.9 m$^3$/s, 5.8 m$^3$/s and 15.9 m$^3$/s, respectively. The empirical rating curve for this study was defined as the least squares fit to available SMHI gaugings following the form:

$$Q = b_0 h^2 + b_1 h + b_2$$

(5)

where $Q$ is discharge, $h$ is stage, and $b_0$, $b_1$ and $b_2$ are constants with values 7.2 s$^{-1}$, -91.8 m s$^{-1}$ and 290.4 m$^3$ s$^{-1}$, respectively ($r^2 = 0.97$).

3.3 Paper V - Nybro gauging station

Paper V was carried out at the Nybro station that is located on the Voxnan River in central Sweden (61.36°N and 15.53°E). The stream drains an area of 2251 km$^2$ where approximately 15% of the catchment area is regulated for hydropower generation. The topography in the catchment is characterized by rolling hills and soils consisting of mainly glacial till and sand. A 30 m wide by 300 m long study reach was chosen for this study. The study reach is straight and excessive bank erosion was not observed during the field campaigns. The streambanks are moderately steep and composed of sand and gravels. Large diameter roughness elements such as boulders are only found outside of the study area (i.e. under the vehicle bridge). The vegetation found on both banks consists of young and mature birch, spruce and willows. Small diameter (< 0.10 m) vegetation is found closest to the water’s edge while the larger diameter (> 0.10 m) vegetation is found near the tops of the banks.

The Nybro stream gauge is located at the downstream end of the study reach and is monitored by SMHI on behalf of the Ljusnans vattenreleringsföretag. The gauging station collects stage with a bubble-gauge sensor at 15-minute intervals and the stage record used in this study was collected between July 1, 1992 and July 1, 2016. Based on this stage record and the official rating curve, the minimum, median and maximum discharges of 4.31 m$^3$/s, 21.86 m$^3$/s, and 218.93 m$^3$/s, respectively. The estimated bankfull discharge in the study reach is 199.17 m$^3$/s (i.e. stage = 193.27 m) and one out-of-bank flood event was recorded in 2000 that coincides with the previously mentioned maximum discharge. In addition, two near-bankfull events were recorded with discharges of 170.75 m$^3$/s and 189.34 m$^3$/s and these occurred in 1995 and 2001, respectively. The official rating curve, which has been valid since 1991, was based on thirteen gaugings made by SMHI (hereafter called evaluation gaugings) and consists of two power law functions intersecting at 191.21 m stage. Permission to reprint the empirical rating curve equation was not granted.
4 Materials and methods

4.1 LiDAR literature review (Paper I)

In Paper I and as a motivation for the thesis, a review of 147 LiDAR published peer-reviewed articles was conducted to investigate the potential transdisciplinary use of LiDAR for furthering critical zone (CZ) science. CZ research is a holistic approach that focuses on the interactions between the geosphere, hydrosphere and biosphere for maintaining life-sustaining resources (http://criticalzone.org/national/). The included articles were gathered via an expert survey of the current literature conducted as the result of a 3-day workshop entitled “The Next Generation of LiDAR Analysis for Critical Zone Research” held in Boulder, Colorado, USA on 12–14 May 2014 (Harpold et al. 2014). A ranking system was devised whereby each article was evaluated based on their contribution for advancing process knowledge within three disciplines (i.e. geomorphology, hydrology and ecology). A maximum of 10 points, partitioned among the three disciplines, were given for each study whereby the summation of points would not exceed 10 for each study. For example, a purely hydrologic study would have been assigned 10 points in the hydrology category, 0 in geomorphology and 0 in ecology. A transdisciplinary study balancing geomorphology, hydrology and with a slight skew towards ecology would have received 3,3,4 points, respectively. To limit the subjectivity of such a ranking system, each paper was assigned three different authors for independent scoring.

4.2 Determining channel roughness with custom laser scanner (Paper II)

Paper II estimated a grain size distribution and Manning’s $n$ at various stages using a custom-built low-cost laser scanning system. A low-cost laser ranging system (SICK LSM111) was adapted to obtain area scans of a temporarily diverted stream channel. The LSM111 employs a near-infrared (NIR) pulsed laser diode operating at a wavelength of 905 nm and the minimum footprint of each laser pulse is 17 mm at 1 m distance with a systematic error of ±30 mm (SICK AG 2008). On its own, the LSM111 camera is only capable of scanning along a single plane at a 270° field of view (FOV). However, area scans can be acquired by moving the laser scanner in a fixed trajectory and constant speed. As such, a custom gondola was built to house the SICK LSM111 and all the necessary components for collecting area laser scans. The components included a drivetrain, Arduino Uno microcontroller (http://arduino.cc/), wireless router and battery power supply. The system was designed to be suspended from a taught cable suspension system to capture the area below the laser scanner (Figure 2).
The weight of the laser scanning system caused the suspension system to stretch, resulting in a sag of the main suspension cable. This sagging of the cable was manifested as a parabolic distortion in the resulting point cloud. To correct for this distortion, a reference cable was setup within the FOV of the laser scanner and perpendicular to the main suspension cable. The reference cable appeared as a parabola in the point cloud and the distortion of the stream channel was corrected by fitting a quadratic equation to the entire area scan. Effects due to yaw, pitch and roll were not considered in this study. Influence of the bed slope on the corrected point cloud was removed and roughness elements were extracted from the point cloud using the proprietary VRMesh software (http://www.vrmesh.com/). A grain size distribution was generated from the extracted roughness elements using a local maxima search algorithm. The resulting grain size distribution was compared to three Wolman pebble counts (1954) and the relative roughness was estimated as Manning’s $n$ coefficient with Equations (3) and (4).

4.3 Airborne laser scanning and acoustic Doppler current profiler surveys (Paper III, IV and V)

Paper III investigated the effects of ALS point cloud resolution on modeling rating curves. This was accomplished by thinning high-resolution ALS data to similar point spacing as national-scale laser scanning data (about 0.5 points/m$^2$). The high-resolution ALS data were acquired using a helicopter-mounted TopEye MkII S/N 425 (Blom 2008) at an average point density of about 2.7 points/m$^2$. The infrared light used by the TopEye MkII was absorbed by the water column and therefore, a manual survey of the bathymetry was required to augment the ALS data for submerged stream channel areas. The manual TS survey was collected with a Trimble S6 robotic total station (Trimble Navigation Limited 2013) and an adjustable prism rod. Georeferenced control points were captured with a Trimble R10 real time kinematic global navigation satellite system (RTK-GNSS) (Trimble Navigation Limited 2014) and used to georeference the manual TS surveys. A total of 29 cross-sections were surveyed along the 90 m reach. This survey system (i.e. S6 and R10) was used to collect and georeference all the
manual surveys for Papers III–V. The ALS and TS surveys were merged and a systematic thinning of elevation information was carried out on the merged topographic and high-resolution ALS surveyed data. In addition to the previously described survey-augmented ALS data, one topographic dataset consisting of the original high-resolution ALS topography with a flat stream bottom was also implemented in the study. For this case, a horizontal line was extended from the lowest available ALS topography point and assumed to represent the bottom of the stream channel. A flat bottom assumption such as this has been previously shown to have minimal impact at this site (Nathanson et al. 2012). This additional dataset was included to provide a potentially “more representative” case of ALS data obtained from a national-scale survey.

To simulate the potential impacts of using lower-resolution scanning within subsequent hydraulic modeling, the merged topographic and high-resolution ALS surveyed data were thinned by removing points within a 3D search radius. The procedure starts by randomly selecting an initial base point and all the subsequent points within a specified search radius are removed. The point thinning was applied for search radii ranging from 0.25 m to 2.00 m and resulted in average point densities ranging from 2.2 points/m² to 0.2 points/m². Although all the thinned ALS scans were implemented in the hydraulic rating curve modeling, only the results for the “most thinned” data (i.e. 0.2 points/m²) were retained and tested in Paper III. These data represent a worst case scenario relative to the specification of the Swedish ALS mapping project (Lantmäteriet 2012). The thinned topographic data were interpolated into curvilinear grids that defined the modeling domain of the hydraulic model and rating curves were developed from these grid surfaces.

Paper IV looked at the potential of coupling ALS and ADCP bathymetric data for developing rating curves. Here, the ALS data are an actual subset of the Swedish national laser scanning survey (Lantmäteriet), rather than ALS that was synthetically thinned to a comparable resolution (Paper III). The data were obtained from Lantmäteriet’s online repository (http://www.geolex.lm.se/). The average point density of the scan scene was 1 point/m². The ALS survey at the Röån River was collected from a fixed-wing mounted Optech ALTM Gemini system (Optech 2007) on 28 June 2012. The Gemini uses a near-infrared laser with a wavelength of 1064 nm and as such, the laser light was unable to penetrate the water column. This resulted in no bathymetric information being collected in this ALS scan scene. A visual inspection of the point cloud indicated that some of the ground, vegetation and water class points were poorly classified. This was primarily due to the classification of the water boundary from existing maps and dense riparian vegetation along the channel banks.

A reclassification of the point cloud (i.e. subset of the Swedish national laser scanning survey) was carried out using the LASTools software suite (Isenburg 2015), which has been shown to have good performance for a variety of terrain (Korzeniowska et al. 2014). Visual inspection of the reclassification indicated a reduction in the number of misclassified ground and vegetation points relative to the original classification. A comparison of the reclassified ground points with a triangulated irregular network (TIN) surface derived from a reference manual TS survey collected along the streambanks revealed a systematic over-estimation of elevation for the ALS point cloud. According to the American Society of Photogrammetry and Remote Sensing (ASPRS) Positional Accuracy Standards for Digital Geospatial Data (Abdullah et al. 2015), the root-mean-square-error (RMSE) can be used to correct the point cloud given the residuals between the reference surface (i.e. TIN surface) and ALS are normally distributed. To facilitate the correction of the ALS data, the distribution of the elevation residuals was statistically tested and found to follow a normal distribution. Therefore, the point cloud was block corrected using the RMSE (equal to 0.36 m) calculated from the ALS data and TS derived
TIN surface. The corrected ALS data were then coupled with bathymetry obtained from an ADCP survey.

The bathymetric information and one discharge value was collected with a SonTek RiverSurveyor M9 multi-beam ADCP and RTK-GPS receiver. The M9 was deployed using the moving-boat method to survey 17 evenly spaced cross-sections along the 80 m stream reach. These were oriented perpendicular to the stream channel, spaced approximately 5 m apart and coincided with the manual TS survey transects of the streambanks. Each cross-section was surveyed twice, resulting in 34 survey transects, and three additional passes were made in the up- and downstream directions to improve the spatial coverage of the bathymetric survey.

To assess the impacts of the ALS correction, three realizations of the stream channel topography were interpolated as curvilinear grids or digital terrain models (DTM) that defined the modeling domain of the hydraulic model. These DTMs were derived from coupling (1) the uncorrected ALS and ADCP bathymetry, (2) the corrected ALS and ADCP bathymetry, and (3) the manual TS and ADCP bathymetry. Hereafter, these will be called ALS/ADCP, UALS/ADCP and TS/ADCP, respectively. In addition, all three DTMs used the same ADCP bathymetric information for defining the submerged stream channel.

Paper V examined the effects of uncertain measurements on rating curve uncertainties made via a hydraulic model. The input measurement uncertainties were propagated to rating curves using MC realizations. The topographic survey consisted of a manual TS survey of the streambanks and a ADCP survey of the wetted channel. The TS survey, bathymetric survey and one of the three discharge values were obtained using the same TS and ADCP setup as Paper IV. The 300 m long stream reach was surveyed at 16 cross-sections and the survey methods employed were similar to those applied in Paper IV with the exception that additional ADCP passes were not collected in the up- and downstream directions. An additional discharge measurement was obtained using a Teledyne RDI StreamPro ADCP (Teledyn 2014). Measurement uncertainties were applied to the original TS and ADCP surveys and these data were used to generate the computational curvilinear grids used in the hydraulic modeling.

### 4.4 Hydraulic modeling of rating curves (Paper III, IV and V)

The hydraulic modeling of rating curves in Papers III, IV and V was accomplished with the procedure developed by Kean and Smith (2005; 2010). For Papers III, IV and V, the computational grid surface required for the modeling procedure was defined using the previously described topographic data. Specifically, these data were interpolated as TIN surfaces and the elevations were then mapped onto curvilinear grids with the Multi-Dimensional Surface-Water Modeling System (MD_SWMS) software package (McDonald et al. 2005). These DTMs formed the basis for generating rating curves using the one-dimensional hydraulic model from Kean and Smith (2005). The model procedure is composed of two parts. The first part quantifies resistance to flow from geometric measurements of the (1) channel shape, (2) physical characteristics of the streambed and bank, and (3) size and spacing of the woody vegetation on the banks. The second part incorporates the roughness contributions into a flow model, whereby vertical velocity profiles are computed for every submerged node on a two-dimensional curvilinear grid surface. In this regard, the model generates a quasi three-dimensional representation of the velocity field over the entire computational grid.

In the hydraulic model, the roughness of the channel banks and streambed material are defined as a roughness height ($z_o$). For streams that permit sampling of the streambed material, the
roughness height can be approximated by \( z_o = 0.1D_{84} \) where \( D_{84} \) represents the 84\(^{th}\) percentile of a streambed particle size distribution (Whiting and Dietrich 1990). However, if a grain size distribution cannot be obtained, \( z_o \) can be empirically determined by inverting the hydraulic model and solving for \( z_o \) as a bulk roughness, from a single stage and discharge measurement and a corresponding water surface slope measurement (as was done in Papers III, IV and V). The calibration of \( z_o \) is typically completed only once and the resulting value is expected to be valid for the entire stage range; from low flow to flood flow. Flow resistance due to woody vegetation is estimated from vegetation density surveys taken within the model reach area. Woody stem vegetation is modeled as an array of randomly distributed cylinders of infinite height where the average drag on an individual stem \( (F) \) is defined as:

\[
F = \frac{1}{2} \rho C_D D_z h(u_{ref})^2
\]

where \( \rho \) is the density of water, \( C_D \) is the drag coefficient on a single stem (fixed constant of 1.2), \( D_z \) is the mean stem diameter and \( u_{ref} \) is the reference velocity. Equation (6) is only applied to nodes on the curvilinear grid that contain submerged stems. Once the contributing roughness elements within the stream reach have been defined, they are incorporated into a step-backwater flow model for computing one-dimensional water surface profiles.

In streams with gradually varied flow conditions, the cross-sectional average velocity \( (u)_{av} \) and the perimeter-averaged shear velocity \( (u^*)_{av} \) are related by a non-dimensional roughness coefficient \( (\beta_r) \) for the cross-section which has the form:

\[
(u)_{av} = \beta_r (u^*)_{av}
\]

In this formulation, the perimeter-averaged shear velocity can be defined as:

\[
(u^*)_{av} = \sqrt{(\tau_b)_{av}/\rho} = \sqrt{\frac{A}{P} S_f}
\]

where \( P \) is the wetted perimeter, \( A \) is the area of the cross section, and \( S_f \) is the friction slope. Equation (7) is analogous to the relation between the local, vertically averaged velocity, \( \bar{u} \), and the local shear stress, \( \tau = \rho g h S_f \), such that:

\[
\bar{u} = \beta(h, z_o) \sqrt{g h S_f} \left( \frac{\ln \left( \frac{h}{z_o} \right) - 0.74}{\kappa} \right) \sqrt{g h S_f}
\]

where \( h \) is the local flow depth, \( z_o \) is the roughness height, \( \beta(h, z_o) \) is the local non-dimensional roughness coefficient, and \( \kappa \) is von Karman’s constant equal to 0.408 (Long et al. 1993).

The average velocity for the cross section \( (u_{av}) \) is determined by averaging the local, unit discharge \( (\bar{u}h) \), across the cross section, such that:

\[
(u_{av}) = \frac{1}{A} \int_{-h_{wr}}^{h_{wl}} \beta(h, z_o) \sqrt{g h S_f} h \ dy
\]

where \( y \) is the cross-stream coordinate direction, and \( h_{wl} \) and \( h_{wr} \) are the left and right half extents of the channel, respectively.
Equations (1) and (6) to (10) are applied to iteratively solve the entire flow field across a two-dimensional curvilinear grid surface whereby discharge at a specific cross-section (i.e. defined gauge location) is determined by taking the product of the cross-sectional area and the integrated cross-sectional velocity for the corresponding stage. As such, rating curves are determined by iteratively solving discharge for a range of stages.

4.5 Impact of measurement uncertainties on rating curves (Paper V)

For Paper V, the previously described hydraulic model was implemented in a MC sampling strategy to assess the potential impact of measurement uncertainties on subsequently modeled rating curves. The field measurements assessed in the simulations were stream channel topography (derived from a coupled TS and ADCP bathymetric survey), water surface slope, vegetation density, stage and discharge. In this study, three stage-discharge values were used to calibrate the model in this study (hereafter called calibration gaugings) and a further thirteen gaugings collected by SMHI were used for evaluation (hereafter called evaluation gaugings). The roughness parameter ($z_o$) was not explicitly sampled, instead $z_o$ was calibrated only once for every MC realization using the sampled discharge, stage and water surface slope measurements. Specifically, this was considered as a one-time calibration executed for each discharge and corresponding stage and water surface slope measurements where $z_o$ is expected to be valid for the entire stage range. As such, a unique $z_o$ value was generated for every MC realization and this value was not re-calibrated or adjusted during the rating curve computation. The $z_o$ estimation was based on three discharge values and their respective probability distributions.

The MC simulations were carried out by sampling the probability distribution for each field measurement to generate 1,000 realizations (i.e. combinations of parameter values) of each parameter. The probability distributions for stream channel topography, water surface slope and vegetation density were determined from the field measurements while the probability distributions for stage and discharge were determined from literature values. The uniform distribution was used to describe all the parameter distributions except for discharge, which was represented by the normal distribution. The uniform distribution was chosen when the likelihood of a value occurring within a measurement range could not be estimated from repeat measurements. For example, manual TS surveys with the prism rod could penetrate the ground surface at different depth depending on the ground surface material (e.g. rock vs. sand). For discharge, the normal probability distribution was used because repeat discharge measurements acquired during the two field campaigns were found to be normally distributed.

For every measurement parameter, the corresponding 1,000 realizations were used to generate an equivalent number of rating curves while holding the other parameters at a constant value. This was repeated for all the measurement parameters to assess the relative importance of each individual parameter on the modeled rating curves. This modeling exercise resulted in 1,000 rating curves for every parameter for a total of 5,000 rating curves. To assess the impact of the total combined uncertainty of the input parameters as well as the potential impact due to linear and non-linear interactions between the input parameters on the modeled rating curves, an additional 1,000 rating curves (hereafter referred to as the full uncertainty rating curves) were generated by simultaneously sampling all the parameters within their defined distributions. These rating curves, in conjunction with the observed stage record, were used to generate hydrographs (hereafter referred to as referred the modeled hydrographs) to illustrate the potential impact of input parameter uncertainties on streamflow estimations.
5 Summary of main results

5.1 Paper I

The aim of Paper I was to provide a review of LiDAR applications within CZ science as well as to suggest potential ways to take full advantage of these novel data and technologies in the future. This was accomplished through a literature review of 147 peer-reviewed studies that resulted in a ranking to highlight the studies with a transdisciplinary focus as well as a proposal of a five-year vision for increasing the transdisciplinary potential of LiDAR in CZ science. The ranking revealed that 38% of the 147 studies were focused in geomorphology, 18% in hydrology, 32% in ecology and the remaining studies (about 12%) had a more interdisciplinary focus. The average scores of all the papers were visualized with a relative ranking triangle (Figure 3) where the corners of the ternary plot represent the three disciplines and the inner triangle highlights studies with a transdisciplinary focus. Three papers were identified to be “most” transdisciplinary (blue dots in Figure 3). These studies demonstrate the potential for integrating LiDAR-based information with field measurements to allow multi-scale observations of the interactions between geomorphological, hydrological and ecological processes. The three transdisciplinary studies resulting from the ranking were Harman et al. (2014), Pelletier (2013), and Perignon et al. (2013). In all three studies, the findings were only possible due to the high-resolution and precise measurements offered by LiDAR technology.

![Figure 3 - Ternary plot illustrating the ranking of 147 published peer-reviewed LiDAR studies. Papers were ranked based on their applicability in the disciplines of geomorphology, hydrology and ecology. (Figure 2 from Paper I).](image-url)
In addition, challenges and opportunities regarding the current application of LiDAR in CZ science were identified during the literature review and ranking process. Three areas of CZ science were identified that could benefit from advancements in LiDAR technologies. These areas were: quantifying change detection, parameterizing and verifying physical models, and improving CZ processes understanding across multiple scales. Change detection with LiDAR are frequently utilized by geomorphologists, however applying these data for quantifying scaling relationships and thresholds remains relatively unexplored. In addition, model parameterization or verification with LiDAR are also limited within CZ science. Therefore, the limited integration of LiDAR data into current workflows potential limits CZ process understanding. Maximizing the future application of LiDAR for transdisciplinary CZ science will require adaptation and development in four key areas. These areas were identified through workshop discussions as: adopting emerging data acquisition technologies, increasing the availability of processing and analysis techniques, encouraging linkages to in situ observations, and improving linkages to other remote-sensing observations. As a result, the workshop participants concluded that maximizing the future potential of LiDAR could be addressed through: (1) developing open lines of communication within and between developers of LiDAR (i.e. sensors, software, data), users of LiDAR products (i.e. researchers, public and private sectors) and funding agencies; (2) reducing the cost associated with the collection of LiDAR data through cost-effective technologies (Paper II); (3) increasing the availability of LiDAR data; and (4) supporting the continued development of new technologies that have the potential to link complementary observations.

5.2 Paper II

The objective Paper II was to implement a custom-built low-cost laser scanning system for characterizing the stream streambed roughness in a temporarily diverted stream. This was accomplished by deploying a custom gondola housing a low-cost laser ranging system (SICK LSM111) from a wire cable suspension system supported by nearby trees.

The laser scan of the stream channel yielded 24 000 individual points in the point cloud where the main topological features, such as the channel banks and slopes along the scanned reached, could be identified. The polynomial equation, used to correct for the point cloud distortion due to cable sag, proved effective and facilitated the extraction of the streambed roughness elements. The point cloud representing the roughness elements along the streambed (Figure 4) was used to estimate the grain size distribution of the streambed and the hydraulic radius of the stream channel. These data were applied in Equations (3) and (4) to determine Manning’s $n$ as a function of grain size.
A comparison of the $D_{50}$, $D_{84}$ and $D_{90}$ values of the estimated (from laser scanner) and mean measured (from three Wolman pebble counts) grain size distributions show a difference of 8 mm, -6 mm and -11 mm, respectively (Table 3). When comparing to the extremes of the grain size distributions, the largest modeled element was 255 mm which was about 35% smaller compared to the largest measured element of 400 mm. Taking into account the results from the $D_{84}$ to the $D_{100}$, some underrepresentation may exist for the larger pebble sizes captured with the scanning method. Looking at the smallest grain sizes, the laser scanning system was capable of estimating sizes down to about 10 mm; however, this may not be practical due to the camera’s minimum footprint of 17 mm at 1 m distance and the 30 mm systematic error. As such, setting a minimum threshold of 30 mm could be appropriate for future applications with this setup.

Table 3 - Results of grain size distributions determined from the three Wolman pebble count surveys and the camera-based laser scan. Grain sizes are represented as percentiles where 50th, 84th, 90th and 100th are denoted as $D_{50}$, $D_{84}$, $D_{90}$ and $D_{100}$, respectively.

<table>
<thead>
<tr>
<th>Percentile</th>
<th>Pebble count Survey 1 (mm)</th>
<th>Pebble count Survey 2 (mm)</th>
<th>Pebble count Survey 3 (mm)</th>
<th>Pebble count Survey mean (mm)</th>
<th>Camera-based laser scan (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$D_{50}$</td>
<td>35</td>
<td>47</td>
<td>42</td>
<td>43</td>
<td>51</td>
</tr>
<tr>
<td>$D_{84}$</td>
<td>105</td>
<td>100</td>
<td>75</td>
<td>96</td>
<td>90</td>
</tr>
<tr>
<td>$D_{90}$</td>
<td>135</td>
<td>125</td>
<td>91</td>
<td>120</td>
<td>109</td>
</tr>
<tr>
<td>$D_{100}$</td>
<td>345</td>
<td>475</td>
<td>380</td>
<td>400</td>
<td>255</td>
</tr>
</tbody>
</table>
Looking at the Manning’s $n$ values estimated from the $D_{50}$ as a function of hydraulic radius (Figure 5), a noticeable difference can be seen for the $n$ values determined from the laser-scan derived grain size and the Wolman pebble count at the lowest possible flow conditions (i.e. hydraulic radii less than 0.07 m). As the hydraulic radii is increased, the estimated $n$ values appeared to converge to about 0.025 for hydraulic radii greater than about 0.19 m. To give some perspective on these results, the hydraulic radius is approximately 0.11 m at the median daily flow (0.002 m$^3$/s) in this stream.

![Figure 5](image)

*Figure 5: Manning’s roughness coefficient ($n$) estimated with Equation (4) as a function of hydraulic radius using the $D_{50}$ obtained through the camera-based laser scan and Wolman pebble counts (Figure 5 from Paper II).*

### 5.3 Paper III

Paper III investigates the potential impact of using low-resolution ALS data for modeling rating curves. This was achieved by synthetically thinning high-resolution (about 2.7 points/m$^2$) ALS data to point densities equivalent to most national-scale ALS specifications (between 2.2 points/m$^2$ to 0.2 points/m$^2$). Only the results for the thinned data with 0.2 points/m$^2$ resolution were retained and tested.

In general, the shape of the modeled rating curves was similar to the empirical rating curve. The average absolute error for quartiles of stage was determined for all the rating curves (empirical and modeled) and the error was found to increase with increasing stage for all the rating curves. The channel geometries along the reach (at 0, 50 and 100% of the reach length) were compared at two representative stages. The stages represent the approximate average annual flow (1 m$^3$/s) and the maximum flow rate (8 m$^3$/s). At these two stages, variability was found in the geometries and cross-sectional areas along the channel. However, the differences were relatively small when considering the width and depth of stream channel for the two representative stages (Table 4).
Table 4 - Stream channel estimated with non-thinned and thinned ALS data where the reference stage is estimated from the corresponding rating curve over the entire model domain, and distance is measured downstream from the reference rating curve cross-section. (Table 1 from Paper III).

<table>
<thead>
<tr>
<th>Property</th>
<th>Distance (m)</th>
<th>Non-Thinned</th>
<th>Thinned (Survey)</th>
<th>Thinned (Flat Bottom)</th>
<th>Non-Thinned</th>
<th>Thinned (Survey)</th>
<th>Thinned (Flat Bottom)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Streamflow (m³/s)</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>8.0</td>
<td>1.4</td>
<td>1.4</td>
<td>1.4</td>
</tr>
<tr>
<td>Reference Stage (m)</td>
<td>0.6</td>
<td>0.6</td>
<td>0.6</td>
<td>1.4</td>
<td>1.4</td>
<td>1.4</td>
<td>1.4</td>
</tr>
<tr>
<td>Area (m²)</td>
<td>0</td>
<td>3.7</td>
<td>4.0</td>
<td>11.7</td>
<td>12.3</td>
<td>12.3</td>
<td>8.8</td>
</tr>
<tr>
<td>Wetted Perimeter (m)</td>
<td>0</td>
<td>7.9</td>
<td>7.8</td>
<td>12.2</td>
<td>13.2</td>
<td>10.4</td>
<td></td>
</tr>
<tr>
<td>Hydraulic Radius (m)</td>
<td>0</td>
<td>0.5</td>
<td>0.5</td>
<td>1.0</td>
<td>0.9</td>
<td>0.8</td>
<td></td>
</tr>
<tr>
<td>Top width (m)</td>
<td>0</td>
<td>7.6</td>
<td>7.5</td>
<td>11.0</td>
<td>12.1</td>
<td>10.2</td>
<td></td>
</tr>
<tr>
<td>Area (m²)</td>
<td>45</td>
<td>2.9</td>
<td>3.5</td>
<td>10.3</td>
<td>11.3</td>
<td>10.9</td>
<td></td>
</tr>
<tr>
<td>Wetted Perimeter (m)</td>
<td>45</td>
<td>8.4</td>
<td>9.1</td>
<td>11.1</td>
<td>11.6</td>
<td>11.1</td>
<td></td>
</tr>
<tr>
<td>Hydraulic Radius (m)</td>
<td>45</td>
<td>0.3</td>
<td>0.4</td>
<td>0.9</td>
<td>1.0</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>Top width (m)</td>
<td>45</td>
<td>8.2</td>
<td>8.8</td>
<td>10.2</td>
<td>10.5</td>
<td>9.9</td>
<td></td>
</tr>
<tr>
<td>Area (m²)</td>
<td>90</td>
<td>1.8</td>
<td>2.2</td>
<td>9.5</td>
<td>10.9</td>
<td>11.6</td>
<td></td>
</tr>
<tr>
<td>Wetted Perimeter (m)</td>
<td>90</td>
<td>7.8</td>
<td>7.9</td>
<td>12.0</td>
<td>14.1</td>
<td>10.9</td>
<td></td>
</tr>
<tr>
<td>Hydraulic Radius (m)</td>
<td>90</td>
<td>0.2</td>
<td>0.3</td>
<td>0.8</td>
<td>0.8</td>
<td>1.1</td>
<td></td>
</tr>
<tr>
<td>Top width (m)</td>
<td>90</td>
<td>7.5</td>
<td>7.6</td>
<td>11.2</td>
<td>12.8</td>
<td>9.3</td>
<td></td>
</tr>
</tbody>
</table>

The potential impact of the ALS thinning on flow estimation was assessed by comparing the differences between the thinned and non-thinned rating curves to the empirical rating curve as a function of stage (Figure 6). This comparison showed that using low-resolution ALS data to generate rating curves resulted in a similar magnitude of error (assessed as the difference to the empirical rating curve) as fitting the empirical rating curve to available gaugings. At higher flows the difference between the observed flows and the empirical rating curve were much larger due to the variability in the flow observations. At these higher flows, the difference between the observed flows and empirical rating curve was also higher than the difference between a rating curve modeled with high-resolution versus a rating curve modeled with low-resolution ALS data. In other words, the potential error resulting from decreasing ALS resolution is in the same order as the errors associated with establishing and maintaining rating curves at the study site. Further, allowing for variable density in vegetation did not have a significant impact on the modeled rating curves (Figure 6).
5.4 Paper IV

In paper IV, national-scale ALS and ADCP bathymetric data were coupled to investigate the potential of these data for developing rating curves. The ALS data used in the study were an actual subset of the Swedish national laser scanning survey rather than a synthetically thinned ALS dataset (Paper III).

The performance of the DTM derived from the coupled ALS/ADCP and UALS/ADCP data were assessed by comparing mean stream channel properties with the reference DTM (TS/ADCP) at three representative stages (Table 5). These stages represent the discharge during the ALS collection, median observed discharge and maximum observed discharge in the gauging record, respectively. Because the same ADCP bathymetry was used in all three DTMs, the differences in the results are primarily due to the differences between the non-submerged portions of the DTMs (i.e. ALS and TS). In general, both the ALS and UALS derived DTMs underestimated the majority of mean channel properties (i.e. top width, wetted perimeter, cross-section area, hydraulic radius). Both ALS and UALS derived DTMs also showed the largest variability for the mean top width and the mean wetted perimeters. For the mean cross-section area, the underestimation by the ALS derived DTM was relatively consistent whereas the underestimation by the UALS derived DTM tended to increase with stage. Finally, the differences in mean hydraulic radii for both ALS and UALS derived DTMs were relatively consistent across all three stages.
Table 5 - Stream channel properties at three water depths determined from digital terrain models derived from total station (TS) survey, corrected airborne laser scanning (ALS) and uncorrected ALS (UALS) and acoustic Doppler current profiler (ADCP) data. Negative or positive differences indicate an underestimation or overestimation of the stream channel properties, respectively. (Table 1 from Paper IV)

<table>
<thead>
<tr>
<th>Stream channel property</th>
<th>TS/ADCP</th>
<th>ALS/ADCP</th>
<th>UALS/ADCP</th>
<th>Difference (TS vs. ALS)</th>
<th>Difference (TS vs. UALS)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stage during ALS survey (m)</td>
<td>7.5</td>
<td>7.5</td>
<td>7.5</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Mean top width (m)</td>
<td>15.1</td>
<td>14.6</td>
<td>11.0</td>
<td>-0.5</td>
<td>-4.1</td>
</tr>
<tr>
<td>Mean wetted perimeter (m)</td>
<td>17.3</td>
<td>17.0</td>
<td>13.6</td>
<td>-0.3</td>
<td>-3.7</td>
</tr>
<tr>
<td>Mean cross-section area (m²)</td>
<td>22.7</td>
<td>22.3</td>
<td>22.1</td>
<td>-0.4</td>
<td>-0.6</td>
</tr>
<tr>
<td>Mean hydraulic radius (m)</td>
<td>1.3</td>
<td>1.3</td>
<td>1.6</td>
<td>0.0</td>
<td>0.3</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Stream channel property</th>
<th>TS/ADCP</th>
<th>ALS/ADCP</th>
<th>UALS/ADCP</th>
<th>Difference (TS vs. ALS)</th>
<th>Difference (TS vs. UALS)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Median stage (m)</td>
<td>7.8</td>
<td>7.8</td>
<td>7.8</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Mean top width (m)</td>
<td>17.2</td>
<td>16.9</td>
<td>11.1</td>
<td>-0.3</td>
<td>-6.1</td>
</tr>
<tr>
<td>Mean wetted perimeter (m)</td>
<td>19.5</td>
<td>19.4</td>
<td>14.0</td>
<td>-0.1</td>
<td>-5.5</td>
</tr>
<tr>
<td>Mean cross-section area (m²)</td>
<td>25.1</td>
<td>24.7</td>
<td>23.8</td>
<td>-0.4</td>
<td>-1.3</td>
</tr>
<tr>
<td>Mean hydraulic radius (m)</td>
<td>1.3</td>
<td>1.3</td>
<td>1.7</td>
<td>0.0</td>
<td>0.4</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Stream channel property</th>
<th>TS/ADCP</th>
<th>ALS/ADCP</th>
<th>UALS/ADCP</th>
<th>Difference (TS vs. ALS)</th>
<th>Difference (TS vs. UALS)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum stage (m)</td>
<td>8.1</td>
<td>8.1</td>
<td>8.1</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Mean top width (m)</td>
<td>23.4</td>
<td>21.6</td>
<td>16.4</td>
<td>-1.8</td>
<td>-7.0</td>
</tr>
<tr>
<td>Mean wetted perimeter (m)</td>
<td>25.8</td>
<td>24.3</td>
<td>19.5</td>
<td>-1.6</td>
<td>-6.3</td>
</tr>
<tr>
<td>Mean cross-section area (m²)</td>
<td>31.2</td>
<td>30.7</td>
<td>28.0</td>
<td>-0.6</td>
<td>-3.2</td>
</tr>
<tr>
<td>Mean hydraulic radius (m)</td>
<td>1.2</td>
<td>1.3</td>
<td>1.4</td>
<td>0.1</td>
<td>0.2</td>
</tr>
</tbody>
</table>

The modeled rating curves were generally in good agreement with the observed flow measurements and empirical rating curve (Figure 7). The modeled rating curves derived from the ALS/ADCP and TS/ADCP were almost identical except for a slight deviation at the highest gauged discharges where slightly lower values for the same stages were estimated by the ALS/ADCP model. Comparing the empirical and modeled rating curves with the gauging measurements, all three modeled rating curves showed much lower errors than the empirical rating curve. When comparing the ALS/ADCP and TS/ADCP models, the ALS/ADCP had slightly higher errors for the entire rating curve. The UALS/ADCP had much larger errors than the TS/ADCP and ALS/ADCP models for the non-submerged portion of the rating curve.
Figure 7 - Results of the modeled rating curves generated from ALS/ADCP (black dotted line), UALS/ADCP (solid grey line), TS/ADCP (green dotted line) and empirical rating curve (solid black line) derived from the gauging measurements (circles). The water surface during the ADCP survey is represented by the horizontal black line that also represents the divide between the ALS and ADCP dominated portions of the rating curves. (Figure 3 from Paper IV)

5.5 Paper V

Paper V considered the potential impact of measurement uncertainties on modeled rating curves. In total, 6000 rating curves were generated from the MC simulations whereby 1000 of these were used to generate hydrographs to emphasize the impact of measurement uncertainties on streamflow uncertainty.

Before starting the MC simulations, a rating curve was developed (hereafter referred to as the calibrated model) using the mean measured values of the input parameters (i.e. without uncertainty) (Figure 8). A comparison of the calibrated model rating curve with the official rating curve indicated that the lower rating curve portion was nearly identical to the official rating curve published by SMHI, except at very low flows where the model performed poorly. On the other hand, the upper calibrated model rating curve overestimated discharge for all stages when compared to the official rating curve. Although the official rating curve had a better overall fit to the evaluation gaugings, the calibrated model rating curve was better at reproducing the most recent evaluation gauging measurements, that were not used in the model calibration. This indicates a potential strength in the modeling approach in that three calibration measurements could be used to develop a reliable rating curve when compared to the official rating curve.
The results from the MC simulations revealed how input measurement uncertainties could manifest in either the rating curves or the calibrated \( z_o \) parameter within the model. When considering only the modeled rating curves, the uncertainties in the calibration discharges were primarily responsible for uncertainties in the rating curve. However, when considering the calibrated \( z_o \) values, uncertainties in stage and water surface slope measurements had the most impact on the calibrated roughness values. The reason the uncertainties in stage and water surface slope measurements had such a large influence on the calibrated \( z_o \) values is because these two parameters are used to define the water surface boundary condition in the hydraulic model. Therefore, during the calibration phase, uncertainties in these parameters were passed onto the calibrated \( z_o \) values instead of the modeled rating curves.

When considering the impacts of the full uncertainty rating curves (i.e. allowing all measurements to vary within their full range of uncertainty during model calibration) on water resources, the modeled hydrographs generated from the full uncertainty rating curve models showed that the 90% uncertainty bounds were -12% and +46% of the official hydrograph for the highest observed stage in the observed record (Figure 9a). At the lowest flows in the stage record (Figure 9b), the 90% uncertainty bounds of the modeled hydrographs were -59% and +149% of the official hydrograph. For the median flows (Figure 9c), the 90% uncertainty bounds of the modeled hydrographs were -12% and +10% of the official rating curve. These results indicate that, for the most part, reliable hydrographs can be generated from measurements of stream channel topography and three calibration measurements.
Figure 9 – Percentiles of streamflow hydrographs developed from the full uncertainty rating curves. Percentiles are within 90% uncertainty bounds calculated at 10% intervals. Official hydrograph is represented as a black line. Inset plots highlight three representative flows (a) largest flood event in stage record, (b) period of lowest flows, and (c) flows within the range of calibration gaugings. (Figure 5 from Paper V).
6 Discussion

**Objective A: Investigate the potential of close-range remote sensing for capturing stream channel topography at various spatial scales**

In this thesis, close-range remote sensing technologies, which have a great potential for advancing our understanding of not only hydrology but also other earth sciences (Paper I), were investigated for their potential to capture the necessary information required for hydraulic modeling purposes at various scales. With regards to benefits of close-range remote sensing in small streams, the low-cost laser scanning system developed in Paper II was capable of determining grain size distribution and Manning’s $n$ with accuracy similar to those determined from the Wolman pebble counts. These findings are encouraging, however there were some discrepancies in the results at the low end of the grain size distribution (due to the systematic error of the system) and some potential underrepresentation at the high end of the distribution. However, when Manning’s $n$ was estimated as function of the $D_{84}$ and hydraulic radii, the laser scanning system appears to be capable of resolving roughness elements comparable to those derived from manual pebble counts.

One of the challenges with the custom laser scanning setup was the need to temporarily divert the stream to enable laser scanning of the streambed. Although diverting the stream worked well at this site, this may not be practical at other field sites. Alternatively, the suspended laser scanning system could be deployed during drought conditions where the amount of water in the stream channel is minimal. The system could also be deployed for ephemeral stream reaches when the channel bed is not submerged. Both of these cases would avoid the challenges of scanning through the water column. Another option could be to employ a green (532 nm) laser, instead of an infrared laser, to allow penetration into the water and possibly capture the bathymetry. However, such a setup would require additional data processing to correct for the refraction and speed change of the laser pulse as it passes through the water column in the in-and outgoing directions (see section 2.2). As demonstrated by Smith et al. (2012) and Smith and Vericat (2014), correcting for the impacts due to the water column is not a trivial task. However, when the intensity information of the return laser pulse is used to define the water surface, bathymetric errors can be less than 10 mm (Smith and Vericat 2014).

Further, reliance on the cable suspension system for deploying the custom laser scanner resulted in a number of challenges. The stretch in the main suspension cable caused a distortion in the point cloud that was corrected with a simple polynomial. The correction only considered distortions in the $z$-plane, however the laser scanner was susceptible to roll, pitch and yaw, and impacts due to these rotational movements were not corrected in the point cloud. These errors could be addressed by installing an Inertial Measurement Unit (IMU) and applying the necessary corrections to the data (http://theccontinuum.com/2012/09/24/arduino-imu-pitch-roll-from-accelerometer/). Even though these corrections were not applied, the laser scanning system was capable of estimating small-scale channel roughness comparable to those collected through manual pebble counts. Alternatively, the laser scanning system could be deployed from unmanned aerial vehicles (UAVs) instead of the custom gondola. The approximate weight of the essential components (i.e. laser scanner, Arduino board, battery) weighs less than 2 kg and could be easily mounted onto a UAV. In addition, UAVs are typically outfitted with GPS and IMU sensors and data from these instruments could be used to correct for roll, pitch and yaw.

With regards to the larger rivers investigated in this thesis, Papers III and IV highlight the potentials and limitations of capturing stream channel topography. In both cases, the ALS data
were capable of representing the stream channel properties necessary for generating reliable rating curves relative to the gauging measurements. At both sites, the ALS data needed to be augmented with additional bathymetry for submerged portions of the stream channel. In the case of Paper III, the thinning of augmented ALS (i.e. with TS and assumed flat bottom) resulted in variability for the stream channel properties evaluated at the two representative stages (Table 4). Although the differences between the thinned and non-thinned ALS data were small relative to the width and depth of the stream, this may not necessarily hold at other sites and across all scales. For this study, the low-flow conditions during the ALS scan provided laser echoes for large portions of non-submerged stream channel area. If the flow were greater, less of the stream channel would have been captured by the ALS scan. In this regard, the flow conditions during which the ALS data are collected can impact both the data quality and the ability to define stream channel geometry.

For Paper IV, the ALS data required were reclassified and corrected for elevation errors before being coupled with the ADCP bathymetry. For the reclassification, the LASTools software suite (Isenburg 2015) was used, specifically the lasground classification tool. Although the lasground classification algorithm gave good results when visually compared to the original classification, other algorithms could have given varying results (Korzeniowska et al. 2014). The elevation correction method was based on the RMSE statistic and despite the variability in the mean top width of the corrected ALS derived DTM (Table 5) the range of mean cross-section areas with increasing stage was found to be relatively small (i.e. between -0.6 m$^2$ and -0.4 m$^2$ which is less than a 2% difference). This indicates that the RSME correction was suitable for correcting the ALS and that reliable stream channel topography can be obtained with national-scale ALS. Although the RMSE correction proved to be effective for this study, the required additional reference data may not be available for other sites. An alternative to manual surveying methods could be to deploy UAV to capture high-resolution aerial photos during leaf off conditions and generate high-resolution DTM using photogrammetric methods such as Structure from Motion (SfM) to correct the ALS (Paper I). SfM has been demonstrated to be a cost-effective method for mapping complex terrain (Westoby et al. 2012; Javernick et al. 2014). Although DTMs generated from SfM can underestimate the ground surface when compared to ALS in densely vegetated areas (Wallace et al. 2016), open areas with good ground visibility could be used to correct portions of the ALS data.

When considering the application of ACDP for collecting bathymetry, the minimal operational water depth must be taken into consideration. For the SonTek M9, used in both Papers IV and V, the minimum operational depth is 0.5 m due to the minimum blanking distance of 0.2 m (SonTek 2000). However, for streams shallower than this minimal operational depth, using ADCP to collect bathymetry may not be practical and manual surveys would be more appropriate. When considering the ACDP bathymetry in Papers IV and V, verification of the depth measurements with another data source was not possible. Conducting manual bathymetric surveys at both sites was not feasible due to the water depths preventing safe wading (i.e. > 2 m at both sites). The inability to verify bathymetric measurements is a common challenge, however controlled laboratory simulations have shown bathymetric errors for acoustic Doppler depths sounders are typically within a 5% margin (González-Castro and Muste 2007). From the perspective of hydrometric agencies, little additional effort would be required to collect the extra ACDP bathymetry. For instance, acquiring the additional measurements for Papers IV and V took approximately 3 and 4 hours (including set up time), respectively. Historically, both sites have been gauged one to three times per year to capture the annual low and high flow events. Including an additional bathymetric survey could provide valuable information regarding morphological changes and aid in rating curve maintenance through hydraulic modeling efforts.
Objective B: Evaluate the performance of these topographic data for generating rating curves within a physically-based one-dimensional hydraulic modeling framework.

As previously discussed, close-range remote sensing technologies are capable of acquiring reliable stream channel topography. However, what is interesting, from the perspective of water streamflow monitoring, is the ability of applying these data with a hydraulic modeling framework to develop rating curves. Paper III demonstrated that synthetically thinned ALS with resolutions similar to national-scale ALS data can be used in a one-dimensional hydraulic model to develop reliable rating curves. The thinning of the ALS data, from high- to low-resolution, had an increasing impact on the modeled rating curves with increasing stage. This was true for both sets of thinned ALS stream channel geometries (i.e. augmented either with TS survey or an assumed flat bottom). However, the order of potential rating curve error, as a result of the decrease in point cloud resolution, was similar to the error encountered with establishing and maintaining the rating curve at the study site (Figure 6). With regards to scale, the hydraulic model is valid for streams with relatively large width-to-depth ratios. In this regard, the study site for Paper III is likely at the lower spatial limit of where the model hydraulics are valid. These findings are encouraging as this implies that national-scale ALS data could potentially be used to establish rating curves.

Building upon these findings, Paper IV coupled ALS data from the Swedish national-scale with ADCP bathymetry to develop rating curves at a site with median flows an order of magnitude greater than the test site of Paper III. The rating curve developed from the corrected ALS/ADCP data had much lower errors than the empirical rating curve. However, the empirical rating curve was based upon a standard least squares method without weighting any of the gauging measurements. A weighted fit was not considered because metadata regarding the quality of the gaugings was not available. This polynomial form was chosen (instead of a typical power law) as it had the best statistical fit to the gaugings and provided the lowest possible error allowing for a robust comparison with our modeling effort. Although the errors were minimized with the least squares fit, a potential bias may exist due to the spread in the gaugings at the upper portion of the fitted empirical rating curve. Therefore, different fitting methods, such as a power law, could lead to different results for Papers III and IV.

Previous studies have shown that accuracy of modeled rating curves is tied to the accuracy of the roughness parameter (Reistad et al. 2007). As described by Powell (2014), there are many different methods to quantify flow resistance within a stream channel. The hydraulic model used in this thesis work determines flow resistance contributions from the stream channel bed and vegetation separately from geometric measurements. However, since the stream bed material could not be sampled, $z_o$ was back calculated from discharge values and their corresponding stage and water surface slope measurements. Even though $z_o$ is unlike an empirical roughness coefficient (i.e. Manning’s $n$) where a one-time calibration would not yield an accurate rating curve over a range of flow stages due to its variation as a function of stage (Ferguson 2010), uncertainties in the calibration measurements would have impact on the accuracy of $z_o$ and ultimately, the resulting rating curve. In addition, one of the discharge values used in the calibration was derived from the empirical rating curve. This source of error could potentially bias the results since calibrating the model with a discharge taken from the validation rating curve leads to some potential circularity in the method.
**Objective C: Quantify potential measurement uncertainty on rating curves**

In any modeling application, all the observations required for calibration, validation or implementation of the model will contain some uncertainty. Paper V investigated the impact of input data uncertainty on the Kean and Smith (2010) hydraulic modeling method for the first time. This study demonstrated that the model was able to develop reliable rating curves from measurements of stream channel topography (i.e. TS and ADCP bathymetry) in conjunction with three calibration measurements. The calibrated model was able to better reproduce the most recent gaugings even though the official two-part rating curve had a better overall fit to all evaluation gaugings. This could potentially indicate that the rating curve developed from the input measurements and hydraulic model is a better representation of the current stage-discharge relationship. However, verification would require additional evaluation gauging measurements, particularly at higher flows.

Applying the hydraulic model in the MC simulation provided insight into the relative importance of the input measurement uncertainties on rating curves. When the rating curves developed in the MC simulations were considered together with their corresponding calibrated $z_o$ values, it was clear that the current model structure was most sensitive to uncertainties in the discharge, stage, and water surface slope. However, when all the uncertainty sources were accounted for, the rating curve uncertainty at the highest observed stage (i.e. -12% and +46%) was relatively constrained considering there were no high flow data for calibration at this level. Within the range of calibration gaugings, the uncertainties in the full uncertainty model rating curves were lowest, however, below this range the hydraulic model was not able to reliably predict flows for the lowest stages. This was likely due to limitations in estimating the water surface boundary conditions at the lowest stages. Specifically, water surface slope boundary conditions were linearly extrapolated from the measured water surface slope surveys at the lower flows. Since conditions to inhibit positive water surface slopes were not imposed during the modeling, the model converged on unrealistic flow estimates. This could be addressed through additional water surface profile surveys; however, since the occurrence of such low flows is extremely infrequent, this may not be feasible.

Similar to Paper IV, one of the discharge values used to calibrate the $z_o$ was obtained from the validation rating curve. This clearly leads to circularity in the method and, if possible, future applications of this method need to avoid this circularity. The best solution would be collect a high flow discharge measurement, however, if this is not possible, one potential solution could be to use a recent stage-discharge measurement from the gauging record and estimate the water surface slope through linear extrapolation. Even though, this method could theoretically work, additional epistemic uncertainty introduced into the modeling would need to be considered.
7 Conclusion

Streamflow is one of the major components of the hydrological cycle but collecting continuous flow measurements remains challenging. Collecting the full range of measurements required to establish and maintain rating curves is time consuming and costly. Having the ability to collect stream channel topography across a range of stream sizes and incorporate these data into hydraulic modeling methods can aid water resource monitoring efforts. This is particularly relevant when considering the global trend of closing monitoring stations where streamflow is actively monitored (Vörösmarty et al. 2001; Brown 2002; USGS 2014). This reduction of streamflow monitoring locations can inhibit our ability to quantify the impacts of climate change on water resource management. In this regard, this thesis highlights the potential of close-range remote sensing technology to acquire stream channel topography for hydraulic modeling applications at various spatial scales. This has been demonstrated through a literature review of current LiDAR applications to better understand the benefits and challenges of these technologies as well as through the deployment of close-range remote sensing technologies with the purpose of extracting information relevant for hydraulic modeling applications. The main findings of the thesis can be summarized by the following conclusions:

- Close-range remote sensing can be used to extract reliable hydraulic parameters, such as Manning’s $n$ (Paper II) and various stream channel properties for use in a hydraulic model (Papers III, IV and V). Although there was some variation in the estimated hydraulic and stream channel parameters, rating curves developed from these parameters can have similar (or less) error than empirical methods for sites similar to the ones investigated in this thesis.
- Low-resolution national-scale ALS, in combination with additional bathymetric information, can be used to define the overall shape and channel geometry required for modeling reliable rating curves. However, the lower limit of streams that can be reliably acquired by national-scale ALS is likely about 3 m wide (Paper III). Streams below this width may not be sufficiently represented with national-scale ALS.
- Applying close-range remote sensing technologies in riverine environments can be potentially challenging and may require additional processing steps. Some examples include the need to divert the water to expose stream bed (Paper II), reclassify point cloud data and define a suitable elevation correction (Paper IV), and/or combine data from different measurement platforms (Paper III, IV, V).
- Measurement uncertainties need to be considered when modeling rating curves (Paper V), as these uncertainties are inherited by the rating curve and therefore, directly translated into the hydrograph. Rating curves developed from close-range remote sensing data and physically based hydraulic models can help constrain uncertainties at high flows, which are typically the domain of the largest uncertainty in discharge time series.
8 Future work

This thesis focused on the application of close-range remote sensing for collecting stream channel topography in riverine environments. During the thesis work, challenges were identified that could guide future research. One of the motivations for this thesis work was to reduce the amount of effort required to develop rating curves. Collecting the required water surface slope and vegetation density measurements needed in the one-dimension hydraulic model was time consuming. With regards to the water surface slope measurements, the main challenge was being able to hold and level the prism rod exactly at the surface of the water. Being able to resolve the water surface with close-range remote sensing would reduce this effort and potentially increase the precision of the water surface slope. This could be accomplished, for example, with TLS where the intensity of the laser echoes could be used to differentiate the laser echoes returning from the land and the echoes returning from the water. A drop in the return signal intensity could be used to identify the land-water interface and thus estimate the water surface slope. Although this approach has been applied by Smith and Vericat (2014) who used a green laser light TLS, these systems are not overly common. The application of infrared TLS for detecting water surfaces would be interesting as these make up the majority of TLS devices on the market. In addition, TLS could be used to obtain both the vegetation density surveys (Pirotti 2012), as well as the spatial distribution of vegetation, simultaneously with the water surface scans, which could further reduce manual field measurement efforts. In summary, TLS holds exciting promise for scanning riparian regions and developing information relevant for hydraulic modeling.

There is clear potential of using close-range remote sensing data and hydraulic models to constrain rating curves. For example, hydraulic models provide a consistent technique for estimation of high-flow values beyond the highest observed flows. These values could help reduce the uncertainty propagated within rating curve estimations (and subsequent flow monitoring) by providing information to methods such as McMillan and Westerberg (2015). Specifically, the value of having an estimated (and uncertain) extreme high-flow value from a hydraulic model constrained by physical flow relationships could outweigh not having any observations at all for extreme events. However, the impacts of input measurement uncertainties on the resulting model-generated rating curves and flow estimates needs to be taken into consideration.
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