Doctoral Thesis

Macro-roughness, flow resistance and sediment transport in steep mountain streams

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MACRO-ROUGHNESS, FLOW RESISTANCE AND SEDIMENT TRANSPORT IN STEEP MOUNTAIN STREAMS

A dissertation submitted to

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for the degree of

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presented by

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2012
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Summary

Steep mountain streams constitute the majority of the total stream length in mountainous regions such as the Swiss Alps, and they play an important role in the fluvial system. They are the major agents of erosion and sediment transfer from the headwaters to lower stream reaches. At the same time, sediment transport is a natural hazard that poses a threat to humans, settlements and infrastructure. Therefore, the accurate prediction of sediment transport is important to assess the risks related to mountain streams and minimize the potential damage. This can be supported by a better understanding of the relation between sediment transport, flow resistance and macro-roughness. The present doctoral thesis tackles three key aspects of these relations:

In the first study the effects of macro-roughness on flow resistance and flow velocity are assessed. The between-site variations of flow resistance are analyzed and related to various measures of macro-roughness, such as boulder concentration and step density. Macro-roughness and flow data were collected in six steep mountain streams. The between-site differences in flow resistance can be explained using new non-dimensional flow velocity and discharge variables, both non-dimensionalized by channel slope and a macro-roughness length scale. Employing boulder concentration as macro-roughness parameter, the non-dimensional variables are used for improved flow velocity predictions. Furthermore, an empirical and dimensional justification for the dimensionless variables is given.

In the second study, methods are presented to quantify the additional flow resistance generated by macro-roughness elements in steep streams. These approaches are combined with bedload transport equations to correct for the energy losses due to macro-roughness. The bedload transport predictions are then compared to field measurements of discharge, transported bedload volumes and channel characteristics of 13 Swiss mountain streams. It is shown that all tested equation combinations achieve an improvement in bedload prediction compared to a reference equation that is uncorrected for macro-roughness.

A new method for accurately measuring channel-bed roughness is assessed in the third study. It is demonstrated that range imaging cameras, using a novel time-of-flight technology, can be used to measure complex surfaces in the field. Measurement errors are quantified, and a comprehensive workflow for field measurements and data post-processing is presented. It is shown that for small- to medium-scale field sites, range imaging can be a useful alternative or complement to conventional surface measurement methods, such as terrestrial laser scanning or photogrammetry.

Each of these three studies elucidates an important sediment-transport related problem and contributes to the better understanding of transport processes in steep streams. The findings presented in this thesis are based on field observations and can be used to develop and improve methods for flow velocity and sediment transport predictions.
Zusammenfassung


In der dritten Studie wird untersucht, ob Range Imaging, eine neue time-of-flight Distanzbildmessmethode, geeignet ist, um komplexe Oberflächen im Feldeinsatz zu vermessen. Dazu werden Experimente zur Fehlerabschätzung durchgeführt und eine umfassende Anleitung für Feldmessungen bis hin zur Datenbearbeitung entwickelt. Anhand der Messergebnisse zeigt sich, dass Range Imaging eine praktikable Alternative zu etablierten Messverfahren wie
Laserscanning oder Photogrammetrie für klein- bis mittelskalige Untersuchungsflächen darstellt.

Chapter I

Introduction

1 Motivation and project background

Steep mountain streams play an important role in fluvial systems. They are major agents of erosion and sediment transfer from headwaters to lower stream reaches. The sediment carried by a mountain stream is a key variable in channel dynamics. The amount, size and distribution of the sediment on the bed influences channel hydraulics, channel stability, groundwater exchange through the streambed, and the quality of aquatic habitats. Sediment inflow determines the lifetime of reservoirs used for hydroelectric power plants and high-intensity sediment transport is a risk for any infrastructure in or near stream channels, such as water intakes or dams. Notably, steep mountain streams occupy the majority of the total stream length in mountainous areas. In Switzerland, for example, streams with slopes steeper than 3 % constitute 74 % of the total stream length (Figure 1).

Figure 1. Stream network of Switzerland classified into steep slope (≥ 3 %) and gentle slope (< 3 %) channels. (Source data: DTM-AV © 2012 swisstopo)
Chapter I

At the confluences of steep streams and flatter valley floors, sediments are deposited on cones or fans. These valley floors are a preferred settlement area in the Alps. There, floods and sediment transport are major natural hazards and pose a serious threat to humans, road networks and buildings. Debris flows, log jams and fluvial sediment depositions beyond river banks are typical sediment transport related risks that can cause severe damage: In August 2005, a heavy storm caused damages totaling approximately 3 billion Swiss Francs in Switzerland [Bezzola and Hegg, 2007; Bezzola and Hegg, 2008] (Figure 2). Interpreting data from the Swiss flood and landslide damage database [Hilker et al., 2009], roughly one third to one half of the total costs were associated with sediment transport processes. To minimize the scale of such damage in the future, it is essential to be able to accurately predict sediment transport. The understanding of steep streams is crucial for improving our scientific knowledge of fluvial systems as a whole, and in particular for better estimating the risks posed by such systems.

For the estimation of stream discharge runoff, various methods are already available. Data quantifying the flow regime of steep streams (i.e., the catchment’s response to rain or snow melt and the magnitude and recurrence of runoff peaks) are essential for using water resources wisely and protecting humans from flood damage. In most cases small mountain streams have no runoff gauges for measuring the river’s flow regime. Therefore, the Swiss Federal Office for the Environment (FOEN) has set up a Group for Operational Hydrology (GHO), which investigates and evaluates flood events. They published a collection of methods for the estimation of flood water runoff in ungauged catchments for practitioners [Spreafico et al.,

Figure 2. Severe sediment deposition and channel erosion in the Chärstelenbach near Bristen after a large flood in August 2005, canton Uri, Switzerland. (Photo: Amt für Tiefbau, canton Uri)
2003]. After the release of that manual, natural hazards experts pointed out that similar methods are lacking to predict sediment transport associated with these floods, although such methods are urgently needed. The present study was initiated and co-financed by FOEN and the Swiss Federal Institute for Forest, Snow and Landscape Research (WSL) to generate a basis for improved bedload transport estimates.

2 Research gaps

Bedload transport has been explored from diverse scientific perspectives for more than 100 years, and still remains an active area of research. There is a strong connection between channel-roughness, flow resistance and sediment transport, but we still do not properly understand important details of these interactions, for example how exactly roughness affects the flow and how flow resistance controls sediment transport. Thus, the accurate prediction of bedload transport remains one of the major challenges. To tackle this problem, the two main factors controlling sediment transport have to be assessed: (i) the transport capacity, and (ii) the sediment availability. While the availability of sediment generally becomes larger for increasing catchment areas, the transport capacity becomes generally smaller (Figure 3). Interestingly, predictions of transport capacity become less reliable for smaller catchments and thus for steeper streams. It has been shown that even in steep streams with sufficient available sediment, bedload transport equations still overpredict transport rates significantly [Rickenmann and Koschni, 2010]. Consequently, a better understanding of transport capacity appears to be a key factor for improved sediment predictions.

Transport capacity

Transport capacity describes the maximum sediment volume that a stream is able to move per unit time. It is determined by the maximum energy of the flow available for sediment trans-
port. The flow’s energy is mainly a function of discharge, channel slope, and channel roughness. Many authors have proposed equations for estimating the transport capacity of natural streams [e.g. Bagnold, 1980; Bathurst et al., 1987; Meyer-Peter and Müller, 1948; Parker et al., 1982; Rickenmann, 1991; Schoklitsch, 1962; Smart, 1984; Wilcock and Crowe, 2003]. These commonly used transport equations typically overestimate bedload volumes by up to three orders of magnitude, if no adjustment is made to account for the flow resistance in steep streams (Figure 4) [Bathurst et al., 1987; Chiari and Rickenmann, 2011; Lenzi et al., 1999; Rickenmann, 2001].

Typical characteristics of steep mountain streams include: (i) high channel gradients, exceeding approximately three percent, (ii) wide grain size distributions, (iii) rough channel beds and boundaries, (iv) large-scale bedforms such as step-pool units, (v) shallow and highly turbulent flows, (vi) variable channel width, and (vii) rather limited sediment supply (Figure 5). These features lead to additional roughness and flow resistance that are absent in lower-gradient channels. Many sediment transport equations have been developed and calibrated with data from flume experiments or low gradient streams, which have channel bed and transport characteristics that differ significantly from those in steep streams. This is one possible reason why the existing equations overestimate sediment transport.

In low-gradient rivers, flow resistance is mainly generated by the drag of stationary sand and gravel grains on the water. Because the scale of these roughness elements is usually much smaller than the flow depth, they are referred to as small-scale or grain roughness and a characteristic grain size is usually used as roughness measure. Steep streams, by contrast, are typically dominated by macro-roughness elements, such as large immobile boulders, channel-spanning bedforms, or woody debris. The importance of accounting for additional energy loss (or increased total flow resistance) due to a higher channel roughness in the context of bedload transport calculations was pointed out in several publications [e.g. Chiari and Rickenmann, 2011; Govers and Rauws, 1986; Palt, 2001; Rickenmann, 2001, 2005; Rickenmann and Koschni, 2010; Yager et al., 2012; Yager et al., 2007; Zimmermann, 2010].

![Figure 4. Bedload observations and predictions from three widely used bedload transport equations for a bedload transport event on 14.07.1995 in the Erlenbach, Switzerland. Transport rates were indirectly measured with bedload sensors [Rickenmann and McArdell, 2007].](image)
Macro-roughness elements are a physical source of flow resistance. Turbulence is increased through acceleration and deceleration of the flow around boulders, and through jets of critical or supercritical flow over step crests and cascades. As a result, total flow resistance significantly increases with more pronounced macro-roughness elements. Compared to low gradient streams, an increase of total flow resistance was observed by many studies in natural streams with gradients larger than approximately 1% [e.g. Bathurst, 1985; Hodel, 1993; Palt, 2001; Rickenmann, 1996; Zeller, 1996]. Reid and Hickin [2008] show that for steep streams with channel slopes of 1.9-7.5%, flow resistance due to macro-roughness generates about 90% of the stream’s total flow resistance. Zimmermann [2010] also concluded that a major part of the flow energy in steep streams is dissipated by form and spill drag around macro-roughness elements such as step-pools.

Just like in lower-gradient channels, roughness in steep streams is usually represented by a characteristic grain size. There are only a few approaches that explicitly take into account the effects of macro-roughness features using measures of boulder concentration [Pagliara and Chiavaccini, 2006; Whittaker et al., 1988; Yager, 2006; Yager et al., 2007] or step geometry [Egashira and Ashida, 1991; Yager et al., 2012]. None of these approaches has been tested with field observations and validated for a wide range of natural conditions. Each of the approaches deals with a specific measure of roughness, either step geometry or boulder concentration, even though flow resistance is produced by very different roughness elements on very different scales. Aberle and Smart [2003] and Lee and Ferguson [2002], among others, have argued that grain size does not represent roughness in steep streams and they suggest the standard deviation of bed elevations as a more appropriate roughness measure. However, a general agreement on how to best relate flow resistance to bed properties in steep or shallow flows is currently lacking. This is partly due to (i) a disagreement on how to quantify roughness and (ii) a scarcity of combined flow and roughness measurements in the field. Measuring the complex roughness in steep streams often requires creative or costly approaches. As a result, the influence of macro-roughness on flow resistance and bedload transport has not been fully explored.
Chapter I

Sediment availability
Sediment availability characterizes the volume of sediment that can be easily entrained by flows larger than the transport threshold. It depends on the sediment stored in a channel and on the supply from hillslopes. Sediment availability can be limited for several reasons: (i) compared to alluvial river beds, the alluvial cover in mountain stream beds is usually thin, (ii) some portion of the coarse sediment is barely mobile under common flow conditions, and (iii) finer grains are often covered by coarser grains, which protect the bed from erosion until the so-called armor layer breaks up [Bathurst, 2007; Palt, 2001]. Estimating sediment availability in a river is challenging, and the identification of sediment sources and their transport paths to the river bed typically requires time-consuming field investigations. There are few semi-quantitative methods to estimate sediment availability in small catchments [e.g. Frick et al., 2008; Spreatico et al., 1996]. Yager et al. [2007] found two parameters that may serve as proxies for sediment availability. They observed in flume experiments that with greater sediment supply, the protrusion of large grains decreased and the proportion of bed covered by gravel increased. These observations still need to be verified.

A river carries sediment in different modes. Bedload moves along the bed by rolling, sliding or saltation, while suspended load moves over considerable distances in the water column and is rarely in contact with the bed. Dissolved load is carried in solution. The partitioning of the total sediment load in steep streams is highly variable. However, for small catchments and large discharges, bedload transport becomes relatively more important [Turowski et al., 2010], and the bedload fraction can be in the order of tens of percent of the total load. This thesis focuses on bedload transport as the dominant transport mode in steep streams, since it is relevant for engineering applications and natural hazards research.

3 Objectives
In this thesis I aim at a better understanding of the interactions between channel roughness, flow resistance and sediment transport in steep mountain streams. Since there is a lack of a widely applicable method for realistic predictions of the bedload transport capacity, relevant field parameters to better characterize these interactions have to be identified and analyzed. The thesis further aims at creating a basis for future methods that explicitly account for the characteristics of roughness elements and channel geometry in steep streams. To this end three major aims have been pursued, and are discussed in chapters II, III, and IV:

Aim 1
Macro-roughness elements have an important effect on flow resistance and flow velocity. However, currently there is no agreement on how to best measure roughness and how to relate flow resistance to bed properties in steep or shallow streams. Furthermore, roughness is often described using a single parameter, and none of the roughness measures proposed so far can completely explain the observed variability of flow velocity between different field sites. For this study, macro-roughness was quantified for several steep mountain channels and flow velocity was measured over a wide range of discharges. The objectives of this study were:
Introduction

- to test how macro-roughness can be measured,
- to evaluate the relations between measures of macro-roughness and channel slope,
- to compare the flow parameters of different rough streams, and
- to explain the observed between-site variations in flow velocity and macro-roughness.

This study is presented in chapter II and has been submitted as a research article:

**Aim 2**

Many commonly used bedload transport equations overestimate transport rates in steep streams by orders of magnitude, if there is no appropriate accounting for the typical macro-roughness found in steep streams. The few existing approaches that include a direct measure of macro-roughness have not been tested with field observations and thus the feasibility of the approaches and the roughness measures remains unclear. The objectives of the second study were:

- to assess several approaches that allow calculating the contribution of macro-roughness elements to total flow resistance,
- to combine these approaches with bedload transport equations,
- to compare the transport predictions with field measurements of discharge, transported bedload volumes, and channel characteristics in 13 Swiss mountain streams, and
- to find the best-performing approaches.

This study is presented in chapter III and has been published as a research article:

**Aim 3**

There is a lack of data characterizing channel-bed roughness, especially for steep mountain streams, mainly because steep streams are difficult to measure, they are complex in shape, and they have a wide grain size distribution which complicates measuring all scales with a single method. Therefore, creative approaches are needed. Measurement apparatus like terrestrial laser scanners or airborne Lidar systems are sometimes difficult to successfully apply in such environments. These instruments need free sight, elevated positions and good aerial or road access, which is generally not the case in mountain streams. The objectives of this study were:
Chapter I

- to test range imaging cameras for their potential to generate high resolution data of streambed topography,
- to identify and quantify major measurement errors of this new method,
- to assess the suitability of range imaging for developing roughness measures in mountain streams, and
- to evaluate its advantages and disadvantages compared to traditional surface measurement techniques such as terrestrial laser scanning and photogrammetry.

This study is presented in chapter IV and is an article in review: Nitsche, M., J. M. Turowski, A. Badoux, D. Rickenmann, T. K. Kohoutek, M. Pauli, and J. W. Kirchner (2012), Range Imaging: a new method for high-resolution topographic measurements in small- and medium-scale field sites, *Earth Surface Processes and Landform*.

For all three of the studies a variety of field measurements were carried out. In total, 17 sites across the Swiss Alps and Pre-Alps were studied and measurements of channel roughness and flow velocity were collected (Figure 6). Furthermore, available data of event and long-term bedload measurements were assessed for several streams.

4 Structure of the thesis

The thesis consists of five chapters. An introduction and motivation is given in Chapter I. The main results of the three studies are presented in Chapters II-IV. These studies were also pub-
lished or submitted as research articles in peer-reviewed journals (see publication list). The outcome of this work is summarized and concluded in Chapter V. Additional articles published in conference proceedings and in a German-language scientific journal are included in the appendix at the end of this document.

References


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Chapter II

Macro-roughness and variations in reach-averaged flow resistance in steep mountain streams

Manuel Nitsche, Dieter Rickenmann, James Kirchner, Jens Turowski, Alexandre Badoux

ABSTRACT – Steep mountain streams typically feature macro-roughness elements like large immobile boulders or channel-spanning bedforms such as step-pool sequences. The effects of macro-roughness on resistance and flow velocity are not well understood and appropriate field parameter for representing macro-roughness in flow velocity equations have not been identified. The prediction of flow velocity in rough and steep streams therefore remains challenging. We measured flow velocity and several macro-roughness parameters, i.e. boulder concentration, boulder diameter and protrusion, and roughness of longitudinal channel profiles) in six reaches of steep mountain streams with plane bed/riffle, step-pool and cascade channel morphologies. The between-site variations in flow resistance can be explained to some extent by non-dimensionalization of discharge and flow velocity using channel slope and a characteristic roughness length. Using any of our roughness parameters as the characteristic roughness length, this non-dimensionalization leads to a similarity collapse of the entire data set. The remaining differences in flow resistance among the streams are related to dimensionless measures of macro-roughness that describe the concentration of boulders or step density in a reach. Boulder concentration represents the measure best describing the data and is used in a simple regression equation for flow velocity. The predictions were somewhat better than predictions by the variable power-law equation of Ferguson. Although the regression might not be statistically significant, the observed trends suggest that measures of macro-roughness, particularly boulder concentration, explain a large portion of between-site variation of flow resistance.

In review in Water Resources Research

1 Introduction

Steep streams (here, streams with gradients greater than about three percent) occupy the majority of the total stream length in mountainous areas. Typically, they differ from low-gradient streams by their greater roughness, characterized by wide grain size distributions, variable channel widths, large bedforms, and shallow flows. These streams are important agents of erosion and sediment transfer from headwaters to lower basins. Sediment mobility controls natural channel dynamics, and high-intensity sediment transport episodes pose hazards for
buildings, water intakes and other infrastructure in or near streams. To accurately predict bedload transport rates it is crucial to estimate the reach-average flow velocity. In steep streams, however, good flow velocity estimates require a better understanding of the effects of channel roughness.

Flow velocity is mainly a function of the flow depth $h$ (or the hydraulic radius $R_h$), the gravitational acceleration $g$ in the direction of the channel slope $S$, and the channel roughness. The relationship between these parameters is most commonly described with the Darcy-Weisbach equation:

$$v = \sqrt{\frac{8ghS}{f_{tot}}},$$

where $v$ is the mean flow velocity and $f_{tot}$ is the dimensionless Darcy-Weisbach friction factor, which scales with a roughness length. The friction factor is an empirical value that is highly variable between individual stream reaches and is difficult to measure in the field. However, it remains crucial for the calculation of flow resistance and flow velocity.

Alternatively, several authors have proposed non-dimensional hydraulic geometry equations that link the mean flow velocity to total water discharge $Q$ [Rickenmann, 1994; Rickenmann, 1996] or unit discharge $q$ [Aberle and Smart, 2003; Comiti et al., 2007; Ferguson, 2007; Rickenmann, 1994; Rickenmann, 1996; Zimmermann, 2010], because discharge is much easier to determine in rough streams than flow depth. These equations are given in dimensionless form:

$$v^* = cq^* S^{(1-m)/2},$$

where $v^* = v/(gD_{84})^{0.5}$, $q^* = q/(gD_{84}^3)^{0.5}$, $q$ is the discharge per unit channel width, $D_{84}$ is the 84th percentile of the grain size distribution, and $c$ and $m$ are empirically determined prefactor and exponent, respectively. Ferguson [2007] found that this type of equation better describes flow velocity measurements in natural streams than other equations. The dimensionless variables were particularly successful in describing at-a-site variations of flow resistance. To better account for the variations between different sites, it was suggested to include the water surface or channel slope as a further factor [Aberle and Smart, 2003; David et al., 2010; Ferguson, 2007; Rickenmann and Recking, 2011; Zimmermann, 2010]. As a consequence, Rickenmann and Recking [2011] introduced two new dimensionless variables to describe a large set of data using a power function similar to equation (2):

$$v^{**} = cq^{**m},$$

where $v^{**} = v/(gSD_{84})^{0.5}$ and $q^{**} = q/(gSD_{84}^3)^{0.5}$. These new variables resulted in a similarity collapse of a large data set in the study by Rickenmann and Recking [2011].

Both Ferguson [2007] and Rickenmann and Recking [2011] used the characteristic grain size $D_{84}$ as the single explicit roughness measure. A characteristic grain size is also used in the standard logarithmic (Keulegan type) or power law equations (Manning-Strickler type). How-
ever, in order to allow for form drag on protruding clasts in shallow flows, the characteristic grain size is usually increased by multiplying it by an empirical factor [Bathurst, 1985; Bray, 1979; Hey, 1979; Thompson and Campbell, 1979].

Aberle and Smart [2003] and Lee and Ferguson [2002], among others, have argued that grain size might not be an appropriate roughness measure in steep streams. Aberle and Smart [2003] found that hydraulic roughness varied among different sites or different flows even though the characteristic grain size (for example $D_{84}$) remained the same. Instead, they identified the standard deviation of bed elevation as a roughness parameter that additionally accounts for the arrangement of grains [Aberle and Smart, 2003; Smart et al., 2002].

Steep streams typically feature large grains that can be randomly distributed in the channel or can be organized in patches or clusters [e.g. Lamarre and Roy, 2008; Nelson et al., 2009] or in channel-spanning steps [e.g. Chin and Wohl, 2005; Church and Zimmermann, 2007; Whittaker and Jaeggi, 1982; Zimmermann et al., 2008]. These macro-roughness features lead to additional flow resistance that is absent in lower gradient channels. In low-gradient streams the main source of resistance is skin friction, i.e. from drag on individual particles and viscous friction on their surfaces [Ferguson, 2007]. In steep streams, by contrast, flow resistance mainly results from macro-roughness, including form drag around large boulders due to acceleration, deceleration, and turbulent wakes, as well as spill loss, particularly behind steps or larger particles if flow is locally supercritical [Chin, 2003; Ferguson, 2007]. Zimmermann [2010] concluded that a major part of the flow energy in steep streams is dissipated by form and spill drag around roughness elements like step-pools. The contribution of these structures to total flow resistance increases with increasing relative protrusion (or equivalently, with decreasing relative submergence of the bed). However, for some mountain streams with very pronounced step-pool structures, Comiti et al. [2009] and David et al. [2010] found that variations in flow resistance were mostly explained by unit discharge and slope, whereas $R_0/D_{84}$ was not an appropriate explanatory variable. David et al. [2010] also found that the relations between flow resistance and these variables were distinct for different channel types.

These macro-roughness features are rarely taken into account explicitly in flow resistance equations. The effects of boulder diameter and areal boulder concentration on flow resistance have been studied in laboratory flumes, resulting in empirical or semi-theoretical resistance equations [Pagliara and Chiavaccini, 2006; Whittaker et al., 1988; Yager, 2006; Yager et al., 2007]. Other equations include the effects of steps and pools on flow resistance, using step height and step length as the relevant measures of macro-roughness [Canovaro and Solari, 2007; Egashira and Ashida, 1991; Whittaker, 1986]. There are few systematic tests of these approaches with field observations [e.g. Nitsche et al., 2011].

Currently there is no agreement on how best to relate flow resistance to bed properties in steep or shallow streams. This is partly due to (i) a disagreement over how to quantify roughness, and (ii) a scarcity of combined flow and roughness measurements in the field. Furthermore, roughness is often described using a single parameter, and none of the roughness measures proposed so far can completely explain the observed variability of flow velocity among different sites.
Chapter II

In the present study we measured flow velocity over a wide range of discharges, in six stream reaches with widely varying channel bed slopes and grain size distributions. In addition, we quantified macro-roughness for each of these stream reaches by measuring characteristic grain sizes, boulder concentrations, and the roughness of the longitudinal channel profiles. These data were used (i) to test how macro-roughness can be measured, (ii) to evaluate the relations among various measures of macro-roughness and channel slope, (iii) to compare the flow parameters of different rough streams, and (iv) to explain the observed between-site variations in flow velocity and macro-roughness, using non-dimensional variables and regression analysis.

2 Data and methods

2.1 Field sites

Data were collected from five mountain streams located in the Swiss Alps and Prealps (Table 1, Figure 1). The alluvial streams cover a wide spectrum of channel characteristics, with morphologies ranging from plane bed to cascade channel types and step-pool types [after Montgomery and Buffington, 1997], with channel slopes ranging from 2 % to 38 %. Three of the stream catchments feature a significant proportion of forest (Table 1), however, in the study reaches only small amounts of woody debris are present. The steps generally contain few woody debris, thus wood is assumed unimportant as a source of roughness.

Table 1. Basin characteristics (upstream of study reach)

<table>
<thead>
<tr>
<th></th>
<th>Spöl</th>
<th>Riedbach</th>
<th>Gornera</th>
<th>Erlenbach</th>
<th>Vogelbach</th>
<th>Riedbach</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basin area (km²)</td>
<td>295ᵇ</td>
<td>14</td>
<td>82</td>
<td>0.7</td>
<td>1.6</td>
<td>16</td>
</tr>
<tr>
<td>Basin elevation range (m)</td>
<td>1674-3302</td>
<td>2035-4327</td>
<td>2005-4634</td>
<td>1110-1655</td>
<td>1055-1540</td>
<td>1810-4327</td>
</tr>
<tr>
<td>Mean upstream channel slope</td>
<td>0.01ᶜ</td>
<td>0.07</td>
<td>0.14</td>
<td>0.18</td>
<td>0.19</td>
<td>0.16</td>
</tr>
<tr>
<td>Lithology</td>
<td>Dolomite, Moraine</td>
<td>Moraine, Gneiss</td>
<td>Moraine, Granite, Ophiolite</td>
<td>Flysch</td>
<td>Flysch</td>
<td>Gneiss</td>
</tr>
<tr>
<td>Forest/glacier extent (%)</td>
<td>30/0ᶜ</td>
<td>0/60</td>
<td>0/67ᶠ</td>
<td>39/0</td>
<td>65/0</td>
<td>1/50</td>
</tr>
<tr>
<td>Discharge regimeᵃ</td>
<td>perturbedᵈ</td>
<td>a-glaciaire</td>
<td>a-glaciaire</td>
<td>nivo-pluvial prealpine</td>
<td>nivo-pluvial prealpine</td>
<td>a-glaciaire</td>
</tr>
<tr>
<td>Mean annual precipitation (mm)</td>
<td>800-1200ᵉ</td>
<td>2000-3000ᵉ</td>
<td>610ᵍ</td>
<td>2300</td>
<td>2200</td>
<td>2000-3000ᵉ</td>
</tr>
<tr>
<td>Highest discharge (m³s⁻¹)/return period (years)</td>
<td>perturbedᵈ</td>
<td>no data</td>
<td>70ᵇ/ no data</td>
<td>14.6¹/50ⁱ</td>
<td>6.8/50</td>
<td>no data</td>
</tr>
</tbody>
</table>

ᵃ After Weingartner and Aschwanden [1992a].
ᵇ Data: Swiss Federal Office for the Environment.
ᶜ Basin up to reservoir.
ᵈ Discharge managed by a upstream hydropower plant, which provides ecological minimum discharge (0.7-1.4 m³/s) and one or two reservoir releases per year with artificial flows of up to 70 m³/s.
ᵉ Weingartner and Aschwanden [1992b].
ᶠ Farinotti et al. [2009].
ᵍ At 1638 m, data: MeteoSwiss.
ʰ Bezinge [1999].
ⁱ Turowski et al. [2009].
Measurements of mean flow velocity and roughness were carried out in one reach per stream, except in the Riedbach, where two reaches were selected (Table 3). The length of the study reaches ranged from 11 to 28 times the bankfull stream width, and thus were adequate for relating stream morphology and channel processes [Montgomery and Buffington, 1997]. The reaches were chosen for their proximity to gauging facilities and their relative morphological homogeneity. The measurements in the Spöl were carried out during an artificial
flooding experiment, in which flow stages were held constant for predefined periods. To enlarge the dataset of roughness measurements additional roughness data from another eight Swiss mountain streams was used. These streams include the Rappengraben, Sperbelgraben, Melera, Rotenbach, Schwändlibach, Lonza, Buholzbach and Steinibach, which are characterized in the publication of Nitsche et al. [2011].

2.2 Flow measurements

For flow measurements the tracer dilution method [e.g. Foster, 2000; Kilpatrick and Wilson, 1989; Leibundgut et al., 2009] was applied using the fluorescent tracer Uranine (color index 45350), and for some measurements the salt tracer sodium chloride (see Table 2). At low and intermediate flow conditions Uranine concentrations were measured in situ with the flow-through field fluorometer model GGUN-FL30, developed at the University of Neuchâtel, Switzerland [Schnegg, 2003; Schnegg and Doerflinger, 1997]. Salt concentrations were obtained from conductivity measurements. In the Erlenbach and the Vogelbach, we also injected and measured tracer automatically at infrequent high flows with a self-developed system, without the need of on-site personnel. The tracer concentration curves allowed the identification of tracer travel times; we used the harmonic mean tracer travel time to calculate the reach-averaged flow velocity. The harmonic mean has been identified by Waldon [2004] as the theoretically correct, unbiased estimate of the mean velocity. Zimmermann [2010] has also experimentally shown that the harmonic mean is the most accurate measure for the mean velocity compared to peak or centroid velocities.

In all experiments the tracer was instantaneously injected (slug injection) into a preferably well mixed cross section, assuming that lateral mixing is complete after short distances relative to the reach length. The tracer probes were placed relatively close to the sides of the stream, missing the center of the flow. Both incomplete mixing and probe location cause errors in the velocity measurement. We estimate these errors at a constant five percent. Further sources of uncertainty are: (i) the determination of injection time, (ii) the sampling rate, and (iii) the accuracy of flow path measurement. For each stream the combined uncertainty estimate in flow velocity was individually calculated (Table 2).

<table>
<thead>
<tr>
<th>Study reach</th>
<th>Velocity</th>
<th>Error (%)</th>
<th>Discharge</th>
<th>Error (%)</th>
<th>N</th>
<th>Flow range (m³/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spöl From h, with ( v = \frac{Q}{A(h)} )</td>
<td>20</td>
<td>Gauge</td>
<td>10</td>
<td>10</td>
<td>2-40</td>
<td></td>
</tr>
<tr>
<td>Riedbach (flat)</td>
<td>Tracer travel time (^a)</td>
<td>10</td>
<td>Tracer dilution</td>
<td>10</td>
<td>20</td>
<td>0.3-2</td>
</tr>
<tr>
<td>Gornera</td>
<td>Tracer travel time (^a)</td>
<td>10</td>
<td>Stream gauge + tracer</td>
<td>10</td>
<td>78</td>
<td>0.2-20</td>
</tr>
<tr>
<td>Erlenbach</td>
<td>Tracer travel time (^a,b)</td>
<td>11</td>
<td>Stream gauge</td>
<td>10</td>
<td>78</td>
<td>0.0005-2</td>
</tr>
<tr>
<td>Vogelbach</td>
<td>Tracer travel time (^a,b)</td>
<td>10</td>
<td>Tracer dilution</td>
<td>10</td>
<td>31</td>
<td>0.04-3</td>
</tr>
<tr>
<td>Riedbach (steep)</td>
<td>Tracer travel time (^a)</td>
<td>11</td>
<td>Stream gauge</td>
<td>10</td>
<td>27</td>
<td>0.06-4</td>
</tr>
</tbody>
</table>

\(^a\) Dye tracer: Uranine.
\(^b\) Salt tracer: sodium chloride.
\(^c\) Average summed squared relative error (estimated for each stream using uncertainty propagation).
\(^d\) N is the number of measurements.
Flow discharge was independently measured with stream gauges in four study reaches, and for two reaches it was derived from the tracer concentration curves (Table 2). Uncertainty in discharge gauging is approximately ten percent. The uncertainty in the present discharge measurements from tracer concentration curves is mainly affected by the accuracy of the injection mass and the calibration solution. Additionally, the relationship between fluorescence and dye concentration (and thus inferred discharge) is affected by photochemical decay under exposure to light [Leibundgut et al., 2009]. Uranine has a half-life time of eleven hours in daylight [GSF, 1978], and thus Uranine degradation can be neglected at the much shorter exposure times (tens of seconds) during our experiments. Potential errors due to the influence of pH-value, temperature and turbidity on the fluorescence intensity were eliminated through fluorometer calibration just before each measurement. Sorption and filtration of the tracer were assumed to be insignificant, because of the short flow paths (< 110 m) and short flow times (tens of seconds). The mean error for the discharge measurements was explicitly calculated for each of the streams (Table 2).

2.3 Hydraulic parameters
A representative channel cross-section was interpolated from the vertical mean of multiple measured cross-sections (see example in Figure 2). Using this reach-averaged cross-section, we solved for hydraulic parameters (i.e. flow depth $h$, width $w$, hydraulic radius $R_h$, cross sectional area $A$) corresponding to each measured value of discharge and reach-averaged velocity. Because flow width varies with the discharge $Q$, the unit discharge was determined by $q = Q/w$, where $w = A/h$. The resulting flow parameters are not exact for any particular cross-section in the reach, but instead represent an average of the reach. This reach-averaged approach is justified because we know only the reach-averaged flow velocity, rather than the flow velocity at each cross section.

2.4 Macro-roughness measurements
We measured macro-roughness through the grain size distributions and geometric channel parameters of the study reaches. For boulder-based macro-roughness measures, we used the
mean diameter \( (D_b) \) and the concentration \( (I) \) of large, relatively immobile boulders, where 
\[
I = n_b \pi D_b^2/(4WL_r),
\]
with \( n_b \) the number of boulders, \( W \) the width and \( L_r \) the length of the reach. Ideally, the definition of a critical boulder diameter should be based on the grain size that is moved at a discharge corresponding to a specific reoccurrence interval. Since we do not have the necessary information on the frequency of boulder movement, we fixed the critical boulder diameter at 0.5 m. Every grain whose b-axis was larger than this critical diameter was measured. Moreover, this assumption allowed more robust data acquisition in the field, where measuring smaller grains would involve greater uncertainties and much greater effort. If the b-axis was not identifiable, the longest axis protruding above the channel bed was measured instead.

Longitudinal profiles of the reaches were obtained with a total station or a laser slope and distance meter. Instead of using a fixed point density, the measurements were taken at breaks in slope, as recommended by Zimmermann et al. [2008]. The resulting profiles feature a variable horizontal resolution of 0.2-2 m and they were used to identify steps and pools using the step-pool classification approach of Zimmermann et al. [2008]. The Zimmermann et al. [2008] algorithm is scale-free and independent of the point density of the profiles, and allows derivation of the step height \( H_s \), which is defined here as the vertical distance from the top of a step to the downstream end of its associated pool, and step length \( L_s \), which is the horizontal distance between a step and the next step downstream. From these main step characteristics further parameters were derived, including the step slope \( H_s/L_s \), the step density \( n/L_r \) (where \( n \) is the number of steps in a reach and \( L_r \) is the effective reach length), and the fraction of total reach height accounted for by steps \( \Sigma H_s/H_r \).

The standard deviations of elevations of the longitudinal profiles \( s \) were derived by a procedure similar to that of Smart et al. [2004]. First, the longitudinal profiles were interpolated to an equidistant point spacing of 0.5 m, in order to have an equal spacing for all streams. Because trends in the elevation data, introduced by channel slope or large bedforms, would blur the scaling region of macro-roughness, the profiles were then flexibly detrended. To do this, we inserted knot points into the longitudinal profile at a spacing of 10 times the mean boulder diameter \( D_b \). The elevations at these knot points were determined by averaging all elevations in the original profile within a distance of 5 \( D_b \) up- and downstream of each knot point. Cubic spline interpolation was used to interpolate between these knot points to generate a trend line. This trend was then subtracted from the original profile elevations, which removed the slope of any forms larger than the biggest boulders or boulder clusters (Figure 3).

Channel geometry and the measured roughness parameters may vary considerably within a given reach. Therefore, reach-averaged values of roughness and channel geometry were used throughout our analysis. This simplification is logical, because the analysis is made at the reach scale and, moreover, our flow measurements also represent an average of the flow conditions within the reach. See Table 3 for an overview of the measured parameters and additional definitions.
Macro-roughness and variations in flow resistance

Figure 3. Longitudinal profile of the Erlenbach study reach with trend spline and the resulting detrended profile.

Table 3. Reach geometry and roughness measures of the study reaches

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Spöl Pool rifle</th>
<th>Riedbach flat</th>
<th>Gornera Plane bed</th>
<th>Erlenbach Cascade</th>
<th>Vogelbach Step pool</th>
<th>Riedbach Step pool</th>
<th>Cascad Cascade</th>
</tr>
</thead>
<tbody>
<tr>
<td>Channel type</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Channel slope</td>
<td>S</td>
<td>0.02</td>
<td>0.04</td>
<td>0.11</td>
<td>0.12</td>
<td>0.13</td>
<td>0.38</td>
<td></td>
</tr>
<tr>
<td>$D_{54}$ (m)</td>
<td>$D_{54}$</td>
<td>0.11</td>
<td>0.22</td>
<td>1.17</td>
<td>0.29</td>
<td>0.35</td>
<td>0.86</td>
<td></td>
</tr>
<tr>
<td>Bankfull width (m)</td>
<td>$W_{bf}$</td>
<td>18.7</td>
<td>13.4</td>
<td>10.7</td>
<td>4.7</td>
<td>5.7</td>
<td>13.0</td>
<td></td>
</tr>
<tr>
<td>Width of streambed (m)</td>
<td>W</td>
<td>16.0</td>
<td>6.0</td>
<td>9.0</td>
<td>3.5</td>
<td>5.0</td>
<td>6.0</td>
<td></td>
</tr>
<tr>
<td>Mean boulder size (m)</td>
<td>$D_b$</td>
<td>0.70</td>
<td>0.83</td>
<td>0.78</td>
<td>0.82</td>
<td>0.62</td>
<td>0.82</td>
<td></td>
</tr>
<tr>
<td>Boulder protrusion (m)</td>
<td>$p$</td>
<td>0.41</td>
<td>0.45</td>
<td>0.45</td>
<td>0.51</td>
<td>0.25</td>
<td>0.22</td>
<td></td>
</tr>
<tr>
<td>Boulder concentration</td>
<td>$\Gamma$</td>
<td>0.05</td>
<td>0.01</td>
<td>0.29</td>
<td>0.11</td>
<td>0.12</td>
<td>0.37</td>
<td></td>
</tr>
<tr>
<td>Boulder step spacing</td>
<td>$\lambda_s$</td>
<td>14.9</td>
<td>69.7</td>
<td>2.7</td>
<td>7.5</td>
<td>5.3</td>
<td>2.2</td>
<td></td>
</tr>
<tr>
<td>Mean step height (m)</td>
<td>$H_s$</td>
<td>-</td>
<td>0.4</td>
<td>0.9</td>
<td>0.4</td>
<td>0.5</td>
<td>1.3</td>
<td></td>
</tr>
<tr>
<td>Mean step length (m)</td>
<td>$L_s$</td>
<td>-</td>
<td>7.5</td>
<td>13.1</td>
<td>4.1</td>
<td>5.0</td>
<td>29.1</td>
<td></td>
</tr>
<tr>
<td>Step slope</td>
<td>$H_s/L_s$</td>
<td>-</td>
<td>0.05</td>
<td>0.07</td>
<td>0.10</td>
<td>0.10</td>
<td>0.05</td>
<td></td>
</tr>
<tr>
<td>Reach length (m)</td>
<td>$L_t$</td>
<td>53.4</td>
<td>108.4</td>
<td>252.2</td>
<td>40.8</td>
<td>81.6</td>
<td>100.5</td>
<td></td>
</tr>
<tr>
<td>Reach height difference (m)</td>
<td>$H_t$</td>
<td>0.9</td>
<td>4.1</td>
<td>28.8</td>
<td>6.0</td>
<td>9.8</td>
<td>34.1</td>
<td></td>
</tr>
<tr>
<td>Number of steps</td>
<td>n</td>
<td>0</td>
<td>3</td>
<td>19</td>
<td>9</td>
<td>12</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>Step density</td>
<td>$n/L_t$</td>
<td>0</td>
<td>0.03</td>
<td>0.17</td>
<td>0.22</td>
<td>0.15</td>
<td>0.03</td>
<td></td>
</tr>
<tr>
<td>Standard dev. of elevations (m)</td>
<td>s</td>
<td>0.07</td>
<td>0.10</td>
<td>0.32</td>
<td>0.26</td>
<td>0.25</td>
<td>0.47</td>
<td></td>
</tr>
</tbody>
</table>

* After Montgomery and Buffington [1997].
* Grain sizes were calculated after Fehr [1987] based on line-by-number pebble counts of around 500 grains of down to 1 cm in diameter for each study reach.
* Average of field measurements which were taken at least every ten meters.
* Upstream height of an boulder that protrudes above the finer bed material, after Yager et al. [2007].
* Area fraction covered by boulders, after Pagliara and Chiavaccini [2006].
* After Yager [2006].
Chapter II

3 Results

3.1 Relationships between roughness parameters and slope

In many studies measures of boulders and steps were primarily developed from laboratory experiments to quantify ideal type elements of large-scale roughness. In nature, however, macro-roughness elements are not distinct or well-defined features. Channel-spanning steps, for example, often co-occur with randomly arranged boulders. The comparison of roughness measures of 14 study reaches (Figure 4) identifies various proxy variables and their dependence on slope.

Despite the large range of channel types, the channel slope correlates well with several macro-roughness measures, for example with boulder concentration $\Gamma$, with the standard deviation of elevation $s$, and to some extent with the boulder protrusion $p$. This indicates that the effects of channel slope and the effects of roughness cannot be separated in field data from steep streams. Slope $S$ and step features like step slope $H_s/L_s$ and step density $n/L_r$ do not significantly correlate in the study reaches. Also, the characteristic grain size $D_{84}$ is not strongly correlated with the slope of the study streams.

Several macro-roughness measures show clear correlations with other macro-roughness measures. The standard deviation of elevations $s$ scales well with the step height $H_s$, and also boulder concentration $\Gamma$ and $D_{84}$ are well correlated (Figure 4). These well-correlated measures can be considered proxies for each other. However, there are also roughness measures that are relatively independent, for example $D_{84}$ and standard deviation of elevations $s$ and step height $H_s$ (Figure 4). Boulder concentration $\Gamma$ is also relatively independent from step slope $H_s/L_s$.

3.2 Variations of flow properties with discharge

Flow velocity

Every stream reach shows a well-defined increase in flow velocity $v$ with discharge $Q$ or discharge per unit width $q$ (Figure 5a,b). The relationship between flow velocity and discharge or unit discharge is plotted in Figure 5a,b. Mean velocity scales on average with an exponent of about 0.47 with the discharge (Figure 5a), and with an exponent of about 0.6 with the unit discharge (Figure 5b). The well defined $v$-$Q$ trends have exponents from 0.39-0.52, which are somewhat low compared to the range of 0.51-0.84 found by Lee and Ferguson [2002] for step-pool streams. Typical exponents for lowland streams are in the range of 0.3 to 0.5 [Knighton, 1998]. The rather large exponent for both Riedbach reaches (0.52) might be due to the very slow increase in depth with discharge. The $v$-$Q$ data for each site give a rather smooth trend with no sharp discontinuities, which is rather unexpected given the differences in local hydraulic conditions at low and high flows. At higher flows the curves slightly flatten, which might be unexpected because roughness elements are drowned out, but it is in agreement with a large number of observations from steep streams [Ferguson, 2007]. Furthermore, flow velocity increases faster with discharge than it does with either width or depth. The dif-
Macro-roughness and variations in flow resistance

Different intercepts of the trend lines of the v-Q relation (Figure 5a) do not relate in any simple way to measured properties of the channels.

For five reaches, the hydraulic radius $R_h$ is systematically lower than $D_{84}$, except at high flows, when they are approximately of the same scale (Figure 5d). These flows would presumably not submerge the roughness elements. One other stream (Spöl) has $R_h$ values that are systematically higher than $D_{84}$. These flows could potentially submerge the roughness elements and therefore a faster increase in $R_h$ or $h$ might be expected, compared to the other streams. However, the exponents in the power-law relationships between unit discharge $q$ and flow depth $h$ are not significantly different for the two groups (Figure 5e).

Figure 4. Correlation of roughness measures and channel slope or $D_{84}$ in the six study reaches (black points) and the eight reaches of the test data set (grey points, cf. section 2.1). Power law fit lines for the complete data set were drawn when $r^2 > 0.4$. 

\[ y = 1.17 x^{1.25}, \quad r^2 = 0.52 \]

\[ y = 0.06 x^{0.61}, \quad r^2 = 0.71 \]

\[ y = 0.69 x^{0.27}, \quad r^2 = 0.62 \]

\[ y = 2.18 x^{0.47}, \quad r^2 = 0.45 \]

\[ y = 0.31 x^{1.02}, \quad r^2 = 0.85 \]
Figure 5. Variation of flow parameters with increasing discharge or relative flow depth. Power-law trend lines are fitted to data of each reach. RMSE is the root mean squared error of all data in a) and b), respectively.
Macro-roughness and variations in flow resistance

Flow resistance
Flow resistance was calculated with equation (1) and is plotted against unit discharge \( q \) in Figure 5c. One reach, Riedbach flat, stands out with a fast decrease in roughness with increasing discharge (exponent 0.66). The exponents for the other five reaches range from 0.31 to 0.47. If the prefactors derived from the trend lines in Figure 5c are compared to the measured roughness properties of the channels, a distinct sorting can be observed. Small prefactors are related to steeper streams, higher boulder concentrations and a larger standard deviation of elevations. These observations are explained in more detail in the next section.

When flow resistance is plotted against the relative submergence \( R_{h}/D_{84} \), the data points show some flattening at higher relative submergence (Figure 5d). This flattening is particularly pronounced for Erlenbach, Gornera, Spöl and Riedbach steep. In these streams, the relation could be also described by two power functions or a variable power-law equation instead of one power law.

Hydraulic geometry
The variation of flow width \( w \), mean flow depth \( h \) and mean velocity \( v \) with increasing discharge can be approximated by power functions with exponents summing to one to fulfill the continuity equation \( Q = hwv \). Instead of a standard set of exponent values, the relative rates of change of width and depth depend on cross-section shape and the relative rates of change of velocity depend on how fast frictional resistance is reduced as depth increases [Ferguson, 1986]. The mountain streams presented here have either near-vertical banks formed by boulders (Erlenbach, Vogelbach, Riedbach steep, Gornera) or somewhat flatter banks formed by smaller grains or bedrock (Riedbach flat, Spöl).

The mean water-surface width increases gradually with discharge, flattening off at higher flows for Erlenbach, Vogelbach and Riedbach steep (Figure 5f). The fitted power function exponents of these three streams are very similar (0.11–0.18). A steepening at higher flows can be observed for the Riedbach flat, Spöl and the Gornera, with significantly larger exponents (0.37-0.48). This might be caused by overflowing of the banks.

Mean flow depth increases more rapidly with discharge than width does at three sites (Erlenbach, Vogelbach, Riedbach steep) with best-fit exponents of 0.49 and 0.36 (Figure 5e). Depth increases more slowly than width at Gornera and Spöl (0.36-0.40) and much slower at the Riedbach flat (0.21). The values for these four streams are well in the range of observations for step-pool streams [Lee and Ferguson, 2002]. However, the large exponents for the discharge-depth relation in two streams (Erlenbach, Vogelbach) were expected because these channels feature relatively steep banks, and any increase in discharge has to be accommodated by increases in depth and velocity. It has been shown for lowland rivers that width typically increases most slowly and depth most rapidly [Knighton, 1998]. Our data show, that this is true for only three streams, and the reverse is true for the reaches Spöl, Riedbach flat and Gornera, the latter of which have flatter banks and are less confined than the other streams.
3.3 Non-dimensionalization of velocity and discharge

To better describe the relation between discharge and flow velocity and to obtain a predictive velocity equation, we conducted a dimensional analysis, assuming that the velocity \( v \) [L/T] is a function of slope \( S \) [L/L], unit discharge \( q \) [L\(^2\)/T], gravitational force \( g \) [L/T\(^2\)], and channel roughness \( R \) [L]. Viscosity is neglected because we assume fully turbulent flow. The water density \( \rho \) drops out, and there is no dimension of mass anywhere else. We assume that \( S \) is only relevant as a component of downslope gravitational force, therefore we only work with \( gS \) as a combined variable. Note that \( S \) and \( R \) vary among sites but are constant at each site. Only \( q \) varies within each site. With four variables (\( gS, q, v, R \)) and two dimensions (T, L), we expect two independent dimensionless groups. There is only one possible pair of non-dimensional groups that keeps \( v \) and \( q \) separate:
Macro-roughness and variations in flow resistance

\[ q^{**} = \frac{q}{\sqrt{gSR^3}}, \]  
\[ v^{**} = \frac{v}{\sqrt{gSR}}. \]  

These non-dimensional variables are similar to those introduced by Rickenmann and Recking [2011], who used \( D_{84} \) as their roughness parameter \( (R) \). As a characteristic channel roughness length we can additionally use our macro-roughness measurements, including average step height \( H_s \), standard deviation of elevations \( s \) and boulder protrusion \( p \). The non-dimensionalization given by equations (4) and (5) yields a similarity collapse, in which the data from different sites plot close to a single power-law relationship, in which \( v^{**} \) is almost proportional to the square root of \( q^{**} \) (Figure 6). Note that the similarity collapse works almost equally well with the different roughness length. As a measure for the form of the collapse we indicated the root mean square error (RMSE) of the data in relation to the variable power-law equation (VPE) of Ferguson [2007], shown by the heavy line in Figure 6. For the measured flow range, the VPE has a slope of 0.6. The tightest similarity collapse was obtained using \( D_{84} \) as the roughness measure (RMSE=0.09), followed by standard deviation of elevations \( s \) (RMSE=0.12), and boulder protrusion \( p \) and step height \( H_s \) (RMSE=0.13) (Figure 6).

3.4 Dependence of \( v^{**} \) on \( q^{**} \) and dimensionless roughness

The non-dimensional variables \( v^{**} \) and \( q^{**} \) in the previous section explained a large portion of the variation in the relation between velocity and discharge. However, the introduced roughness length \( R \) did not produce a perfect similarity collapse; there is still variation between the individual sites. While there was no simple relationship between channel macro-roughness and the elevations of the trend lines in \( v-Q \) plot (Figure 5a), there is a systematic relationship between roughness and the trend lines that relate the non-dimensional velocity \( v^{**} \) and discharge \( q^{**} \). Here we introduce the boulder concentration \( \Gamma \), the step density \( n/L_r \) and the step slope \( H_s/H_t \) as non-dimensional roughness parameters \( R^* \), which – in contrast to the dimensional roughness length \( R \) – also contain information about the concentration or the character of the roughness elements in the channel. As a rough empirical approximation, we estimated the dependence of \( v^{**} \) on \( q^{**} \) and \( R^* \) by a simple regression analysis. At first, a power-law equation was fitted to each data set in the \( v^{**}-q^{**} \)-relations with the form:

\[ v^{**} = k q^{**0.6}. \]  

where \( k \) is the site specific prefactor of the power-law fit. The exponent was fixed at 0.6, which approximates the mean of the slopes in Figure 6 and equals the slope of the VPE function for the observed \( q^{**} \) range. Then the site-specific prefactors \( k \) of equation (6) were related to the non-dimensional measures of macro-roughness \( R^* \). Linear regression of \( R^* \) and the prefactors \( k \) give a regression equation with the form:
where $k'$ is the predicted prefactor $k$ of equation (6), and $a$ and $b$ are the empirically derived regression coefficients. Because $q^{**}$ and $v^{**}$ were calculated with four different roughness length, namely $D_{84}$, $s$, $p$ and $H_s$ (see section 3.3), there are also four different relationships between $k$ and the dimensionless roughness measures $R^*$. As an example, the relationship derived from $v^{**}$ and $q^{**}$ using $D_{84}$ is shown in Figure 7. The relations obtained from the other parameter combinations are given in Table 4. Among the dimensionless roughness parameters, only the boulder concentration $\Gamma$ has a strong correlation with the prefactor $k$, regardless of the used roughness length $R$ in the $q^{**}$-$v^{**}$ relations (Figure 6). The regression coefficients $a$ and $b$ and the correlation coefficient $r$ are given in Table 4. Because the velocity data of the Spöl stream were significantly less accurate than the data of the other streams, the regression was performed only on the remaining five study reaches.

The regression equation (7) for estimating the prefactor $k'$ can be used as input to a predictive equation for flow velocity, here given in dimensional form:

$$v_{\text{prod}} = k' q^{**} 0.6 \sqrt{g SR}.$$  

The predictions of equation (8) were compared to the measured absolute velocities, and their agreement illustrates the goodness of the regression. The best predictions were obtained using the $v^{**}$-$q^{**}$ relation based on $D_{84}$ combined with the regression equation for $k'$ using boulder concentration $\Gamma$. For this combination the coefficient of determination $r^2$ is 0.94 (Figure 8). For comparison the flow velocity predictions are also given for the variable power-law equation (VPE) by Ferguson [2007], an equation which performed best in the comprehensive test of flow velocity equations by Rickenmann and Recking [2011]. The $r^2$-value of the VPE approach (0.92) was slightly worse than the $r^2$ obtained with equation (8) (Figure 8).
Discussion

4.1 Performance of non-dimensional variables

Our data set includes flow measurements taken at six reaches at discharges varying by nearly four orders of magnitude. The data thus represent variations in flow resistance both at a site and between sites. The dimensionless variables $v^* = v/(gD_{84})^{0.5}$ and $q^* = q/(gD_{84})^{0.5}$ as used in equation (2) have been successfully used to describe at-a-site variations of flow resistance in various studies [Rickenmann and Recking, 2011]. To explain variations between different sites it has been found to be important to account for the channel slope as a further factor [Aberle and Smart, 2003; David et al., 2010; Ferguson, 2007; Rickenmann, 1994; Rickenmann and Recking, 2011; Zimmermann, 2010]. In the present study we used two slightly modified dimensionless variables that include the factor slope: $v^{**} = v/(gSD_{84})^{0.5}$ and $q^{**} = q/(gSD_{84})^{0.5}$.

![Figure 8](image)

Figure 8. Predicted against observed flow velocities, where $v_{\text{pred}} = k' q^{** 0.6} (gSR)^{0.5}$ (equation (8)) and $k' = aR^* + b$ (equation (7)), with $R^* = \Gamma$. The regression equation for $k'$ was derived from the non-dimensional variables $v^{**}$ and $q^{**}$ using $D_{84}$. The coefficient of determination $r^2$ is given for the predictions of equation (8) as well as for predictions with the variable power equation (VPE) by Ferguson [2007].

Table 4. Correlation of dimensionless macro-roughness $R^*$ with prefactor $k$. The prefactor $k$ was derived from the $q^{**-v^{**}}$ relation, using various roughness length $R$. $r$ is the coefficient of correlation, $a$ and $b$ are the regression coefficients in the regression equation $k' = aR^* + b$ (equation (7)).

<table>
<thead>
<tr>
<th>$R^*$</th>
<th>$k$ from $q^{<strong>-v^{</strong>}}$ ($R=D_{84}$)</th>
<th>$k$ from $q^{<strong>-v^{</strong>}}$ ($R=p$)</th>
<th>$k$ from $q^{<strong>-v^{</strong>}}$ ($R=s$)</th>
<th>$k$ from $q^{<strong>-v^{</strong>}}$ ($R=H_s$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Gamma$</td>
<td>$r$</td>
<td>$a$</td>
<td>$b$</td>
<td>$r$</td>
</tr>
<tr>
<td>$H_s/L_s$</td>
<td>-0.30</td>
<td>-3.11</td>
<td>1.71</td>
<td>-0.16</td>
</tr>
<tr>
<td>$n/L_s$</td>
<td>-0.54</td>
<td>-1.75</td>
<td>1.69</td>
<td>-0.46</td>
</tr>
</tbody>
</table>
\[ q^{**} = q / (g S D_{84}^3)^{0.5} \] (as used in equation (3)). These variables were previously introduced by Rickenmann and Recking [2011] to better investigate the transitional behaviour between shallow and deep flows and they achieved a similarity collapse for a large data set (2890 measurements). In the present study we give a dimensional justification of these variables (section 3.3). The new dimensionless variables \( v^{**} \) and \( q^{**} \) have an advantage over \( v^* \) and \( q^* \) because they account for both at-a-site and between-site variations of flow resistance and thus better describe our data.

Converting our velocity and discharge measurements to the dimensionless variables \( v^{**} \) and \( q^{**} \) significantly decreased the flow resistance variation between our sites, confirming the similarity collapse achieved by Rickenmann and Recking [2011] for their set of flow measurements. Plots of \( v^{**} \) against \( q^{**} \) showed some scatter within each of our study reaches, but generally the data followed the same power trend with an exponent of approximately 0.6 (Figure 6). Only for very shallow flows (\( q^{**} < 0.1 \) or \( q < 0.01 \)) could the trend of the data also be described by a somewhat larger exponent. There is no discontinuity in flow resistance with increasing discharge, however. This suggests a smooth transition between processes of energy dissipation, e.g. from tumbling flow to skimming flow. This is possibly due to the fact that at the same time different locations feature different individual flow transitions, which should reduce the importance of a single transition when considering flow resistance at the reach scale.

The grain size \( D_{84} \) was used by Rickenmann and Recking [2011] as a sole roughness length in the non-dimensional variables (as uses in equation (3)). We introduced alternative roughness measures, namely boulder protrusion \( p \), the standard deviation of profile elevations \( s \) and step height \( H_s \). Of these four candidates for the roughness length scale (\( R \)) in the non-dimensionalization, \( D_{84} \) was superior (in terms of RMSE) in explaining the variations among the different sites. This might be due to the interdependency of channel slope \( S \) and channel roughness \( R \). While \( p \), \( s \) and \( H_s \) are strongly correlated with \( S \), the least slope-dependent roughness length is \( D_{84} \) (Figure 4). Consequently \( D_{84} \) might have more additional explanatory power than the other roughness length, whose effects might be already explained implicitly by \( S \) itself.

In general, channel slope shows strong correlations with several macro-roughness measures (Figure 4). This means that the effects of the driving forces represented by downslope gravity channel slope and roughness cannot be separated on statistical grounds alone. But they could be distinguished physically, because they have opposite effects on flow velocity. The scaling exponent of the power law relation of \( s \) and \( S \), for example, is close to 2/3 (Figure 4). This scaling relationship could reflect the fact that bed roughness is generated by the inability of the flow to move sediment above some particular size, and thus that roughness and slope co-vary in a particular way. Obviously slope and roughness characteristics do not create large site-to-site differences in the flow velocity, at least when compared to the remaining differences in the \( v^{**}-q^{**} \) relation.

Since slope \( S \) and the channel roughness \( R \) are contained in both dimensionless variables \( v^{**} \) and \( q^{**} \) there might be some degree of spurious correlation involved in the scaling of \( v^{**} \)
and $q^{**}$. Rickenmann and Recking [2011] discussed and tested the validity of this scaling and concluded that spurious correlation is not a major problem. Furthermore, the use of $v^{**}$ and $q^{**}$ can be justified dimensionally (section 3.3.) and the scaling exponent $m = 0.6$ in equation (6) has been shown to be theoretically correct. Ferguson [2007] found that several different heuristic and empirical analyses of shallow flows all converged on $(8/f_{tot})^{0.5} \propto h/D$, which is equivalent to the exponent 0.6 in a $v$-$q$ or $v^{**}$-$q^{**}$ plot. $D$ is a representative grain diameter. Ferguson [2007] suggested this “roughness layer relation” as a default model for shallow flows without having to justify any particular interpretation of the dominant physical processes.

4.2 Between-site variations after non-dimensionalization

Collapsing our data using the non-dimensional variables $v^{**}$ and $q^{**}$ leaves some degree of variation between the study reaches (Figure 6). The remaining variation can be quantified by comparing the stream-specific prefactors $k$ of the fitted power trend lines as used in equation (6). In the present study, these prefactors varied within a factor of two (Figure 7), and the data plot well within the range of the large data set studied by Rickenmann and Recking [2011] (Figure 9). However, a factor-of-six range in the prefactors $k$ was observed by Rickenmann and Recking [2011] for different sites when they included the step-pool and cascade stream data of David et al. [2010].

The comparatively small $k$ values of the David et al. [2010] data might be due to additional roughness sources that were absent in our data. The small prefactors could be influenced by the large amounts of woody debris present in many reaches studied by David et al. [2010], and the wood load actually has shown to significantly increase flow resistance. Furthermore, woody debris has contributed to the formation of steps and has caused complex log jams, which also added to total roughness. The co-occurrence of wood and steps is not surprising; woody debris is known to be important for the development of steps [e.g. Church and Zimmermann, 2007; Hassan et al., 2005; Zimmermann, 2009]. Moreover, significant morphologic changes in the streams described by David et al. [2010] are not expected, because the runoff is snowmelt-dominated and the availability of sediment is limited. The smaller grains are carried out of the reaches but the snowmelt events are rather incompetent to break up larger morphologic structures, gradually resulting in a rougher bed. In our study reaches, channel-spanning steps and pools are relatively infrequent and woody debris is unimportant as a source of roughness (see Figure 1).

For five reaches of the present study, the prefactors $k$ were related to dimensionless roughness measures, i.e., boulder concentration $\Gamma$, step slope $H_s/L_s$ and step density $n/L_s$ (Figure 7). Boulder concentration was best related to $k$, regardless of the roughness length ($R$) used in the non-dimensionalization (Table 4). The trend line of the $k-R^*$ relation indicates that the prefactor $k$ increases with decreasing dimensionless roughness $R^*$. The trend equation (7) was used for a simple flow velocity prediction equation (equation (8)). This procedure resulted in an improvement of the flow velocity predictions compared to predictions using the VPE equation by Ferguson [2007] (Figure 8). However, the $r^2$ values for the agreement of pre-
dicted and observed flow velocities are only marginally different for equation (8) and the VPE equation. Moreover, the statistical significance of the predictive regression equation should not be overrated, because there is pseudo replication with respect to boulder concentration $\Gamma$: there were only five independent values of $\Gamma$ used.

Only few data from natural streams are published that include both flow velocity measurements and measurements of macro-roughness like boulder concentration or longitudinal profile roughness. Thus, it is currently not possible to validate and compare the trends observed between the prefactor $k$ and roughness measures with a larger or independent set of data. However, for some published flow resistance data, information about channel type is available. Montgomery and Buffington [1997] classified channel types partly according to grain sizes and dominant roughness sources, implying that channel type reflects processes and magnitudes of roughness and can be regarded as a qualitative measure of macro-roughness. Based on this assumption we compared our flow velocity data (six sites) with some of the available data in the literature (David et al. [2010], 15 sites; Ryan et al. [2002], five sites; Reid and Hickin [2008], two sites; Lepp et al. [1993], two sites; Andrews [1994], one site). Plane bed and pool-riffle channels plot rather in the upper part of the entire data range and step-pool and cascade streams rather in the lower part (Figure 10a). Plane bed streams on average have larger $k$ values than cascade or step-pool streams (Figure 10b). Assuming that step-pool and cascade streams represent rougher channels than plane bed and pool riffle streams, this finding confirms our previous results that the prefactor $k$ scales with roughness. Additionally, the sorting of the $k$ values after channel type coincides with a slope-dependence of the channel type (Figure 10c). This also confirms the interdependence of macro-roughness and channel slope in our data.

![Figure 9. Dimensionless velocity $v^{**}$ against dimensionless discharge $q^{**}$ for at-a-site data of the present study, data of David et al. [2010], and the large dataset of Rickenmann and Recking [2011], which defines a general trend of flow resistance. The lines are the fitted power trends to the data of the present study.](image-url)
Macro-roughness and variations in flow resistance

The $k$ value is relatively similar for step-pool and cascade streams. The median $k$ value of the cascade streams (0.85) is only marginally smaller than the median value for step-pool reaches (0.86) (Figure 10b). But if one extreme data point was excluded from the cascade streams, the two data distributions would differ more markedly (Figure 10c). However, cascade and step-pool stream types as defined by Montgomery and Buffington [1997] are not straightforward to distinguish morphologically in the field. The different types of roughness elements (individual large grains or steps) often coexist in natural streams, and it is difficult to determine which one is the dominant roughness source. Therefore similar energy dissipating processes such as tumbling, jet and wake flow over and around grains might dominate in both channel types. In the step-pool streams of our study, large immobile boulders between the steps occur frequently and might significantly contribute to total flow resistance. We currently lack channel type classification that explicitly refers to these residual boulders as the dominant source of roughness, even though their concentration is less than in a typical cascade channel. Interestingly, Bathurst [1985] used the term boulder-bed channel, but it has not been widely used in the literature.

4.3 Similarities between theoretical flow velocity equations and empirical findings

Energy can be dissipated in many ways in steep streams. The dominant processes of energy dissipation depend on the flow magnitude (plunging jets or skimming flow). The magnitude of flow resistance, however, may also depend on the dominant type of macro-roughness element. Thus it is possible that an individual roughness measure, e.g. step slope or boulder con-
centration, represents only a specific range of dissipation processes. That could explain why a single roughness measure is not sufficient to explain the between-site flow velocity variations.

The identification of a single roughness parameter is additionally complicated by the interdependence of several roughness parameters with channel slope. However, the empirical analysis showed that some measures of macro-roughness are capable to explain to some extent the differences of flow velocity between sites. Is this empirically observed effect reflected by theoretical flow velocity equations accounting for the influence of boulders and steps? Here we discuss two flow velocity equations, the theoretical model developed by Yager [2006] and Yager et al. [2012] and the semi-empirical equation by Egashira and Ashida [1991], and test them against the measured flow velocities. These authors used measures of macro-roughness that were developed to quantify ideal types of large-scale roughness related to specific flow resistance processes. In nature, however, macro-roughness is not a distinct and well-defined feature, and different types of roughness can occur at the same site.

Yager [2006] studied the influence of immobile boulders on the stresses acting on mobile grains in steep streams. Her flow equation is based on stress-partitioning between immobile and mobile grains. Boulder concentration and the boulder protrusion $p$ are formulated as the main controls on shear stresses and flow velocities, whereas boulder concentration was given by the downstream length of immobile grain-steps $\lambda_w$ divided by the grain-step spacing $\lambda_x$. For resistance of the mobile sediment she assumes a constant friction coefficient $C_m = 0.44$, calculated from independent data by Marcus et al. [1992]. Resistance of the immobile material is given as a friction coefficient $C_I$ that depends on protrusion and flow depth, which are scaled with the cross-sectional area of the immobile grains $A_{IF}$. Rewriting the stress equations by Yager [2006] as the reach-averaged flow velocity gives:

$$v_y = \sqrt{\frac{2}{A_{IF} C_I / (\lambda_x w) + C_m (1 - \lambda_w / \lambda_x)}} \sqrt{ghS}$$  \hspace{1cm} (9)

Egashira and Ashida [1991] developed a friction law for the flow over step-pool bed forms, hypothesizing that the rate of energy dissipation in the separation zone downstream from step crests plays an important role in flow resistance in both sub- and supercritical flows. Their flow resistance equation takes into account the resistance due to the base material $f_0$ between the steps (formulated as a logarithmic law) and the additional resistance ($f_{add}$) due to entrained eddies in separation zones and the energy dissipation in wall regions, assuming that the flow depends on the step height $H_s$ and the step spacing $L_s$. Rewriting the Egashira and Ashida (1991) flow resistance equations in terms of the reach-averaged flow velocity gives:

$$v_{Ed} = \sqrt{\frac{8L_s}{2.5H_s (f_{add} - f_0) + f_0 L_s}} \sqrt{ghS}$$  \hspace{1cm} (10)

With the approach of Yager [2006], predicted flow velocities were 5-50 % lower than the measurements (Figure 11a). Notably, the accuracy of the predictions generally increased with boulder concentration. The Spöl data plot a bit off the trend of the other streams, which might
Macro-roughness and variations in flow resistance

be due to the relatively high observed flows and large relative flow depths $h/D_{84}$, leading to higher flow velocities (Figure 11a). For the Gornera and Riedbach steep sites, which feature boulder concentrations larger than twelve percent, the predicted velocities are very close to the measurements (with deviations $< 5\%$). This indicates that the influence of boulder roughness becomes important at boulder concentrations somewhere between 12 and 30 percent. This is also apparent in the low ratio of base level resistance $f_0$ to total resistance $f_{tot}$ at high boulder concentrations (Figure 11b). The approach by Yager [2006] also performed better at higher boulder concentrations in predicting bedload volumes in combination with accounting for large scale roughness [Nitsche et al., 2011], which is an indirect confirmation of our findings.

Using the equation by Egashira and Ashida [1991], predicted flow velocities are up to 50\% above or 30\% below the measurements for five streams (Figure 11c). For one stream, the Gornera, the predicted velocities are about twice as high than the measured velocities. Even though step density is relatively high at the Gornera, step heights and step slope are small, resulting in a large fraction of base level resistance (relative to total resistance) in the approach of Egashira and Ashida [1991] (Figure 11d).

Interestingly the velocities for the Gornera were much better predicted by the equation of Yager [2006] than by the equation of Egashira and Ashida [1991]. This is partially due to the different roughness measures used by the equations, which per definition of the equation’s authors relate to a different range of processes. While the equation of Egashira and Ashida [1991] was primarily supposed to model spill resistance, Yager’s (2006) approach is based on the turbulent flow around boulders. In nature, these different processes emerge simultaneously, although in different proportions. This is in agreement with the observation that the differences in flow velocity are partly related to boulder concentration $\Gamma$ and partly related to

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Figure 11. Calculated divided by observed flow velocities (a,b) and base level to total flow resistance ($f_0/f_{tot}$)\(^{0.5}\) (c,d) plotted against boulder concentration and step density using the equations by Yager [2006] and Egashira and Ashida [1991]. Plotted are data of the six study reaches, each represented by a distinct boulder concentration or step density. Boxes define the 25\(^{th}\) and 75\(^{th}\) percentile of the data, whisker define 5\(^{th}\) and 95\(^{th}\) percentile and circles define the median values.
step density or other step features (Figure 7). The comparison of the two flow velocity equations has shown that roughness measures are not interchangeable, suggesting instead that they are related to specific energy dissipation processes. Thus, for a better description of macro-roughness a measure is needed that combines the effects of various roughness elements.

5 Conclusions

Both slope and macro-roughness are important factors explaining the variation of flow resistance between different sites. We found empirical and dimensional justification for the dimensionless velocity and discharge variables previously introduced by Rickenmann and Recking [2011]. These variables include the channel slope and a roughness length for non-dimensionalization. Applying these dimensionless variables resulted in a similarity collapse around a simple power-law relationship, in which the dimensionless velocity was approximately proportional to the 0.6 power of dimensionless discharge. As roughness length we used various measures of macro-roughness, i.e. a characteristic grain size, the standard deviation of long profile elevations, the step height, and the boulder protrusion, all of which explained most of the observed between-site differences in flow resistance. Although channel slope and roughness have distinct physical effects on the flow, both have been shown to co-vary in a particular way. Channel slope, for example, correlates strongly with the standard deviation of elevations and boulder protrusion, and thus could be used as proxy variable.

The non-dimensionalization of Rickenmann and Recking [2011] did not perfectly collapse our data. To explain the remaining variation between the sites we introduced dimensionless macro-roughness measures which describe the concentration of roughness elements in a channel. Among these, the boulder concentration correlated best with the remaining between-site variation of flow resistance. Moreover, including the boulder concentration in a simple regression-based prediction equation further improved the prediction of flow velocities slightly compared to predictions with the variable power-law equation proposed by Ferguson [2007] and used by Rickenmann and Recking [2011].

Although the inclusion of boulder concentration improved the predictions of flow velocity, the regression relationship is based on only five sites and more data are needed to confirm its validity for predictive purposes. Another uncertainty may be due to the variability of macro-roughness in time, an issue which has not been treated in the present study, but which might be important to account for in future predictive equations. However, the trends of our empirical findings confirm the predictions of theoretically-based flow resistance equations by Yager [2006] and Egashira and Ashida [1991]. These equations, both of which directly include macro-roughness measures, performed better for streams with high concentrations of macro-roughness elements. Moreover, the equation of Yager [2006], which uses boulder spacing as a roughness measure, performed better overall than the equation by Egashira and Ashida [1991], which used step height as a roughness measure. This indicates that these roughness measures are not interchangeable, and each represents different processes of flow resistance.
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Chapter III

Evaluation of bedload transport predictions using flow resistance equations to account for macro-roughness in steep mountain streams

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ABSTRACT – Steep mountain streams typically feature macro-roughness elements like boulders, step-pool sequences, and a varying channel width. Flow resistance due to such roughness elements appears to be an important control on bedload transport rates. Thus, many commonly used bedload transport equations overestimate the transport in steep streams by orders of magnitude. Few approaches take into account the typical macro-roughness elements, and systematic tests of these models with field observations are lacking. In the present study several approaches were considered that allow calculating the contribution of macro-roughness elements to flow resistance. These approaches were combined with bedload transport equations and the predictions were compared to field measurements of discharge, transported bedload volumes, and channel characteristics in 13 Swiss mountain streams. The streams have channel slopes ranging from 2 to 19 %, and catchment areas of 0.5 to 170 km². For six streams there were time series of sediment yields, mostly measured annually, and for the other seven streams sediment volume estimates were available for large flood events in 2000 and 2005. All tested equation combinations achieved an improvement in bedload prediction compared to a reference equation that was uncorrected for macro-roughness. The prediction accuracy mainly depended on the size and density of macro-roughness and on flow conditions. The best performance overall was achieved by an empirical approach accounting for macro-roughness, based on an independent data set of flow resistance measurements.

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1 Introduction

In densely populated areas like the European Alps, bedload movement during floods is a frequent natural hazard. Using data from the Swiss flood and landslide damage database [Hilker, et al., 2009], we estimated that one third to one half of the total damage of three billion Swiss Francs was associated with sediment transport processes during the large storm events of 2005 in Switzerland. To prevent or reduce this damage, it is of great importance to be able to accurately predict bedload transport rates. However, conventional transport equations typi-
cally overestimate bedload volumes in steep mountain streams by up to three orders of magnitude [e.g. Bathurst, et al., 1987; Chiari and Rickenmann, 2011; Lenzi, et al., 1999; Rickenmann, 2001]. One possible reason for this is that many equations were developed and calibrated with data from flume experiments or low gradient streams, with channel bed and transport characteristics that differ from those in steep mountain streams.

Typically, steep streams with channel slopes above five percent feature (i) wide grain size distributions, (ii) large boulders that remain immobile during most floods, (iii) channel-spanning bedforms such as step-pool morphologies, (iv) shallow flows, and (v) variable channel widths. The channel bed tends to organize into patches or clusters of similar grain sizes [e.g. Lamarre and Roy, 2008; Yager, 2006], or steps spanning the width of the channel develop around large grains [e.g. Church and Zimmermann, 2007; Whittaker and Jaeggi, 1982; Zimmermann, et al., 2008]. These features lead to additional roughness and flow resistance that is absent in lower-gradient channels, and is rarely taken into account in laboratory investigations.

Macro-roughness elements are physical sources of flow resistance. Boulders sitting in a bed of finer material disrupt the flow and increase turbulence [e.g. Bathurst, 1978; Canovaro, et al., 2007; Papanicolaou, et al., 2004; Wohl and Thompson, 2000; Yager, et al., 2007]. Jets of critical or supercritical flow originate at steps and plunge into downstream pools, where velocity decreases abruptly and hydraulic jumps, roller eddies, and substantial turbulence result [e.g. Nelson, et al., 1993; Wilcox, et al., 2006; Wilcox and Wohl, 2007; Wohl and Thompson, 2000]. Zimmermann [2010] concluded that a major part of the flow energy in steep streams is dissipated by form and spill drag around roughness elements like step-pools. The contribution of these structures to total flow resistance increases with decreasing relative submergence of the bed.

Several authors have proposed resistance equations specifically for shallow flows in mountain streams [Bathurst, 1978; Bathurst, 1985; 2002; Jarrett, 1984; Katul, et al., 2002; Rickenmann, 1991; Smart, et al., 2002]. Some have derived empirical flow resistance equations from velocity measurements in gravel and boulder bed streams [Bathurst, 1978; Ferguson, 2007; Hey, 1979; Rickenmann and Recking, 2011]. In most of these approaches the friction factor may be described as a function of the relative submergence $d/D$, where $d$ is the average flow depth, and $D$ is a representative grain size. However, it has been shown for some mountain streams with very pronounced step-pool structures that for example channel type and unit discharge are factors that might better predict flow resistance than $d/D$ [Comiti et al., 2009; David et al. 2010]. Few approaches directly include a measure of boulders or steps to account for macro-roughness in the flow resistance equations [Canovaro and Solari, 2007; Egashira and Ashida, 1991; Pagliara and Chiavaccini, 2006; Papanicolaou, et al., 2004; Whittaker, 1986; Whittaker, et al., 1988; Yager, 2006; Yager, et al., 2007]. Moreover, none of the latter mechanistic approaches has been validated for a wide range of natural conditions and systematically tested with field observations.

The importance of accounting for additional energy losses (or increased total flow resistance) in steep streams in the context of bedload transport calculations was pointed out in
Evaluation of bedload transport predictions

several contributions [Chiari and Rickenmann, 2011; Govers and Rauws, 1986; Palt, 2001; Rickenmann, 2001; 2005; Rickenmann and Koschni, 2010; Yager, et al., 2007; Zimmermann, 2010]. In some of these studies, concepts similar to the grain and form resistance partitioning in lowland rivers were also applied in steep streams with some success. Flow resistance partitioning has been found to be particularly important for flow conditions with intermediate and large scale roughness [Rickenmann and Recking, 2011], as compared to small scale roughness conditions [sensu Bathurst, et al., 1981] with deeper flows for which most bedload transport equations were developed.

In the present study, we tested how the use of different flow resistance equations affect predictions of bedload volumes transported in mountain streams. Four out of five tested equations for flow resistance explicitly include a measure of macro-roughness, while one approach is based on an empirical relationship that depends mainly on relative flow depth.

Flow resistance partitioning was used to estimate the flow energy available for bedload transport. The reduced energy due to the macro-roughness was accounted for in the bedload transport equations by reducing the energy slope. The results of the bedload transport predictions were tested against field observations of bedload transport from 13 Swiss mountain streams. In six of the streams, bedload volumes were regularly measured for several decades using retention basins located near discharge gauges. In the remaining seven streams, bedload volumes transported in a single extreme event were estimated in the field. The systematic evaluation of flow resistance partitioning approaches permits an assessment of their suitability for bedload transport prediction in steep natural mountain streams. Their suitability with regard to the type of dominant bed morphology and problems of parameter identification in the field are also discussed.

2 Flow resistance and bedload transport equations

Total flow resistance in streams is typically defined with a roughness or friction parameter, namely Manning’s $n$, the Darcy-Weisbach friction factor $f$ or the Chezy coefficient $C$. These are related by:

$$\frac{v}{f} = \frac{C}{n} = \sqrt[3]{\frac{8gDS}{f}}$$

Here, $v = \text{depth-averaged flow velocity}$, $S = \text{friction slope}$ which is often approximated by the water surface slope or the channel bed slope (for steady uniform flow in a prismatic channel), and $g = \text{acceleration due to gravity}$. The friction factor $f$ is preferable over $C$ or $n$, because it is a non-dimensional quantity that can be physically interpreted as a drag coefficient [Ferguson, 2007]. It will therefore be used throughout this study.

Published equations to calculate flow resistance and bedload transport include approaches that explicitly account for the effects of large roughness elements. The flow resistance approaches described here were applied to natural streambeds, with the simplifying assumption that the streambed is composed of a heterogeneous combination of finer base material and
larger roughness elements like boulders and steps. In the literature the total resistance is often written as the sum of so-called ‘grain resistance’ and ‘form resistance’ [Meyer-Peter and Müller, 1948; Parker and Peterson, 1980; Carson and Griffiths, 1987; Gomez and Church, 1989; Millar and Quick, 1994; Millar 1999]. However, we think that these terms do not appropriately reflect the physical conditions in steep channels with shallow flows (see for example the discussion of Rickenmann and Recking [2011]). Therefore, the total flow resistance \( f_{\text{tot}} \) was considered to be composed of two main components: (i) the base-level resistance, \( f_0 \), which can be defined as the total resistance corresponding to deep flows, and (ii) an additional resistance due to large roughness elements at small relative flow depth, \( f_{\text{add}} \) [Rickenmann and Recking, 2011]. The latter refers to the same range of conditions as intermediate and large-scale roughness as defined by Bathurst et al. [1981]. In analogy to the grain/form flow resistance partitioning, the total flow resistance is the sum of the two components:

\[
f_{\text{tot}} = f_0 + f_{\text{add}}
\]  

Such an additive approach has been applied previously for example by Einstein and Banks [1950], Manga and Kirchner [2000]; Ferguson [2007] and Comiti et al. [2009].

The studied flow resistance approaches used for bedload transport calculation are briefly described below. If necessary, equations were modified from the original notation for better comparison. For further information, the reader is referred to the original publications. The flow resistance equations were combined with a bedload transport equation by using a reduced energy slope based on flow resistance partitioning [Chiari, et al., 2010] (see section 2.2).

2.1 Flow resistance equations

Whittaker et al. [1988] presented design guidelines for river stabilization techniques with placed blocks in block ramps. The authors were interested in threshold conditions for the movement of blocks. In an experimental study they arranged blocks on a mobile bed in a flume and measured water and bed levels at equilibrium conditions for different tailwater levels. Whittaker et al. [1988] considered total shear stress acting on the flow as the sum of two components: resistance due to base material and to blocks. They calculated flow resistance due to base material \( f_0 \) after Keulegan [1938]:

\[
\sqrt{\frac{8}{f_0}} = 2.5 \ln \left( \frac{12r_h}{1.5D_{90}} \right)
\]  

where \( r_h \) is the hydraulic radius and \( D_x \) is the grain size for which \( x \) percent of the material is finer. Flow resistance due to the blocks \( (f_{\text{add}}) \) was expressed as:

\[
\sqrt{\frac{8}{f_{\text{add}}}} = 2.5 \ln \left( \frac{12r_h}{k_b} \right)
\]  

Herein \( k_b \) is the roughness height associated with the blocks given as:
Evaluation of bedload transport predictions

\[ k_b = \alpha D_b \left(17.8 - 0.47 \frac{d}{D_b}\right) \]  \hspace{1cm} (5)

in which \(D_b\) is the mean block diameter and \(\alpha\) is the areal block concentration, given as:

\[ \alpha = N \cdot D_b^2 \]  \hspace{1cm} (6)

where \(N\) is the number of blocks placed per square meter of bed. In equations (3) and (4), a logarithmic velocity profile is assumed, which is not true for flow around blocks in wake zones. But Whittaker et al. [1988] argued that at least with respect to velocity and water depth the trends given by a logarithmic law can be considered correct. They further assumed stationary and uniform flow and limited application of their approach to block concentrations \(\alpha < 0.15\) and relative roughness in the range \(0.5 < d/D_b < 4\).

Egashira and Ashida [1991] developed a friction law for the flow over step-pool bed forms, taking into account the energy dissipation of the mean flow due to entrained eddies in separation zones and the energy dissipation in wall regions. They performed flume experiments for flows over artificial step-pool forms, finding a good agreement with their friction law. For flow resistance of the base material (\(f_0\)) along the sections between steps, they assumed a logarithmic law very similar to equation (3) to be valid:

\[ \sqrt{\frac{8}{f_0}} = 2.5 \ln \left(\frac{11r_h}{1.5D_{90}}\right) \]  \hspace{1cm} (7)

Egashira and Ashida [1991] found that both in sub- and supercritical flows, the rate of energy dissipation in the separation zone downstream of the crest plays an important role in the flow resistance. For the flow resistance in the region of the separation zone they gave:

\[ \sqrt{\frac{8}{f_{add}}} = \sqrt{\frac{2r_h}{KE \cdot H}} \]  \hspace{1cm} (8)

in which \(KE\) is an empirical constant equal to 0.48, and \(H\) is the step height. The total flow resistance was given by:

\[ \sqrt{\frac{8}{f_{tot}}} = \sqrt{\frac{8L}{aH(f_{add} - f_0) + f_qL}} \]  \hspace{1cm} (9)

where \(L\) is the step spacing and \(a\) is an empirical value, expressing the ratio between the length of the separation zone and the step height. The parameter \(a\) was suggested to take the value of 2.5, but might strongly vary for different stream conditions. Equations (8) and (9) suggest that flow resistance depends on the relative step height \(H/r_h\), the step spacing \(L\), and the resistance due to the base material \(f_0\). In case of chutes and pools the energy dissipation might also be controlled by hydraulic jumps, expressed in the term \(\delta \cdot 8(Fr^2 \cdot L)\), which needs to be added to the right-hand side of equation (9). \(\delta\) is the energy loss due to hydraulic jumps.
and $Fr$ is the Froude number. $Fr$ and $\delta$ are difficult to determine for steep mountain rivers, and are therefore neglected in the calculations below.

**Pagliara and Chiavaccini [2006]** conducted experiments in a steep laboratory flume to investigate flow resistance in the presence of boulders. Boulders were mimicked by metallic hemispheres with smooth and rough surfaces, arranged randomly or in rows over a granular base material. Pagliara and Chiavaccini [2006] found that the increase in flow resistance due to the boulders can be related to their areal concentration $\Gamma$, their disposition and their surface roughness $c$. Two empirical equations were proposed to evaluate flow resistance, both in the presence (equation (10)) and the absence (equation (11)) of boulders:

$$
\sqrt{\frac{8}{f_{tot}}} = 3.5(1 + \Gamma)^{0.17} \left( \frac{d}{D_{84}} \right)^{0.1}\quad (10)
$$

$$
\sqrt{\frac{8}{f_0}} = 0.43\ln \left( S^{-2.5} \frac{d}{D_{84}} \right) + 2.8\quad (11)
$$

The increase in flow resistance was found to be directly proportional to the boulder concentration $\Gamma$, where $\Gamma = n \pi D_b^2 / (4 W L)$, with $n$ the number of boulders, $W$ the width and $L$ the length of the reach. The exponent $c$ in equation (10) was empirically derived and depends on the disposition of boulders (random or rows) and on the smoothness of the boulder surface (rounded or crushed). Rows of boulders act as sequences of steps which produce intense flow accelerations and decelerations. Both equations (10) and (11) are recommended to be used for block ramps and constructed riprap channels in steep slopes (0.08-0.4) only, because they are characterized by a regular geometry that differs from natural mountain streams. Equation (10) is further limited to boulder concentrations of less than 0.3 [Pagliara, 2008].

**Yager [2006]** studied the influence of immobile boulders on the stresses acting on mobile grains in steep, rough streams. She presented a theoretical flow resistance model that uses stress partitioning rather than empirical expressions to account for the resistance due to macro-roughness. Yager [2006] hypothesized that the total bed shear stress can be partitioned into the shear stress borne by mobile grains and the stress borne by immobile grains with a characteristic diameter $D_b$. The total shear stress $\tau_t$ for a reach is given as the sum of the stress on immobile grains $\tau_I$ and the stress on the mobile grains $\tau_m$, scaled with the area covered by the immobile ($A_{IP}$) and mobile grains ($A_m$), respectively, divided by the total bed area ($A_t$):

$$
\tau_t = \tau_I A_{IP} + \tau_m A_m / A_t\quad (12)
$$

in which $\tau_m = \rho C_m v^2 / 2$, and $C_m$ is the drag coefficient for the mobile sediment. $\tau_I$ is given as $\tau_I = \rho A_{IP} C_l v^2 / (2 A_{IP})$, where $A_{IP}$ is the bed perpendicular area of immobile grains, $A_{IP}$ is the bed-parallel area occupied by the immobile grains and $C_l$ is the drag coefficient for immobile grains, calculated by $C_l = 157(d/p_u)^{1.6}$, in which $p_u$ is the portion of immobile grains that protrude above the mobile bed surface. Since immobile grains are often not isolated roughness
elements, but arranged into clusters or steps, Yager [2006] assumed closely packed immobile grains in the cross-stream direction that have a characteristic downstream spacing \( \lambda_x \). The total bed area is then given by \( A_t = W\lambda_x \), the bed area occupied by immobile boulders is \( A_{IP} = W\lambda_w \), where \( \lambda_w \) is defined here as the equivalent downstream length of the bed area occupied by boulders, and the area occupied by the mobile grains is \( A_m = W\lambda_x - A_{IP} \). The cross-sectional area of the immobile grains \( A_{IF} \) (perpendicular to the flow) is a function of \( d, D_b \) and the upstream immobile grain protrusion \( p_u \). Yager [2006] found the boulder density (which is given here by \( \lambda_w/\lambda_x \)) and the boulder protrusion to be main controls on shear stresses and flow velocities. Here, we rewrite the shear stress of the mobile sediments \( \tau_m \) and the shear stress of the immobile grains \( \tau_I \) in terms of Darcy-Weisbach friction factor, using the notation \( f_0 \) for the friction due to \( \tau_m \), and \( f_{add} \) for the friction due to \( \tau_I \):

\[
\sqrt{8} \sqrt{f_0} = \sqrt{\frac{2}{C_m(1-\frac{\lambda_w}{\lambda_x})}} \tag{13}
\]

\[
\sqrt{8} \sqrt{f_{add}} = \frac{2\lambda_x W}{A_{IP}C_t} \tag{14}
\]

Yager’s theoretically based shear stress partitioning equations require little empirical calibration and may thus apply to a wide range of bed conditions. But they were tested only on a single set of simplified flume experiments [Yager, et al., 2007] and data of a single steep mountain stream [Yager, 2006].

Rickenmann and Recking [2011] evaluated several flow resistance equations with 2890 individual field measurements of flow velocity in gravel bed rivers, including many steep streams. They concluded that the variable power flow resistance equation (VPE) of Ferguson [2007] gave the best overall performance. The VPE approach of Ferguson was used to develop a flow resistance partitioning approach for large and intermediate scale roughness conditions [sensu Bathurst et al., 1981]. A base-level resistance \( f_0 \) can be calculated with a Manning-Strickler type equation representing flow conditions with small scale roughness:

\[
\sqrt{8} \sqrt{f_0} = \frac{v_0}{\sqrt{g \cdot r_h \cdot S}} = 6.5 \left( \frac{r_b}{D_{54}} \right)^{0.167} \tag{15}
\]

in which, if used in the domains of large and intermediate scale roughness, \( v_0 \) is a virtual velocity characterizing flow conditions similar to those for which bedload transport equations were developed. For flow conditions with intermediate and large scale roughness, the total resistance \( f_{tot} \) can be calculated as:

\[
\sqrt{8} \sqrt{f_{tot}} = \frac{v_{tot}}{\sqrt{g \cdot r_h \cdot S}} \tag{16}
\]
in which \( v_{tot} \) is predicted with the VPE approach of Ferguson [2007]:

\[
v_{tot} = \frac{\sqrt{g \cdot r_h \cdot S \cdot 6.5 \cdot 2.5 \left( \frac{r_h}{D_{84}} \right)}}{\sqrt{6.5^2 + 2.5^2 \left( \frac{r_h}{D_{84}} \right)^{5/3}}}
\]

The partitioning between base-level and total resistance is expressed as:

\[
\frac{f_0}{f_{tot}} = \frac{v_{tot}}{v_0}
\]

The approach represented by equations (15) to (18) is the only approach considered here that does not explicitly include a measure of large roughness elements in its equations. The proposed flow resistance partitioning is basically a function of relative flow depth. However, the information on mean roughness conditions is implicit in the data used to derive the equation. In earlier studies [Badoux and Rickenmann, 2008; Chiari, 2008; Chiari, et al., 2010; Chiari and Rickenmann, 2011; Rickenmann, 2005; Rickenmann, et al., 2006], a similar concept of flow resistance partitioning as proposed by equations (15) to (18) was applied to bedload transport calculations in steep streams. This earlier flow resistance partitioning approach was based on 373 field measurements of flow resistance including shallow flows in steep streams [Rickenmann, 1994; Rickenmann, 1996], in contrast to the 2890 field measurements used by Rickenmann and Recking [2011].

2.2 Bedload transport equations

Rickenmann [1991] proposed a shear stress based equation to compute bedload transport. The equation is based on 252 laboratory experiments conducted by Meyer-Peter and Müller [1948], Smart and Jäggi [1983] and Rickenmann [1991] for a slope range of 0.0004 to 0.2, and can be written as:

\[
\Phi_b = \frac{3.1 \left( D_{90} / D_{30} \right)^{0.2} \sqrt{\theta (\theta - \theta_c)} Fr^{1.1}}{\sqrt{s-1}}
\]

Here, the dimensionless bedload transport rate \( \Phi_b = q_b / [(s-1)gD_{50}]^{0.5} \), \( q_b \) = bedload transport rate per unit of channel width, \( s=\rho_s/\rho \) is the ratio of solid to fluid density, and the dimensionless shear stress \( \theta = r_h S / [(s-1) D_{50}] \). The critical dimensionless shear stress at the initiation of bedload transport \( \theta_c \) is determined here as:

\[
\theta_c = \frac{r_{hc} \cdot S}{(s-1)D_{50}}
\]
where \( r_{hc} \) is the hydraulic radius corresponding to the critical discharge \( q_c \) which is calculated here with an empirical equation of Bathurst et al. [1987], slightly modified by Rickenmann [1991] (see Table 1 and Table 2):

\[
q_c = 0.065 \cdot (s - 1)^{1.67} \sqrt{gD_{50}^{1.5}S^{-1.12}}
\]  

(21)

For quartz particles in water with a relative density \( s = 2.68 \), Rickenmann [2001] simplified equation (19) to:

\[
\Phi_b = 2.5 \sqrt{\theta(\theta - \theta_c)} Fr
\]

(22)

In the present study equation (22) was used as a reference bedload transport equation that does not account for the effects of macro-roughness. For easier comparison with field data on bedload transport, equation (22) can be transformed into [Rickenmann, 2001]:

\[
q_b = 1.5(q - q_c)S^{1.5}
\]

(23)

The bedload transport equation (22) was used in combination with the flow resistance partitioning approaches described above to account for increased flow resistance. The combination procedure is based on earlier approaches of Meyer-Peter and Müller [1948], Palt [2001], and Rickenmann [2005], who introduced empirical functions to account for flow resistance due to macro-roughness through a reduced energy slope. With this method better agreement was obtained between observed and predicted bedload volumes for flood events in 2005 in Austrian and Swiss mountain streams [Chiari, 2008; Chiari, et al., 2010; Chiari and Rickenmann, 2011; Rickenmann, et al., 2006], and for several flood events in 2000 in Swiss mountain streams [Badoux and Rickenmann, 2008]. Using the Manning-Strickler or the Darcy-Weisbach equation, the total energy slope is given as:

\[
S = \frac{v^2n_0^2}{r_h^{4/3}} = \frac{v^2f_{tot}}{8gd}
\]

(24)

The reduced energy slope associated with grain friction only, \( S_{red} \), can be expressed as:

\[
S_{red} = \frac{v^2n_0^2}{r_h^{4/3}} = \frac{v^2f_0}{8gd}
\]

(25)

Thus, \( S_{red} \) can be determined with:

\[
S_{red} = S \left( \frac{n_0}{n_{tot}} \right)^e = S \left( \frac{f_0}{f_{tot}} \right)^e
\]

(26)

Meyer-Peter and Mueller [1948] showed theoretically that \( e \) may vary between 4/3 and 2, and from their flume experiments on bedload transport they empirically determined a best fit value of 1.5. For several bedload transporting flood events in 2005 in Switzerland and Aus-
tria, *Chiari and Rickenmann* [2011] found best fit values for $e$ in the range of 1 to 1.5. We used a fixed value of $e = 1.5$ in our work. The flow resistance partitioning equations (section 2.1) were used to calculate $S_{\text{red}}$, which in turn was used to determine $\theta_r$ and $\theta_{r,c}$ in the bedload transport calculations with equation (22):

$$\Phi_b = 2.5 \sqrt{\theta_r (\theta_r - \theta_{r,c}) Fr}$$

Since equation (21) is an empirical equation, the reduced critical dimensionless shear stress $\theta_{r,c}$ was determined as:

$$\theta_{r,c} = \left( \frac{r_{hc} \cdot S_{\text{red}(r_{hc})}}{(s-1)D_{50}} \right)$$

where both the critical hydraulic radius $r_{hc}$ and the reduced energy slope $S_{\text{red}(r_{hc})}$ were calculated for the critical discharge at initiation of bedload motion with equation (21).

The approach as outlined above needs the hydraulic radius as an input parameter for the calculations. Since only discharge information was available for the study streams, hydraulic parameters were back-calculated using field surveys of slope and channel cross sections (see section 3.2), assuming steady uniform flow using the flow resistance equation of *Smart and Jaeggi* [1983]. In a second step, resistance partitioning is applied through equation (26) to determine the part of the flow energy, that is available for bedload transport.

Alternative bedload transport calculations were performed with the modified equation of *Parker* [1990] in combination with the shear stress partitioning approach of *Yager* [2006]. This approach was added to the study to (i) show the influence of using a different transport model, and (ii) because *Yager* [2006] found the best performance of this particular combination of the transport calculation for the Erlenbach, one of our study streams. The method of *Yager* [2006] further accounts for the limited availability of mobile sediment. The median grain size of the mobile fraction is used as a representative bedload size. In contrast to equation (22) it accounts for the effect of size-selective transport. The volumetric transport rate per unit width for each grain size class of the relatively mobile sediment $q_{bmi}$ is:

$$q_{bmi} = \left( \frac{\tau_n}{\rho} \right)^{1.5} F_{mi} W_{mi}^* \frac{\rho_n}{(\rho_n - \rho)/\rho}$$

where $F_{mi}$ is the volume fraction of the relatively mobile sediment that is in the $i$th grain size class, and $W^*_mi$ is the dimensionless bedload transport rate of each grain size class. Instead of the total stress $\tau$, *Yager* [2006] used the stress on the mobile sediment $\tau_m$ in equation (29). The total transport rate of all the grain sizes in the mobile sediment is given by:

$$q_{Tm} = \left( \sum_{i=1}^{N} q_{bmi} \right) \frac{A_m}{A_n}$$

(30).
The proportion of the bed area that is occupied by the mobile sediment ($A_{m}/A_{t}$) (cf. equation (12)) is used to account for the limited availability of mobile sediment.

3 Study streams and field data

3.1 Bedload and discharge data of study streams

Data were collected from 13 mountain streams located in the Swiss Alps and Prealps (Figure 1, Table 1, Table 2), selected to cover a range of channel characteristics. For each of the streams some information on sediment transport was available. The streams feature alluvial channels with morphologies ranging from plane bed to cascade channel types and accentuated step-pool types [after Montgomery and Buffington, 1997], with channel slopes ranging from 2 % to 19 %. Two main groups of streams can be distinguished, one with periodic sediment yield measurements over several years or decades, and another with bedload data obtained after a single extreme transport event.

The first group of streams (Table 1) includes six catchments with long series of measured sediment yield, here referred to as “long term data”. In the Erlenbach catchment, deposited sediment volumes have been measured in a retention basin at least once each year since 1983 [Hegg, et al., 2006]. Since 1986, an indirect bedload sensor system has also recorded the impact of bedload grains transported over a measuring cross section right above the retention basin [Bänziger and Burch, 1990; Rickenmann and McArdell, 2007; Turowski, et al., 2009]. Bedload transport rates can be estimated from the sensor signal using a calibration relationship obtained from measurements of deposited volumes in the retention basin [Rickenmann and McArdell, 2007]. For the streams Rappengraben, Sperbelgraben, Rotenbach, Schwändlibach and Melera, discharge data was recorded by stream gauging stations [Rickenmann, 1997].

![Figure 1. Location of study streams in Switzerland and types of bedload data; 1 Erlenbach, 2 Rotenbach, 3 Schwändlibach, 4 Sperbelgraben, 5 Rappengraben, 6 Melera, 7 Lonza, 8 Saltina, 9 Baltschieder, 10 Gamsa, 11 Mattenbach, 12 Buoholzbach, 13 Steinibach](image)
Table 1. Stream characteristics, description and sources of discharge and bedload data, for streams with long term periodic bedload measurements (“long term data”)

<table>
<thead>
<tr>
<th>Stream character</th>
<th>Erlenbach</th>
<th>Rotenbach</th>
<th>Schwändlibach</th>
<th>Rappengraben 1</th>
<th>Rappengraben 2</th>
<th>Sperbelgraben</th>
<th>Melera</th>
</tr>
</thead>
<tbody>
<tr>
<td>Catchment area (km²)</td>
<td>0.7</td>
<td>1.7</td>
<td>1.4</td>
<td>0.7</td>
<td>0.6</td>
<td>0.5</td>
<td>1.1</td>
</tr>
<tr>
<td>Elevation, lowest/highest (m)</td>
<td>1110/1655</td>
<td>1274/1630</td>
<td>1217/1642</td>
<td>983/1256</td>
<td>990/1256</td>
<td>911/1203</td>
<td>962/1773</td>
</tr>
<tr>
<td>Geology</td>
<td>Flysch</td>
<td>Flysch</td>
<td>Flysch</td>
<td>Conglomerate</td>
<td>Conglomerate</td>
<td>Conglomerate</td>
<td>Crystalline</td>
</tr>
<tr>
<td>Forest/glacier extent (%)</td>
<td>39/0</td>
<td>14/0</td>
<td>29/0</td>
<td>35/0</td>
<td>30/0</td>
<td>99/0</td>
<td>84/0</td>
</tr>
<tr>
<td>Channel type a</td>
<td>step-pool</td>
<td>step-pool</td>
<td>step-pool</td>
<td>plane bed</td>
<td>plane bed</td>
<td>plane bed</td>
<td>step-pool</td>
</tr>
<tr>
<td>Discharge regime b</td>
<td>nivo-pluvial prealpine</td>
<td>nival</td>
<td>nival</td>
<td>pluvial supérieur</td>
<td>pluvial supérieur</td>
<td>pluvial supérieur</td>
<td>nivo-pluvial</td>
</tr>
<tr>
<td>Mean annual precipitation (mm) c</td>
<td>2300</td>
<td>1840</td>
<td>1840</td>
<td>1570</td>
<td>1570</td>
<td>1590</td>
<td>2060</td>
</tr>
<tr>
<td>Peak flow (m³/s)/return period (yrs) d</td>
<td>14.6⁶ /50</td>
<td>18/40-50</td>
<td>8.5/40-50</td>
<td>2.2/30-40</td>
<td>2.6/50-80</td>
<td>1.2/20-30</td>
<td>8/80-100</td>
</tr>
<tr>
<td>Hydrograph time steps (min)</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>5</td>
</tr>
<tr>
<td>Critical discharge (m³/s) g</td>
<td>0.5</td>
<td>2.5</td>
<td>1.5</td>
<td>0.35</td>
<td>0.3</td>
<td>0.28</td>
<td>0.5</td>
</tr>
<tr>
<td>Peak flow of studied events (m³/s)</td>
<td>10.2</td>
<td>14.7</td>
<td>5.9</td>
<td>1.7</td>
<td>1.7</td>
<td>1.1</td>
<td>8</td>
</tr>
<tr>
<td>Type of sediment measurement</td>
<td>sediment retention basin e</td>
<td>sediment retention basin e</td>
<td>sediment retention basin e</td>
<td>sediment trap e</td>
<td>sediment trap e</td>
<td>sediment trap e</td>
<td>sediment retention basin e</td>
</tr>
<tr>
<td>Mean annual sediment yield (m³)</td>
<td>603</td>
<td>138</td>
<td>69</td>
<td>58</td>
<td>77</td>
<td>42</td>
<td>162</td>
</tr>
<tr>
<td>Number of sediment surveys used</td>
<td>48</td>
<td>35</td>
<td>35</td>
<td>17</td>
<td>28</td>
<td>33</td>
<td>11</td>
</tr>
<tr>
<td>Fraction of bedload volume to total i</td>
<td>0.5</td>
<td>0.6</td>
<td>0.6</td>
<td>0.66</td>
<td>0.66</td>
<td>0.66</td>
<td>0.6</td>
</tr>
</tbody>
</table>

a After Montgomery and Buffington [1997].
b After Weingartner and Aschwanden [1992].
c Rickenmann [1997].
d Turowski, et al. [2009].
e Operated by the Swiss Federal Research Institute WSL.
f Operated by the Swiss Federal Office for the Environment.
g Critical discharge for the initiation of bedload motion, estimated by Rickenmann [1997].
h Estimation, total sediment volume includes bedload, fines and pores.
<table>
<thead>
<tr>
<th>Stream character</th>
<th>Lonza</th>
<th>Gamse</th>
<th>Balschieder</th>
<th>Saltina</th>
<th>Budholzbach</th>
<th>Steinibach</th>
<th>Mattenbach</th>
</tr>
</thead>
<tbody>
<tr>
<td>Catchment area (km$^2$)</td>
<td>170</td>
<td>38</td>
<td>43</td>
<td>78</td>
<td>13.9</td>
<td>12.2</td>
<td>30.8</td>
</tr>
<tr>
<td>Elevation, lowest/highest (m)</td>
<td>630/3994</td>
<td>660/3391</td>
<td>647/3934</td>
<td>670/3438</td>
<td>490/2404</td>
<td>493/1955</td>
<td>1015/2728</td>
</tr>
<tr>
<td>Geology</td>
<td>Gneiss</td>
<td>Gneiss</td>
<td>Gneiss, Granit</td>
<td>Gneiss</td>
<td>Flysch, Limestone</td>
<td>Flysch, Limestone</td>
<td>Flysch</td>
</tr>
<tr>
<td>Forest/glacier extent (%)</td>
<td>8/16</td>
<td>22/2</td>
<td>10/16</td>
<td>21/4</td>
<td>40/0</td>
<td>35/0</td>
<td>23/0</td>
</tr>
<tr>
<td>Channel type</td>
<td>cascade</td>
<td>cascade</td>
<td>step-pool</td>
<td>plane bed</td>
<td>step-pool</td>
<td>step-pool</td>
<td>cascade</td>
</tr>
<tr>
<td>Discharge regime</td>
<td>glacio-nival</td>
<td>nivo-glaciaire</td>
<td>glacio-nival</td>
<td>glacio-nival</td>
<td>nival-alpine</td>
<td>nival-alpine</td>
<td>nival-alpine</td>
</tr>
<tr>
<td>Mean annual precipitation (mm)</td>
<td>600-2400</td>
<td>600-2400</td>
<td>1000-2400</td>
<td>1200-2400</td>
<td>1200-2400</td>
<td>1200-2400</td>
<td>1400-2000</td>
</tr>
<tr>
<td>Type of discharge measurement</td>
<td>runoff modelling $^a$</td>
<td>runoff modelling $^a$</td>
<td>runoff modelling $^a$</td>
<td>runoff modelling $^a$</td>
<td>stream gauge $^a$</td>
<td>rainfall-runoff-modelling $^b$</td>
<td>rainfall-runoff-modelling $^b$</td>
</tr>
<tr>
<td>Hydrograph time steps (min)</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>5</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>Critical discharge (m$^3$s$^{-1}$)</td>
<td>1.08</td>
<td>0.38</td>
<td>0.74</td>
<td>6.62</td>
<td>0.44</td>
<td>0.77</td>
<td>0.8</td>
</tr>
<tr>
<td>Peak flow (m$^3$s$^{-1}$)/return period (yrs)</td>
<td>90-95/100</td>
<td>65-70/-</td>
<td>−100/-</td>
<td>−120/80</td>
<td>−40/30-100/-</td>
<td>−85/100-300/-</td>
<td>−45/-30/-</td>
</tr>
<tr>
<td>Bedload data used</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bedload volume estimation</td>
<td>channel deposition depth $^d$</td>
<td>deposits $^1$</td>
<td>deposits $^m$</td>
<td>deposits $^a$</td>
<td>retention basin, deposits $^1$</td>
<td>retention basin, deposits $^1$</td>
<td>deposition $^b$</td>
</tr>
<tr>
<td>Fraction of bedload volume to total $^o$</td>
<td>0.66</td>
<td>0.66</td>
<td>0.66</td>
<td>0.66</td>
<td>0.66</td>
<td>0.66</td>
<td>0.66</td>
</tr>
</tbody>
</table>

$^a$ After Montgomery and Buffington [1997].
$^b$ After Weingartner and Aschwanden [1992].
$^c$ After Hydrological Atlas of Switzerland.
$^d$ Abgottspon, et al. [2001], BWG [2002].
$^e$ Numerically modelled [BWG, 2002; LCH-EPFL, 2003].
$^f$ Peak flow from field vision, hydrograph from modified Clark model [BWG, 2002; Jäggi, et al., 2004].
$^g$ Operated by the Swiss Federal Office for the Environment.
$^h$ Authors work, model: HEC-HMS [USACE, 2000].
$^i$ Critical discharge for the initiation of bedload motion, calculated after Bathurst et al. [1987].
$^j$ Oeko-B AG [2006].
$^k$ geo7 [1998].
$^l$ Photogrammetrically measured [BWG, 2002].
$^m$ Jäggi, et al. [2004].
$^n$ Burkhard and Jäggi [2003].
$^o$ Estimation, total sediment volume includes bedload, fines and pores.
Sediment volumes delivered by these streams have been measured roughly once a year in sediment traps directly upstream of the gauging stations (Rappengraben, Sperbelgraben) or in sediment retention basins (Rotenbach, Schwändlibach, Melera) [Rickenmann, 1997]. Thus, the bedload data integrate several transport events. More details about measurement facilities and sediment investigations can be found in the publication of Zeller [1985]; discharge and bedload datasets have been previously analyzed by Rickenmann [1997; 2001].

The second group of study streams (Table 2) includes seven catchments, for each of which bedload data are available for a single exceptional transport event, here referred to as “event data”. For four of the streams, the event was triggered by intense rainfall in the Canton Valais in the south-western Swiss Alps in October 2000, one of the most severe flood events of the region in the 20th century, causing 16 fatalities and total damage of around 710 million Swiss Francs [BWG, 2002]. In several steep catchments, large amounts of sediment were transported and deposited on the alluvial fan at the confluence with the main valley river. Deposited sediment volumes were measured after well-documented events in the streams Lonza, Saltina, Baltschieder and Gamsa, and are used in this study. Bedload data from these streams were previously described and compared to simple transport equations by [Badoux and Rickenmann, 2008]. The hydrographs for the Saltina and Lonza streams were measured at a stream gauging station, while the hydrographs for the Baltschieder and Gamsa were reconstructed from flood marks and rainfall-runoff modeling. For the other three streams the sediment transport events were triggered by intense precipitation in the northern part of the central Alps in August 2005, when 220 mm of rain fell within 72 hours, causing six fatalities and total damage of three billion Swiss Francs [Bezzola and Hegg, 2007; Bezzola and Hegg, 2008]. This precipitation event was estimated to have a recurrence interval of over 100 years at 22 rain gauging stations of MeteoSwiss (MeteoSwiss 2006), and led to large changes in stream morphology and sustained fluvial sediment transport in 39 mountain streams. Here, we use bedload data for the streams Buoholzbach, Steinibach and Mattenbach, where transport estimates were based on deposited sediment volumes in sediment retention basins, and on the number of truck loads used for sediment removal from overbank deposits outside of the retention basins [Bezzola and Hegg, 2007; Rickenmann and Koschni, 2010]. Direct discharge measurements were not available and the hydrograph was estimated using HEC-HMS [USACE, 2000], a deterministic rainfall-runoff-routing model. Simulations were calibrated using peak flow estimates based on flood marks in the channel. Due to a lack of validation data we neglected uncertainty in discharge, which, however would affect each transport prediction method in the same way and may not alter the general pattern of the results.

The uncertainty of the measured sediment volumes is variable. For the first group, where sediments were measured in retention basins and traps, we estimated from repeat measurements an uncertainty of less than 5 % in volume. For the second stream group, we relied on measurements of engineers and local authorities shortly after the flood events. On the basis of their detailed reports, the volumes are likely to have an uncertainty of less than 25 %. However, we corrected bulk sediment volumes for pore space and fine material that was not transported as bedload. For the large flood event data and the Rappengraben and Sperbelgraben,
### Table 3. Measured reach parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Rotenbach</th>
<th>Rappen-</th>
<th>Schwant-</th>
<th>Sperbel-</th>
<th>Rappen-</th>
<th>Erlen-</th>
<th>Melkra</th>
<th>Salina</th>
<th>Lonza</th>
<th>Balschieder</th>
<th>Matten-</th>
<th>Gamsa</th>
<th>Buoholz-</th>
<th>Steni-</th>
</tr>
</thead>
<tbody>
<tr>
<td>Channel slope (^a)</td>
<td>S</td>
<td>0.051</td>
<td>0.06</td>
<td>0.098</td>
<td>0.101</td>
<td>0.106</td>
<td>0.115</td>
<td>0.17</td>
<td>0.02</td>
<td>0.064</td>
<td>0.135</td>
<td>0.15</td>
<td>0.165</td>
<td>0.17</td>
<td>0.186</td>
</tr>
<tr>
<td>(D_{90}(m)) (^b)</td>
<td>D_{90}</td>
<td>0.02</td>
<td>0.01</td>
<td>0.02</td>
<td>0.02</td>
<td>0.03</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.03</td>
<td>0.03</td>
<td>0.02</td>
<td>0.03</td>
<td>0.04</td>
<td></td>
</tr>
<tr>
<td>(D_{95}(m)) (^b)</td>
<td>D_{95}</td>
<td>0.05</td>
<td>0.03</td>
<td>0.03</td>
<td>0.04</td>
<td>0.03</td>
<td>0.07</td>
<td>0.04</td>
<td>0.06</td>
<td>0.05</td>
<td>0.07</td>
<td>0.07</td>
<td>0.05</td>
<td>0.07</td>
<td>0.12</td>
</tr>
<tr>
<td>(D_{99}(m)) (^b)</td>
<td>D_{99}</td>
<td>0.18</td>
<td>0.08</td>
<td>0.16</td>
<td>0.08</td>
<td>0.08</td>
<td>0.29</td>
<td>0.16</td>
<td>0.16</td>
<td>0.20</td>
<td>0.18</td>
<td>0.45</td>
<td>0.14</td>
<td>0.23</td>
<td>0.92</td>
</tr>
<tr>
<td>(D_{98}(m)) (^b)</td>
<td>D_{98}</td>
<td>0.25</td>
<td>0.10</td>
<td>0.21</td>
<td>0.09</td>
<td>0.10</td>
<td>0.39</td>
<td>0.22</td>
<td>0.19</td>
<td>0.30</td>
<td>0.21</td>
<td>0.72</td>
<td>0.16</td>
<td>0.54</td>
<td>1.24</td>
</tr>
<tr>
<td>Bankfull width (m) (^c)</td>
<td>W</td>
<td>5.63</td>
<td>4.98</td>
<td>4.96</td>
<td>5.43</td>
<td>4.98</td>
<td>4.70</td>
<td>5.57</td>
<td>14.14</td>
<td>12.44</td>
<td>11.68</td>
<td>13.50</td>
<td>11.80</td>
<td>9.76</td>
<td>8.00</td>
</tr>
<tr>
<td>Width of streambed (m) (^e)</td>
<td>W_{inw}</td>
<td>3.75</td>
<td>4.20</td>
<td>3.50</td>
<td>3.00</td>
<td>3.50</td>
<td>3.50</td>
<td>4.00</td>
<td>12.00</td>
<td>9.50</td>
<td>9.00</td>
<td>11.00</td>
<td>9.50</td>
<td>7.00</td>
<td>6.00</td>
</tr>
<tr>
<td>Boulder concentration (^b)</td>
<td>(\Gamma)</td>
<td>0.02</td>
<td>0.04</td>
<td>0.04</td>
<td>0.11</td>
<td>0.02</td>
<td>0.08</td>
<td>0.09</td>
<td>0.16</td>
<td>0.26</td>
<td>0.16</td>
<td>0.10</td>
<td>0.16</td>
<td>0.10</td>
<td>0.40</td>
</tr>
<tr>
<td>Mean boulder diameter (m) (^e)</td>
<td>(D_b)</td>
<td>0.63</td>
<td>0.75</td>
<td>-</td>
<td>-</td>
<td>0.82</td>
<td>0.72</td>
<td>1.03</td>
<td>1.00</td>
<td>1.31</td>
<td>1.02</td>
<td>1.16</td>
<td>1.07</td>
<td>1.06</td>
<td></td>
</tr>
<tr>
<td>Mean step length (m) (^f)</td>
<td>(L)</td>
<td>10.4</td>
<td>22.91</td>
<td>16.19</td>
<td>60.83</td>
<td>22.91</td>
<td>7.86</td>
<td>15.32</td>
<td>31.39</td>
<td>17.78</td>
<td>7.84</td>
<td>10.85</td>
<td>16.48</td>
<td>10.00</td>
<td>50.83</td>
</tr>
<tr>
<td>Mean step height (m) (^f)</td>
<td>(H)</td>
<td>0.51</td>
<td>1.58</td>
<td>0.81</td>
<td>1.00</td>
<td>1.58</td>
<td>0.69</td>
<td>1.04</td>
<td>1.65</td>
<td>1.04</td>
<td>1.13</td>
<td>0.98</td>
<td>3.02</td>
<td>2.12</td>
<td>2.73</td>
</tr>
<tr>
<td>Step slope (^g)</td>
<td>(H/L)</td>
<td>0.049</td>
<td>0.069</td>
<td>0.050</td>
<td>0.016</td>
<td>0.069</td>
<td>0.088</td>
<td>0.068</td>
<td>0.053</td>
<td>0.058</td>
<td>0.14</td>
<td>0.09</td>
<td>0.183</td>
<td>0.212</td>
<td>0.054</td>
</tr>
<tr>
<td>Immobile grain step spacing (m) (^b)</td>
<td>(\lambda_g)</td>
<td>29.64</td>
<td>13.24</td>
<td>-</td>
<td>4.90</td>
<td>26.38</td>
<td>10.12</td>
<td>9.17</td>
<td>6.40</td>
<td>3.12</td>
<td>5.57</td>
<td>8.30</td>
<td>2.07</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Downstream length of immobile-grain steps (m) (^b)</td>
<td>(\lambda_w)</td>
<td>0.63</td>
<td>0.75</td>
<td>-</td>
<td>1.30</td>
<td>0.72</td>
<td>1.03</td>
<td>1.00</td>
<td>1.31</td>
<td>1.02</td>
<td>1.16</td>
<td>1.07</td>
<td>1.06</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Height of sediment above base of imm. grains (m) (^l)</td>
<td>(z_{bn})</td>
<td>0.25</td>
<td>0.32</td>
<td>-</td>
<td>0.31</td>
<td>0.38</td>
<td>0.40</td>
<td>0.39</td>
<td>0.55</td>
<td>0.63</td>
<td>0.56</td>
<td>0.47</td>
<td>0.47</td>
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<td></td>
</tr>
<tr>
<td>Immobile grain protrusion (m) (^l)</td>
<td>(p_{bn})</td>
<td>0.38</td>
<td>0.43</td>
<td>-</td>
<td>0.13</td>
<td>0.34</td>
<td>0.63</td>
<td>0.61</td>
<td>0.77</td>
<td>0.39</td>
<td>0.60</td>
<td>0.60</td>
<td>0.60</td>
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</tr>
<tr>
<td>Drag coefficient for the mobile sediment (^b)</td>
<td>(C_{bn})</td>
<td>0.44</td>
<td>0.44</td>
<td>0.44</td>
<td>0.44</td>
<td>0.44</td>
<td>0.44</td>
<td>0.44</td>
<td>0.44</td>
<td>0.44</td>
<td>0.44</td>
<td>0.44</td>
<td>0.44</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Median grain size of mobile sediment (m) (^l)</td>
<td>(D_{50n})</td>
<td>0.05</td>
<td>0.03</td>
<td>0.03</td>
<td>0.04</td>
<td>0.03</td>
<td>0.06</td>
<td>0.04</td>
<td>0.06</td>
<td>0.05</td>
<td>0.07</td>
<td>0.07</td>
<td>0.10</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Block concentration (^l)</td>
<td>(\alpha)</td>
<td>0.02</td>
<td>0.06</td>
<td>0.14</td>
<td>0.10</td>
<td>0.03</td>
<td>0.10</td>
<td>0.11</td>
<td>0.20</td>
<td>0.32</td>
<td>0.20</td>
<td>0.13</td>
<td>0.50</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\(^a\) Mean channel slope of the study reach.
\(^b\) Grains sizes were calculated after Fehr [1987] based on line-by-number pebble counts of around 500 grains of down to 1 cm in diameter for each study reach.
\(^c\) Average of field measurements which were taken at least every ten meters.
\(^d\) After Pagliara and Chiavacchini [2006].
\(^e\) Considered are grains with b-axis diameter larger than 0.5 m.
\(^f\) Yager et al.[2007] gives a value of 0.44.
\(^g\) Yager [2007] gives a value of 0.44.
\(^h\) Derived from longitudinal profiles by laser slope and distance meter, where \(H\) is the vertical distance between the top of the step to the bottom of the pool and \(L\) is the effective distance between step tops; a step was identified if the step height exceeded 0.5 m and a pool existed (i.e. negative or very flat positive gradients).
\(^i\) After Yager [2007].
\(^j\) After Yager [2007] with \(z_{bn} = D_{98} - p_{bs}\) in which \(p_{bs}\) is the portion of an immobile grain that protrudes above the mobile bed surface that is upstream of the steps.
\(^k\) Derived from the grain size distribution excluding grains larger than \(D_{98}\).
\(^l\) Coefficient describing boulder disposition and boulder surface texture after Pagliara and Chiavacchini [2006].
where sediments were measured in small sediment traps, we assumed that due to the turbulent flow there was no significant deposition of suspended load. For these streams, pore volume was estimated to be 1/3 of the total volume (Table 1, Table 2). For the Erlenbach we followed the observations of Rickenmann [1997], who estimated that about half of the bulk sediment volume in the large retention basin consisted of bedload material (Table 1). For the Rotenbach, Schwändlibach and Melera suspended material was assumed to have been partially deposited in the somewhat smaller retention basins, implying a likely correction factor between 2/3 and 1/2. We therefore used an intermediate value of 0.6 (Table 1).

3.2 Field measurements of channel characteristics
Channel roughness parameters necessary to evaluate the tested flow resistance and transport equations were measured in the 13 study streams (Table 3). Several approaches are sensitive to a measure of immobile boulders. We used a critical size of 0.5 m to define boulders throughout the study. The choice of this value is further discussed in section 5.3. Some field values, e.g. step spacing or width, vary considerably in a given reach. Here, reach-averaged values were used because calculations were made at the reach scale. Measurements were made for the reach with the lowest bedload transport capacity, because the behavior of this reach limits transported bedload volumes for all sections further downstream. Assuming that channel bed slope is the parameter limiting transport capacity, the surveys have been carried out in the reaches of the stream with the lowest bed slope, which coincides for the study streams with the reaches just upstream of the deposition areas. Reach length varied for the 13 streams, ranging from 10 to 34 times the bankfull stream width; these reach lengths are adequate for relating stream morphology to channel processes [Montgomery and Buffington, 1997]. For the hydraulic calculations we used an irregular channel profile for each stream, obtained by averaging at least ten manually measured cross sections in each study reach. See Table 3 for additional parameter definitions.

4 Results and interpretation
4.1 Flow resistance calculations
The roughness measures used in the flow resistance equations varied greatly between the streams. The characteristic grain sizes showed a tendency to increase with channel slope (Figure 2a). There is no such tendency between $\Gamma$ and step slope $H/L$, which is the aspect ratio of step height $H$ and step length $L$. This suggests that steps and boulders can be independent roughness features (Figure 2b).

Flow resistance partitioning in terms of $(f_0/f_{tot})^{0.5}$ varied considerably across the different approaches over a large range of relative flow depths in the domain of large- and intermediate-scale roughness. For a given relative flow depth the values for $(f_0/f_{tot})^{0.5}$ calculated with a single approach can span almost the complete possible range from 0 to 1 (Figure 3).
Figure 2. Relationship between measured roughness parameters; each point represents one study stream.

Figure 3. Fraction of base-level resistance to total resistance in terms of \( (f_0/f_{tot})^{0.5} \) for a range of relative flow depths \( (r_h/D_{84}) \). Color lines give the predictions by the respective approach (cf. Table 4). Grey areas indicate the range of relative flow depths, defined by the flow conditions for which 90% of the bedload transport occurred during the studied transport events.
Large differences in \( (f_0/\mu)_{0.5} \) arose even if the approaches were based on similar measures of roughness. For example, both Whittaker et al. [1988] and Pagliara and Chiavaccini [2006] use boulder concentration as a roughness measure, but the former approach predicted low \( (f_0/\mu)_{0.5} \) values around 0.2, while the latter approach predicted almost constantly high values around 0.8 (Figure 3) for transport-relevant flows. This might reflect the different concepts and experimental conditions under which the approaches have been developed.

The four examples in Figure 3 show calculations for streams with different densities and distributions of macro-roughness. The Saltina (Figure 3a) features the lowest slope of the study streams, with intermediate values for boulder concentration and step spacing. At the Sperbelgraben (Figure 3b), sediment grains are relatively small and boulders are absent, but the channel bed is stepped, forced by the underlying bedrock. The Erlenbach (Figure 3c) has an intermediate boulder concentration, step slope, and bed slope, and the Gamsa stream (Figure 3d) is characterized by a high boulder concentration and a steep step slope and bed slope.

For the comparatively rough Gamsa stream, the approaches of Egashira and Ashida [1991], Whittaker et al. [1988] and Yager [2006] all resulted in a relatively small fraction of grain resistance \( f_0 \) for all flow conditions. The same approaches gave higher \( (f_0/\mu)_{0.5} \) values for the Erlenbach, because it features less macro-roughness elements. For the Sperbelgraben the same approaches resulted in a \( f_0 \) fraction of one. There, only the approach of Egashira and Ashida [1991], which exclusively accounts for step-pool geometry, yielded a significant portion of additional roughness \( f_{add} \), while the approach of Rickenmann and Recking [2011] resulted in decreasing \( (f_0/\mu)_{0.5} \) values with decreasing \( r_b/D_{b4} \) for all streams.

Considering all 14 of the studied stream reaches, the approaches of Rickenmann and Recking [2011] and – above a threshold value of \( r_b/D_{b4} \) of about 1-2 – also those of Yager [2006] and Whittaker et al. [1988] always showed an increase in the fraction of base-level resistance \( f_0 \) with increasing relative flow depth, and the three methods yielded partly similar trends and \( (f_0/\mu)_{0.5} \) values. The approaches of Egashira and Ashida [1991] and Pagliara and Chiavaccini [2006] were less sensitive to relative flow depth, and the fraction of \( (f_0/\mu)_{0.5} \) varied only slightly within the considered range of relative flow depths. The approach of Pagliara and Chiavaccini [2006] yielded for each stream an almost constant value of \( (f_0/\mu)_{0.5} \).
4.2 Bedload volume calculations

In this section bedload transport calculations are presented, computed with the equation of Rickenmann [2001] and a modified Parker [1990] equation. The Rickenmann equation (equation (27)) was combined with all flow resistance partitioning approaches as described in section 2.2. The Parker equation was used in a form modified by Yager [2006] (equation (30)) to account for the stresses acting on the mobile sediment only. The combinations of equations and their abbreviations used below are listed in Table 4. In the following sections, the combinations are evaluated by the discrepancy ratio $V_{\text{pred}}/V_{\text{meas}}$, which is the ratio of predicted to measured bedload volumes.

The equations’ performance was highly variable for different streams and individual transport events. In Figure 4 the distributions of $V_{\text{pred}}/V_{\text{meas}}$ values for individual events are shown for each stream. Many approaches showed a large variation of $V_{\text{pred}}/V_{\text{meas}}$ spanning one to three orders of magnitude. This can be attributed to the large range of flow conditions observed for the streams and the sensitivity of the approaches to these. The reference equation of Rickenmann [2001] (Ri-no) with no accounting for macro-roughness overpredicted transport volumes by up to two orders of magnitude. Compared to this reference, for streams that feature macro-roughness, all other combinations of equations predicted smaller transport volumes through stress partitioning. The prediction of bedload volumes for large flood events (Figure 4, scatter plots) is generally better than for the long term bedload data (Figure 4, box plots), which included also small transport events with smaller relevant $r_b/D_{84}$ ratios than the long term data (cf. Figure 3).

To study the sensitivity of these approaches to several stream characteristics, the streams were grouped according to (i) high and low boulder concentration, (ii) large and small step slope, and (iii) event magnitude (Table 5). In this way it is possible to characterize the conditions under which an approach might be more or less suitable. The boulder-based approaches (Rickenmann-Pagliara and Chiavaccini [Ri-PC], Rickenmann-Whittaker [Ri-W], Rickenmann-Yager [Ri-Y] – see also Table 4) gave better bedload volume predictions for streams with high boulder concentrations and large step slopes (Figure 5), compared to streams with less pronounced macro-roughness. Furthermore, the predictions were better for approaches with a stronger physical component, i.e. Ri-Y and Ri-W performed somewhat better than Ri-PC. For streams with low boulder concentrations or small step slopes the variability in bedload prediction was high, spanning more than an order of magnitude (Figure 5).

The approach of Yager [2006], both in combination with the transport equations of Rickenmann [2001] (Ri-Y) and Parker [1990] (P-Y), gave median $V_{\text{pred}}/V_{\text{meas}}$ values within an order of magnitude around the observed bedload volumes for streams with high boulder concentration. However, the combination Ri-Y consistently worked better than P-Y, which gave the largest median overprediction of bedload volumes for the complete data set. This indicates that the bedload transport equation of Rickenmann [2001] (equation (22)) may be more suitable for the studied streams than that of Parker [1990] (equation (30)). Moreover, the modified Parker equation (P-Y) was extremely sensitive to the magnitude of the flood event. The approach of Egashira and Ashida [1991] (Ri-EA), which explicitly considers the step slope $H/L$,
yielded $V_{pred}/V_{meas}$ ratios that varied over 1.5 orders of magnitude, which is the largest variation observed among all tested equations. The median $V_{pred}/V_{meas}$ ratio indicated systematic underprediction of measured bedload volumes, except for the streams with small step slope. Thus, the correction of the energy slope appears to be too large in the approach of Egashira and Ashida [1991]. The combination Ri-RR generated relatively unbiased median $V_{pred}/V_{meas}$ values between 0.8 and 1.6 for all stream groups with a relatively small variability within each group (Figure 5).

Figure 4. Ratios of predicted to measured bedload volumes ($V_{pred}/V_{meas}$) for each study stream, calculated with the bedload equation of Rickenmann [2001] in combination with flow resistance partitioning approaches and the modified Parker bedload equation [Parker, 1990] by Yager [2006] (defined in Table 4). Light grey color indicates that a given approach is not applicable. N is the number of considered transport events per stream. The dashed line indicates the value for perfect agreement of predictions and measurements. Boxes define 25- and 75-percentile and median. Whiskers are 5- and 95-percentile of the data. The subplot “Erlenbach extr.” additionally contains data of the two largest floods of the Erlenbach separately.
For streams with high boulder concentration $\Gamma$, the combinations Ri-Y, P-Y, Ri-PC, Ri-W and Ri-RR yielded median $V_{pred}/V_{meas}$ values close to one (Figure 6). Except for the approach of Rickenmann and Recking (Ri-RR), all of these approaches calculated flow resistance based on boulder concentration. Bedload transport in streams with distinct step-pool structure was best predicted by the combinations Ri-RR, Ri-W, Ri-Y and Ri-PC.

In Figure 7 the performance of the combinations is shown related to three data groups, of which one contains data from streams with long term periodic bedload observations and a wide distribution of flood sizes (“long term data”). A second group includes the data of streams with a single large flood (“event data”). The third group (“all data”) consists of the event data and the sums of the long term data. The best predictions for the long term data were attained by Ri-W, Ri-RR and Ri-Y, which predicted 71, 64 and 63 % of the events to within a factor of three of the observed bedload volumes, respectively (Figure 7). The $V_{pred}/V_{meas}$ values for all combinations of equations ranged from 0.04 to 59 (10th and 90th percentile). The combinations Ri-W and Ri-RR gave the best median $V_{pred}/V_{meas}$ value for the

![Figure 5](image)

**Figure 5.** Ratios of predicted to measured bedload volumes ($V_{pred}/V_{meas}$). Each subplot illustrates the performance of one equation combination (Table 4). The dashed line indicates the value for perfect agreement of predictions and measurements. The dataset is grouped according to Table 5.
long term data, which suggests a good overall performance (Figure 7, Table 6). However, the coefficient of variation for both combinations is comparable to that for most other tested combinations. The smallest coefficient of variation was exhibited by combination Ri-Y (Table 6). For the large flood event data, the combination Ri-Y was the only approach in which all predictions fell within a factor of three of the observed volumes. However, the combination Ri-PC gave the best median agreement with the measurements for large flood events. The combination Ri-EA gave the lowest median $V_{\text{pred}}/V_{\text{meas}}$ value, underpredicting more than 70 % of the bedload transport events. The best median prediction for the complete data set including all studied streams was given by the empirical approach Ri-RR with $V_{\text{pred}}/V_{\text{meas}} = 1.0$ and 88 % of the events were predicted within a factor of three of the observed volumes. The median values of the boulder approaches Ri-Y and R-W were only marginally worse. Ri-Y predicted 93 % of the events within a factor of three of the observed.

5 Discussion

The analyses presented above show that predictions of bedload volumes are significantly improved by taking into account macro-roughness using flow resistance partitioning. The partitioning was used to account for additional energy “losses” due to macro-roughness elements or increased total flow resistance in steep streams with shallow flows. Predicted bedload volumes differed among the tested approaches, primarily due to the choice of the transport formula and secondarily due to the resistance partitioning approach.
5.1 Choice of bedload transport equation

Our approach of reducing the energy slope in the bedload transport equations may have different effects on different bedload transport equations. However, the relative differences in the resulting bedload volumes $V_{\text{pred}}$ are small. This is because most of the bedload equations that are applicable to steep streams are dependent on excess shear stress in a similar manner. The dominant differences lie in the calculation of the critical shear stress, which in turn affects only predictions near the initiation of bedload transport. Our data, however, are dominated by flows with elevated discharges, i.e., we have high excess shear stresses, for which many bedload equations give similar relationships [e.g. Gomez and Church, 1989]. Moreover, it has been shown by Recking et al. [2008] in a comparison with more than 1000 experimental observations that our reference equation of Rickenmann [2001] yielded similar deviations...
from measured bedload rates than other excess shear stress equations (e.g. those of Schoklitsch [1962], Julien [2002], Abrahams and Gao [2006]). Consequently, using different bedload equations will have only small effects on the resulting order of the reduction. Thus, the pattern for the predicted bedload volumes $V_{\text{pred}}$ would be similar regardless of the applied bedload transport equation. Since we wanted to focus on the resistance partitioning approaches and we did not want to introduce another source of variability, we limited the number of bedload equations in the present study. We mainly used the equation of Rickenmann [2001] because it was developed for steep slope conditions as in our study streams. One alternative bedload equation was tested in combination with the flow resistance approach of Yager [2006], namely the equation of Parker [1990], because it has shown the best predictive performance in the study of Yager [2006]. A comprehensive test of different bedload transport equations is beyond the scope of this paper.

### 5.2 Performance of flow resistance approaches

Most of the tested approaches to flow resistance partitioning have an empirical component, and the results indicate that a specific approach may not apply to a range of streambed and flow conditions much wider than the range of conditions from which the approach was developed. Most equations performed better for large flow events, for which the relative flow depth was large, the excess shear stress was very high and the majority of all sediment sizes may have been mobile; this finding is in agreement with other studies [e.g. Bathurst, et al., 1987; D’Agostino and Lenzi, 1999; Rickenmann, 2001]. The data from the large flow events were associated with a higher proportion of transport duration with large relative flow depths than the long term data series.

Compared to the reference equation by Rickenmann [2001] (Ri-no), which does not account for macro-roughness, the boulder approach of Pagliara and Chiavaccini [2006] in combination Ri-PC consistently reduced transport rates for streams with substantial concentrations of large boulders and streams with large step slopes. However, the nearly constant value of $(f_{0}/f_{\text{tota}})^{0.5}$ predicted by the flow resistance equation of Pagliara and Chiavaccini [2006] for changing relative flow depth is implausible and not supported by the other tested

---

Table 6. Scores for predicted/measured bedload volumes ($V_{\text{pred}}/V_{\text{meas}}$) for each equation combination and data set

<table>
<thead>
<tr>
<th>Equation</th>
<th>long term data</th>
<th>event data</th>
<th>all data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$P_{10}$</td>
<td>$P_{90}$</td>
<td>med</td>
</tr>
<tr>
<td>Ri-no</td>
<td>0.41</td>
<td>14.5</td>
<td>2.4</td>
</tr>
<tr>
<td>Ri-PC</td>
<td>0.37</td>
<td>10.2</td>
<td>2.1</td>
</tr>
<tr>
<td>Ri-W</td>
<td>0.24</td>
<td>5.2</td>
<td>1.1</td>
</tr>
<tr>
<td>Ri-Y</td>
<td>0.32</td>
<td>6.1</td>
<td>1.7</td>
</tr>
<tr>
<td>Ri-EA</td>
<td>0.04</td>
<td>2.9</td>
<td>0.6</td>
</tr>
<tr>
<td>Ri-RR</td>
<td>0.16</td>
<td>3.9</td>
<td>0.9</td>
</tr>
<tr>
<td>P-Y</td>
<td>2.23</td>
<td>59.1</td>
<td>10.2</td>
</tr>
</tbody>
</table>

$P_{10}$ and $P_{90}$ are the 10th and the 90th percentile of the data, med is the median, SD is the standard deviation and CV is the coefficient of variation.
flow resistance approaches. Nevertheless, at relative flow depths that are relevant for bedload transport, the approach predicted similar \((f_0/f_{tot})^{0.5}\) values as the empirical approach of Rickenmann and Recking [2011]. The concordance may be coincidental, because for smaller flow depths, \((f_0/f_{tot})^{0.5}\) values for the approach of Pagliara and Chiavaccini [2006] were very high relative to predictions by the empirically broadly supported equation by Rickenmann and Recking [2011] and relative to the physically based equation of Yager [2006]. The validity of the Pagliara and Chiavaccini [2006] approach is thus questionable, particularly for smaller relative flow depths. However, although Pagliara [2008] restricted the flow resistance calculation used in combination Ri-PC to channel slopes in the range 0.08 to 0.4 and boulder concentrations smaller than 0.3, the calculated \(V_{pred}/V_{meas}\) values are of similar order outside this range as inside.

The approach of Whittaker et al. [1988], combination Ri-W, was very sensitive to boulder concentration and relative flow depth, which resulted in highly variable values of \((f_0/f_{tot})^{0.5}\). The approach is limited to block concentrations smaller than 0.15 [Whittaker, et al., 1988]. In fact, predicted flow resistance was only plausible for streams with small boulder concentrations. Four of our study streams have larger block concentrations (Baltschieder, Mattenbach, Gamnsa, Steinibach). For these streams the flow resistance due to boulders is overestimated and the transported bedload volumes were underestimated by an order of magnitude. Consequently these calculations were excluded from the analysis (cf. Figure 4, grey dots). The good performance in streams with high boulder concentrations and large step slopes was thus based on data of only two and six streams, respectively.

Figure 8. Transport efficiency in relation to roughness measures. One point refers to summed data of one stream. The floating bars in a) refer to the observed \(r_f/D_{94}\) range above the critical discharge \(Q_c\). Transport efficiency \(TE\) is here defined as \(TE = \Sigma V_{meas}/(1.5 \Sigma (Q-Q_c) S^{1.5})\).
The approach by Egashira and Ashida [1991], combination Ri-EA, was highly sensitive to the step slope $H/L$. The small predicted values of $(f_0/f_{tot})^{0.5}$ due to steps and pools led to a significant increase in total flow resistance. As a result Ri-EA underpredicted the measured bedload volumes. Compared to the other combinations, Ri-EA gave the smallest median $V_{pred}/V_{meas}$ value for the complete dataset. The values of $(f_0/f_{tot})^{0.5}$ did not significantly increase with flow depth. This might be due to differences between the effects of steps in nature and those observed in laboratory experiments, where steps are perfectly shaped width-spanning elements. In nature steps are typically arranged in more three-dimensional patterns, possibly resulting in different energy dissipation than would be observed in a simplified flume set-up.

The stress partitioning approach of Yager [2006], combination Ri-Y, predicted values of $(f_0/f_{tot})^{0.5}$ similar to combination Ri-RR over a large range of relative flow depth, especially for streams with high boulder concentrations or large step slopes. Combination Ri-Y resulted in a median $V_{pred}/V_{meas}$ value of 1.1 for the whole data set with a small coefficient of variation of 0.9, and 93% of the events were predicted within half an order of magnitude of the observed bedload volumes. When Yager’s [2006] approach was combined with the Parker [1990] bedload equation, combination P-Y, predicted bedload volumes were on average 7-fold larger than predicted with Ri-Y.

The approach of Rickenmann and Recking [2011], combination Ri-RR, yielded consistently relatively good bedload predictions over a wide range of relative flow depths, with a median value of $V_{pred}/V_{meas} = 1.0$ for the whole data set and a small coefficient of variation of 1.1. The approach produced a comparatively good prediction accuracy especially for the long term data, where a wide range of relative flow depths occurs.

However, no individual equation performed best across the full range of channel types and the specific macro-roughness elements, i.e. no specific equation yielded consistently good predictions for each single event in a step-pool system or in a boulder bed stream. However, for streams with high boulder concentrations the approaches Ri-PC, Ri-W and Ri-Y usually gave accurate predictions of bedload volumes, i.e. they predicted 90% of the events to within a factor of three of the observed bedload volumes. This represents a significant improvement in prediction accuracy compared to the reference equation Ri-no.

Interestingly, the purely empirical approach Ri-RR, which does not explicitly account for any specific type of macro-roughness element, estimated energy losses (i.e. values of $(f_0/f_{tot})^{0.5}$) that resulted in relatively accurate bedload predictions. This suggests either that the physically based approaches in steep streams may still be insufficient in predicting the influence of macro-roughness on total flow resistance, or that the streambed characteristics and

<table>
<thead>
<tr>
<th>Table 7. Kendall tau rank correlation coefficient for the relationship between transport efficiency and roughness measures</th>
</tr>
</thead>
<tbody>
<tr>
<td>Channel slope $S$</td>
</tr>
<tr>
<td>----------------------</td>
</tr>
<tr>
<td>Long term bedload data</td>
</tr>
<tr>
<td>Large flood event data</td>
</tr>
<tr>
<td>All data</td>
</tr>
</tbody>
</table>

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Interestingly, the purely empirical approach Ri-RR, which does not explicitly account for any specific type of macro-roughness element, estimated energy losses (i.e. values of $(f_0/f_{tot})^{0.5}$) that resulted in relatively accurate bedload predictions. This suggests either that the physically based approaches in steep streams may still be insufficient in predicting the influence of macro-roughness on total flow resistance, or that the streambed characteristics and
flow conditions in these streams cannot be assessed accurately enough when measuring the necessary parameters in the field. Furthermore, flow resistance partitioning for shallow flows in steep streams is not straightforward [Rickenmann and Recking, 2011]. Zimmermann [2010] concluded that it is difficult to distinguish between grain and form resistance for such flow conditions. Even though the flow resistance partitioning concept has been questioned in various studies [e.g. David et al., 2011; Wilcox et al., 2006; Wilcox and Wohl, 2006], its application was shown to result in bedload transport predictions that were up to an order of magnitude closer to observed transport rates than predictions from equations that did not account for additional flow resistance effects. The relatively good performance of the stress partitioning approach of Yager [2006] for streams with higher boulder concentrations indicates that this physically based correction for additional flow resistance is a step forward in better characterizing such stream conditions from a theoretical point of view. The improved bedload predictions support our assumption, that physical roughness measures could consequently have a direct influence on bedload predictions. Moreover, our data showed relationships between macro-roughness in a stream and its transport efficiency (Figure 8, Table 7). For the range of investigated channel and flow conditions, the most significant correlations were observed between transport efficiency and boulder concentration, and between transport efficiency and the characteristic grain size $D_{90}$ (Table 7). Transport efficiency $TE$ is a ratio equivalent to an ideal dimensionless prefactor in the simple bedload equation (23) (with no accounting for macro-roughness), defined here by $TE = \Sigma V_{\text{meas}} / (1.5 \Sigma (Q - Q_c) S^{1.5})$.

5.3 Uncertainty of roughness parameter estimation

The flow resistance partitioning approaches presented here are based on measurements of channel parameters in flume experiments, often with simple geometric arrangements of roughness elements. Transferring the definitions of these roughness measures to the field situation is not straightforward, and parameter identification and measurement in the field may introduce some uncertainty for the flow resistance partitioning calculations. Morphologic features such as step-pool sequences are not unambiguously identifiable and are subject to variable definitions [e.g. Zimmermann, et al., 2008]. The natural conditions in a mountain stream complicate measurements, when rough water or dense vegetation makes field work difficult.

One important measure, which was incorporated in three of the presented flow resistance partitioning approaches, was the mean boulder diameter $D_b$. This parameter depends on the choice of a minimum diameter $D_c$, which a grain must possess to be regarded as a boulder or immobile grain. Since $D_c$ is mainly controlled by flow conditions, an optimal definition for field measurements is challenging. For a specific flow $D_c$ could be estimated using an equation for the initiation of bedload motion [e.g. Bathurst, et al., 1987; Lamb, et al., 2008]. But to prevent problems in comparing different streams, $D_c$ should be defined as the grain size that is moved at a flow magnitude of a specific reoccurrence interval. Since we do not have the necessary information on the frequency of boulder motions, we made the most practical assumption and fixed $D_c$ at 0.5 m. Moreover, this assumption allowed more robust data acquisition in
the field, where measuring grains below a certain size is either uncertain, or requires very costly or time-demanding investigations.

Whatever definition for $D_c$ is used, uncertainty in the latter affects the roughness parameters of the flow resistance equations (Table 8) and consequently affects bedload predictions (Figure 9). As an example, for the Gamsa river, a 40 % and 80 % increase of $D_c$ increased the mean boulder size, because smaller grains were not counted as boulders (Table 8). Boulder concentration slightly decreased and boulder step spacing became larger. The changed parameters lead to increased bedload transport rates in the approaches of Yager [2006] (Ri-Y) and Pagliara and Chiavaccini [2006] (Ri-PC) (Figure 9a,b) and also in the equation combination Parker-Yager (P-Y). The larger transport rates resulted in larger total bedload volumes for the example of the Gamsa stream event. Bedload volumes were up to 11 % larger than in calculations with the reference critical diameter $D_c$ (Figure 9c). The increase of $D_c$ had an inverse effect on the predictions with the approach of Whittaker et al. (Ri-W): bedload volumes were reduced by up to 24 % (Figure 9c). This contrasting effect is due to the dominant influence of $D_b$ in relation to the block concentration $\alpha$ in the flow resistance calculation of Whittaker et al. [1988].

![Figure 9. Sensitivity of bedload transport rate per unit width and bedload event volumes to variation of the critical immobile grain size $D_c$; data from Gamsa stream; stress partitioning equations are defined in Table 4.]

Table 8. Variation of roughness parameter with the critical grain diameter $D_c$; data from Gamsa stream

<table>
<thead>
<tr>
<th>Parameter</th>
<th>$D_c = 0.5$ m</th>
<th>$D_c = 0.7$ m</th>
<th>$D_c = 0.9$ m</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of boulders N</td>
<td>150</td>
<td>140</td>
<td>109</td>
</tr>
<tr>
<td>Mean boulder diameter $D_b$ (m)</td>
<td>1.164</td>
<td>1.199</td>
<td>1.304</td>
</tr>
<tr>
<td>Boulder concentration $\Gamma$</td>
<td>0.164</td>
<td>0.163</td>
<td>0.150</td>
</tr>
<tr>
<td>Boulder step spacing $\lambda_s$ (m)</td>
<td>5.57</td>
<td>5.94</td>
<td>7.01</td>
</tr>
<tr>
<td>Height of sediment $z_{in}$ (m)</td>
<td>0.561</td>
<td>0.585</td>
<td>0.671</td>
</tr>
<tr>
<td>Boulder protrusion $p_u$ (m)</td>
<td>0.602</td>
<td>0.614</td>
<td>0.633</td>
</tr>
<tr>
<td>Block concentration $\alpha$</td>
<td>0.205</td>
<td>0.204</td>
<td>0.188</td>
</tr>
</tbody>
</table>

*Height of sediment above base of immobile grains
In small streams shear stresses at high flows can get competent to move boulders that are larger than 0.5 m in diameter [Turowski et al., 2009]. When all grain sizes (including boulders) are mobile at high flow, the validity of the approaches using boulder concentration is in question. This is because the sensitive parameter boulder concentration should theoretically become zero and therefore the predicted additional flow resistance should also equal zero. A further uncertainty in predicting bedload volumes is the variability in threshold discharge for the onset of transport. There have been few attempts to relate discharge and initiation of bedload transport based on field data from steep streams [Bathurst, et al., 1987; Lamb, et al., 2008; Turowski, et al., 2011]. However, for large floods the influence of transport thresholds on predicted bedload transport rates is smaller than for small flood events, because flows are much higher than the threshold flow.

6 Conclusions

Bedload transport and flow resistance equations were combined to account for flow resistance due to macro-roughness elements and shallow flows in steep streams. Several flow resistance partitioning methods were used to estimate a reduced energy slope as a basis for modified bedload transport calculations. This procedure significantly reduced the over-prediction of observed bedload volumes, as compared to the predictions with the reference transport equation of Rickenmann [2001] that did not account for macro-roughness effects.

The tested approaches yielded highly variable improvements in bedload transport prediction accuracy, mainly depending on the size and density of macro-roughness elements and on the flow conditions. The approaches which account for the effects of large boulders generally performed better in streams featuring a high boulder concentration or a step-pool system. For rough channels with a high boulder concentration, the transport equation of Rickenmann [2001] combined with the flow resistance equations of Pagliara and Chiavaccini [2006], Yager [2006] and Whittaker et al. [1988] predicted at least 75 % of the events to within a factor of three of the observed values. The approach by Egashira and Ashida [1991], which estimates flow resistance by a measure of step-pool geometry, did not improve bedload predictions compared to the reference equation.

For practical applications, if no detailed roughness information is available for a given stream, the approach of Rickenmann and Recking [2011] represents a simple way to account for additional flow resistance in steep streams with small relative flow depths. The approach generated the best average performance for all study streams, including a large range of streambed characteristics and flow conditions. This suggests either that the more physically based approaches in steep streams may still be insufficient in predicting the influence of macro-roughness on total flow resistance, or that the identification and measurement of macro-roughness and flow conditions in these streams are not accurate enough. The results indicate that the physically based approaches may not apply to the wide range of streambed and flow conditions represented by the study streams. However, the approaches that take into account a measure of macro-roughness resulted in bedload transport predictions that were up
to an order of magnitude closer to observed transport rates than predictions from equations that did not account for additional flow resistance effects. The relatively good performance of the stress partitioning approach of Yager [2006] for streams with higher boulder concentrations indicates that this physically based correction for additional flow resistance is a step forward in better characterizing such stream conditions from a theoretical point of view.

Acknowledgements
This study was supported by the Swiss Federal Office for the Environment (contract no. 06.0083.PJ/G063-0651). Additional support to DR and JMT was obtained through SNF Grant 200021_124634/1. Thanks to Fabian Blaser and Michael Pauli for field assistance, Angela Klaiber for assistance in data compilation, Ingo Völksch for programming support. We thank Rob Ferguson and two anonymous reviewers for their constructive comments that improved the paper.

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Chapter IV

Range imaging, a new method for high-resolution topographic measurements in small- to medium-scale field sites

Manuel Nitsche, Jens Turowski, Alexandre Badoux, Dieter Rickenmann, Tobias Kohoutek, Michael Pauli, James Kirchner

ABSTRACT – Topographic measurements are essential for the study of earth surface processes. Three-dimensional data have been conventionally obtained through terrestrial laser scanning or photogrammetric methods. However, particularly in steep and rough terrain, high-resolution field measurements remain challenging and often require new creative approaches. In this paper, range imaging is evaluated as an alternative method for obtaining surface data in such complex environments. Range imaging is an emerging time-of-flight technology, using phase shift measurements on a multi-pixel sensor to generate a distance image of a surface. Its suitability for field measurements has yet not been tested. We found ambient light and surface reflectivity to be the main factors affecting error in distance measurements. Low-reflectivity surfaces and strong illumination contrasts under direct exposure to sunlight lead to noisy distance measurements. However, regardless of lighting conditions, the accuracy of range imaging was markedly improved by averaging multiple images of the same scene. For medium ambient lighting (shade) and a light-coloured surface the measurement uncertainty was approximately 9 mm. To further test the suitability of range imaging for field applications we measured a reach of a steep mountain stream with a horizontal resolution of circa 1 cm (in the focal plane of the camera), allowing for the interpolation of a digital elevation model on a 2 cm grid. Comparison with an elevation model obtained from terrestrial laser scanning for the same site revealed that both models show similar degrees of topographic detail. Despite limitations in measurement range and accuracy, particularly at bright ambient lighting, range imaging offers three dimensional data in real time and video mode without the need of post-processing. Therefore, range imaging is a useful complement or alternative to existing methods for high-resolution measurements in small- to medium-scale field sites.

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1 Introduction

High-quality surface models help to advance the understanding of earth surface processes. The rapid development of digital survey techniques in the last decade has led to a dramatic
increase in terrain information and opened up new opportunities for hydrologic and geomorphologic studies [Tarolli et al., 2009]. However, there is still a growing need for data to document and explore the full range of spatial and temporal variability in landscapes such as river corridors [e.g., Marcus and Fonstad, 2010].

Photogrammetry and laser scanning have become widely used, and specialized workflows have been developed for obtaining three-dimensional (3-D) data at various scales in diverse environments. Aerial photogrammetry has also been used over a wide range of scales, for example to measure the substrate size of gravel bed rivers [Dugdale et al., 2010], to identify reach-scale gully morphology [Giménez et al., 2009], and to detect debris-flow activity at the catchment scale [Berger et al., 2011]. Close-range applications of photogrammetry have been shown to be viable for extracting digital elevation models of small-scale roughness of exposed gravel bed surfaces [e.g. Butler et al., 1998a; Carbonneau et al., 2003; Lane et al., 2001]. Today, even consumer cameras can be employed with reasonable accuracy (few centimetres) for scientific applications [Rieke-Zapp et al., 2010]. To obtain a bird’s eye view, digital cameras can conveniently be mounted on poles [Bird et al., 2010] or kites [Giménez et al., 2009], even below the forest canopy, where airborne or satellite images are not feasible. Under some circumstances, it is possible to assess the topography of submerged surfaces with multimedia photogrammetry techniques [Butler et al., 2002; Maas, 1995].

Airborne and terrestrial laser scanning (ALS/ TLS) constitute another group of measurement techniques that have been applied on a wide range of scales. TLS for example was used for small scale measurements of weathering rates [e.g. Schaefer and Inkpen, 2009] or the characterization of open gravel surfaces [Heritage and Milan, 2009] or other sedimentary structures [Lamarre and Roy, 2008]. Airborne laser scanning was used for example for the recognition of channel bed morphology [Cavalli et al., 2008]. Moreover, protocols have been published presenting workflows for the measurement and the calculation of high-resolution elevation models on various scales, for example for rock surfaces [Schaefer and Inkpen, 2009], for alluvial river beds at grain-scale resolution [Hodge et al., 2009], or for reach morphology [Heritage and Hetherington, 2007].

Even though photogrammetry and laser scanning have proven to be successful techniques to measure fluvial morphologies, high-resolution field measurements remain challenging and often require new creative approaches. In the present study we introduce range imaging (RIM) as a novel method to capture centimetre- to meter-scale surface data in the field. While laser scanning or photogrammetry is suitable for specific measurement problems, each method has its disadvantages, for example with respect to cost or weight (TLS) or with respect to processing time or surface texture (photogrammetry). RIM represents a versatile and relatively inexpensive alternative which opens up new topographic mapping possibilities in steep and rough small- to medium-scale terrain, although it cannot compensate for all the disadvantages of the other methods. One of the main advantages of RIM cameras is the possibility to acquire 3-D data in real time and video mode without the need for post-processing, allowing better control over the measurements in the field.
RIM is a young but quickly developing technology. Early RIM techniques were tested and reviewed in the 1980s by Jarvis [1983] and Besl [1988]. In the 1990s and early 2000s, concepts for time-of-flight solid-state range cameras were published [Lange and Seitz, 2001; Schwarte et al., 1995; Spirig et al., 1997] and the cameras were used in industrial applications, for example for object recognition, collision prevention, 3-D modelling, mixed reality, and gesture recognition. A more recent overview of RIM cameras was given by Kolb et al. [2010]. The suitability and accuracy of range cameras for scientific measurements has been evaluated mostly for indoor applications, for example for person height measurements [e.g. Dorrington et al., 2010], and indoor distance accuracies of tens of millimetres were reported [Boehm and Pattinson, 2010]. To date, there are few published applications of range cameras in the field, e.g. for scanning window frames and architectural friezes in a cultural heritage study [Chiabrando et al., 2010a, b], and for measuring canopy density [Schulze, 2010].

The potential of range cameras in field applications has not yet been extensively explored, and the suitability of RIM for measurements in complex and rough terrain has not been shown. The present study aims at identifying the main error sources for field RIM measurements, and quantifying the uncertainty in controlled laboratory and field measurements, expanding on the work of Nitsche et al. [2010]. Additionally, a simple but comprehensive workflow is developed which includes field measurements, robust post-processing and the generation of a digital elevation model. As an example, we present a survey of a narrow, high-gradient mountain streambed, which provides a challenging field application with complex topography, a wide range of particle sizes, and abundant vegetation and organic material in and around the survey site. Finally, the surface model is compared to a model generated with TLS to evaluate the potential of RIM measurements.

2 Sources of measurement errors in time-of-flight range cameras

Range cameras acquire 3-D point clouds at video frame rates and in real time, using an indirect time-of-flight method. Their main components are an infrared signal emitter, a lens, and a sensor using Complementary Metal Oxide Semiconductor (CMOS) technology [Lange and Seitz, 2001]. The emitter illuminates a scene with amplitude-modulated continuous-wave infrared light, and the reflections are projected through a lens onto a CMOS sensor. The near infrared light (850 – 870 nm), which is typically modulated at frequencies \( f_{\text{mod}} \) between 10 and 60 MHz, is regularly sampled at the sensor. Each sample corresponds to photo-generated charge carriers integrated over a fraction of the modulation period. Integrating multiple samples permits determination of the signal parameters intensity \( I \), amplitude \( A \) and phase \( \phi \). The intensity \( I \) is a measure of the strength of the total light (i.e. the number of electrons per pixel generated by both the ambient light and the incoming modulated light), whereas the amplitude \( A \) is a measure of the modulation amplitude (i.e. the number of electrons per pixel generated by the incoming modulated light) [Lange et al., 1999]. Via an autocorrelation function the phase shift \( \Delta \phi \) between the emitted and reflected light can be detected [Möller et al.,
The phase shift $\Delta \phi$ being proportional to the target distance, and the absolute target distance $D$ can be calculated by

$$D = \frac{c \Delta \phi}{4\pi f_{\text{mod}}},$$

where $c$ is the speed of light.

For each pixel the distance to an object is measured independently at video rate (typically 20-60 frames per second). The distance image containing the spherical distances can be transformed into a three-dimensional Cartesian coordinate point cloud using the projection parameters of the lens. The maximum distance $D_{\text{max}}$ that can be unambiguously measured is limited to half of the modulation wavelength $\lambda_{\text{mod}}$. At a modulation frequency of 20 MHz the modulated wavelength is 15 m and thus $D_{\text{max}}$ is 7.5 m. Objects that are beyond $D_{\text{max}}$ are still measured, but the distances are folded back into the non-ambiguity range, and are aliased as a distance less than $D_{\text{max}}$ that has the same phase shift as the actual object distance.

In this study, two off-the-shelf camera models were used (Table 1): the SR4000 by Mesa Imaging, Switzerland (www.mesa-imaging.ch) and the CamCube 2.0 by PMD Technologies, Germany (www.pmdtec.com). Both cameras need an external power supply and have to be connected to a computer for data acquisition.

The quality of the phase shift measurements is strongly affected by the integration time, which is the time the sensor is collecting light for a single measurement. The integration time is inversely proportional to the noise in the measurements. Too long integration leads to sensor saturation, while too short integration results in a low signal-to-noise ratio (SNR). Moreover, the phase shift measurements of range cameras are susceptible to random and systematic errors, including errors originating from the optical system and the semiconductor technology itself, and errors caused by the environment, e.g. through multiple reflections and surface reflectivity properties. An error model for range imaging noise has not yet been established [Lindner et al., 2010].

### Table 1. Range camera specifications

<table>
<thead>
<tr>
<th>Model</th>
<th>SR4000</th>
<th>CamCube 2.0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manufacturer</td>
<td>Mesa Imaging</td>
<td>PMD Technologies</td>
</tr>
<tr>
<td>Modulation frequency (MHz)</td>
<td>29-31</td>
<td>18-21</td>
</tr>
<tr>
<td>Unambiguous measurement range (m)</td>
<td>0.8-5</td>
<td>0.3-7.5</td>
</tr>
<tr>
<td>Sensor pixels</td>
<td>176 x 148</td>
<td>204 x 204</td>
</tr>
<tr>
<td>Field of view (degree)</td>
<td>43.6 x 34.6</td>
<td>40 x 40</td>
</tr>
<tr>
<td>Mean resolution at 3 meter (mm)</td>
<td>13.6</td>
<td>10.7</td>
</tr>
<tr>
<td>Footprint area at 3 meter (m²)</td>
<td>4.48</td>
<td>4.77</td>
</tr>
<tr>
<td>Camera weight (g)</td>
<td>470</td>
<td>1370</td>
</tr>
<tr>
<td>Camera dimensions (mm)</td>
<td>65 x 65 x 68</td>
<td>180 x 194 x 180</td>
</tr>
<tr>
<td>Frame rate (fps⁻¹)</td>
<td>54</td>
<td>25</td>
</tr>
<tr>
<td>Illumination wavelength (nm)</td>
<td>850</td>
<td>870</td>
</tr>
<tr>
<td>Price (€)</td>
<td>~5500</td>
<td>~7500</td>
</tr>
</tbody>
</table>
2.1 Internal sources of error

Scattering of light within the camera is a major error source and leads to significant distortion of the distance measurements [e.g. Chiabrando et al., 2010a; Karel et al., 2010; Kavli et al., 2008]. This effect is caused by multiple reflections between the lens, the optical filter and the sensor. As a result the light measured by each pixel is a mixture of the light reflected by the geometrically corresponding pixel footprint on the object plus a parasitic signal reflected at other pixels in the background. Scattering can cause distance errors of up to tens of millimetres, which is within the noise of Range cameras [Jamtsho and Lichti, 2010]. These errors increase from the sensor centre to the edges [Nitsche et al., 2010]. There are several methods to model and compensate scattering [e.g. Kavli et al., 2008; Mure-Dubois and Hugli, 2007], and this particular source of error is not treated further within the present paper. Wiggling is another error source resulting in range dependent distance errors, and it is due to the optical signal shape that is far from the theoretically assumed sinusoidal shape [Lindner et al. 2010].

The measurement accuracy is physically limited by noise generated in the range sensor itself. Primary noise types are shot noise from dark electron current dominant in low light conditions and photon-generated electron current dominant in high intensity light conditions [Büttgen et al., 2005; Möller et al., 2005]. Furthermore, noise originates from changes in the internal temperature of the camera [Kahlmann and Ingensand, 2005; Kahlmann et al., 2006; Karel et al., 2010]. Considering only shot noise, which cannot be reduced or eliminated by signal processing techniques, the distance accuracy can be estimated by [Lange et al., 1999]:

\[
\sigma_D = \frac{D \sqrt{I}}{\sqrt{8} A},
\]  

where \(\sigma_D\) is the standard deviation of the distance error, \(D\) is the target distance, \(I\) is the signal intensity and \(A\) is the signal amplitude. From equation (2) it can be seen that measurement standard deviations are inversely proportional to the amplitude of the reflected light, which in turn is affected by the distance to the object and its reflectivity. Moreover, stronger ambient light increases the noise of the measurement.

2.2 Environmental sources of error

In addition to internal errors, many environmental factors can also contribute to measurement uncertainties. High ambient light and low surface reflectivity have been described as the main external sources of RIM error [Büttgen et al., 2005; Guomundsson et al., 2007]. Different rock types or different degrees of surface wetness have different reflectivity, which influences the measurement accuracy [Chiabrando et al., 2010b]. Multipath effects can arise when backscattered light is reflected by more than one surface before reaching the sensor. This error is particularly prevalent when scanning highly reflective surfaces at close range [Guomundsson et al., 2007; Karel et al., 2010] or in the proximity of corners [Runne et al., 2001]. Multipath errors can be of any magnitude up to the maximum unambiguous range [Andrews et al., 2001]. Large errors can be identified and edited within the point cloud, but it
is more problematic to identify small errors that occur in concave corners. Another error, referred to as “mixed pixels” by Hebert and Krotkov [1992] may occur, when one pixel on the range sensor collects light from adjacent surfaces of different distance and the signal is integrated. Mixed pixel errors also occur in TLS measurements [Lichti et al., 2005]. Using full waveform analysis, like in state-of-the-art laser scanners, it would be possible to separate the first pulse reflection from any other reflections. Mixed pixels can be removed as outliers by geometric shape fitting or the use of median filters [Langer et al., 2000].

More generally, the distance measurement uncertainty increases with increasing distance [MacKinnon et al., 2008]. Small influences of the angle of incidence on distance measurement uncertainty have been reported by Chiabrando et al. [2010a], and Kahlmann and Ingensand [2005]. Measuring on or through translucent materials (multimedia photogrammetry) like water or glass can create additional errors [Maas, 1995; Okamoto, 1982]. Light propagates slower in such materials and consequently distances are overestimated. For good conditions, i.e. high target reflectivity and little ambient light, overall distance measurement precision of about one centimetre and an accuracy up to a few centimetres has been reported in the literature [Büttgen et al., 2005; Dorrington et al., 2010; Kahlmann and Ingensand, 2005; Kahlmann et al., 2006; Nitsche et al., 2010]. Manufacturers of range cameras specify an achievable accuracy of less than one centimetre [Mesa, 2011].

3 Quantification of typical errors

In the experiments described below, we quantified how distance, reflectivity and ambient light influence the uncertainty of distance measurements with the CamCube 2.0 and the SR4000 camera (Table 1), both under controlled conditions in the geodetic calibration laboratory of ETH Zürich (distance, reflectivity) and outdoors (ambient light). Some of these experiments have been previously described by Nitsche et al. [2010], and are summarized and supplemented here.
3.1 Experiment 1: Target distance and reflectivity

In the first experiment the precision (i.e. the repeatability) and the accuracy of distance measurements at the central pixel of the range sensor were investigated in a series of laboratory experiments for distances from one to seven meters. The camera was set up normal to a flat wooden board that could be moved on a calibrated rail to adjust the measuring distance (verified to within 0.2 μm with an interferometer). As a result of small flexions of the board, the adjusted camera-target distance could not be guaranteed throughout the whole surface of the board. Thus, an absolute error could only be identified to approximately ± 2 mm. Two boards were used, one black and one white, to explore two very different levels of reflectivity. The white board had an approximately 8-fold higher reflectivity in the infrared spectrum than the black board. Ambient light was turned off. For each setting the measurement was repeated 250 times. The uncertainty increased significantly with the distance between the board and the camera (Figure 1). At one meter the standard deviation of measured distances was 3.9 mm for the white board and 14.1 mm for the black board. At five meter distance the standard deviation was 21.9 mm and 208.8 mm, respectively.

The distribution of the repeat measurements was approximately Gaussian (Figure 2). Only measurements on the black surface at 7 m distance showed a very different distribution with some very small distance values (Figure 2h). These were likely a result of dust particles, which created some strong early reflections, compared to the weak signal from the dark surface in the distance. The measured distances were on average overestimated when the surface was white and they were underestimated on the black surface (Figure 2).

Taking the median of multiple measurements significantly improved the accuracy compared to a single measurement. The median was preferred over the mean, because it was less sensitive to outliers or measurement errors (as seen in Figure 2h). The highest accuracy (i.e. the smallest error) was achieved for measurements at three meter distance on the white board.
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(1.9 mm), where accuracy was defined as the measured distance minus the independently adjusted camera-target distance. The lowest accuracy (i.e. the largest error) was observed for the black board at five meter distance (-61.3 mm). The measurement accuracy was clearly dependent on the reflectivity of the surface: it was on average better for the white board than for the black board (Table 2). Even though the measurement accuracy varied with distance, a clear functional relationship was not observed.

3.2 Experiment 2: Ambient light

In experiment 2, the influence of ambient light on measurement quality was assessed using a flat unicoloured surface of known geometry. The measurements were performed outdoors on a white board positioned normal to the camera at approximately 3 m distance. The distance was manually adjusted using a laser distance meter, thus the assumed true distance could be identified to an accuracy of approximately ± 20 mm. For a single image of Cartesian z-coordinates captured in direct sunlight the standard deviation was 124.5 mm (Figure 3a, dashed lines and grey dots). Significant reduction of the standard deviation to 60.3 mm could be achieved by simple temporal averaging; here the median of 250 repeated measurements was taken (Figure 3a, straight lines and dark dots). The standard deviation was an order of magnitude smaller at night with very little ambient light: it was 13.5 mm for a single image, and 4.8 mm for the averaged data (Figure 3c). In the shade, the standard deviation was 23.2 mm for a single image and 8.5 mm for the averaged data (Figure 3b), intermediate between the results obtained in direct sunlight and night-time conditions.

Experiment 2 has shown that regardless of light conditions, averaging together multiple frames significantly reduces the uncertainty of distance measurements across the sensor, such that the random noise components of the measurement error are averaged out at each pixel. The maximum achievable reduction in per-pixel distance error depends on the number of
frames. A minimum of twenty to forty consecutive measurements was needed to achieve an improvement by a factor two to three, for both the ambient light and no ambient light experiments (Figure 4). Taking more frames did not significantly improve the image quality further. At the typical frame rates of range cameras (Table 1), the time needed to acquire fifty frames is only one to two seconds.

3.3 Experiment 3: Field conditions

Real channel surfaces are much more complex than the flat, single-colour surfaces used in the tests above. On a natural streambed, the material reflectivity varies greatly in space and so does the measurement uncertainty. Other error sources such as surface colour contrasts, relief, and varying ambient light also affect the measurement and lead to higher uncertainty than would be observed under laboratory conditions. To assess these effects, a natural streambed surface was measured in a further experiment with range cameras looking vertically down on the channel, in a setup similar to that in Figure 8. The obtained distance images were then classified into zones of relatively high, medium and low reflectivity, based on the signal intensity measured at the sensor. The standard deviation of distances was on average 52 mm for pixels representing highly reflective surfaces (i.e. surfaces that reflected a large portion of the emitted infrared signal) (Figure 5). For medium-reflectivity surfaces, which in our tests represented more than half of the footprint area, the standard deviation was 96 mm. Very low-reflectivity surfaces featured even larger uncertainties (Table 2).

The same area was also measured under different lighting conditions, i.e. under direct sunlight at midday, in shade, and under no ambient light at night. The resulting point clouds are
of very different quality (Figure 6). Night-time measurements revealed the greatest details of the surface (Figure 6b). Under direct sunlight exposure the point cloud became indistinct and more scattered (Figure 6d). The increased noise in the distance data is illustrated by comparing the standard deviations of measured distances from the mean surface height: The standard deviation was 0.36 m under direct sunlight, but decreased to 0.17 m under shady conditions and decreased further to 0.11 m at night. Under direct sunlight, the noise within a single measurement (in terms of distance standard deviation) was of a similar magnitude as the total surface relief (0.92 m). Water surfaces, depicted in Figure 6a, caused pronounced variations in distance measurements; turbulent water appears to cause larger measurement errors than still water surfaces. Still water permits the modulated light to penetrate and measure the underwater surface of the riverbed (although with some exaggeration of distances owing to the lower speed of light in water).

Table 2. Measurement statistics for the error experiments

<table>
<thead>
<tr>
<th>Exp.</th>
<th>Analyzed data</th>
<th>Number of images</th>
<th>Ambient light</th>
<th>Surface colour or reflectivity</th>
<th>Target distance (m)</th>
<th>Mean measured distance (m)</th>
<th>Median measured distance (m)</th>
<th>Standard deviation (mm)</th>
<th>Accuracy (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>central pixel</td>
<td>250 none flat board white</td>
<td>1.00 ± 0.002</td>
<td>1.0092</td>
<td>1.0092</td>
<td>3.9</td>
<td>9.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>central pixel</td>
<td>250 none flat board white</td>
<td>3.00 ± 0.002</td>
<td>3.0017</td>
<td>3.0019</td>
<td>9.7</td>
<td>1.9</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>central pixel</td>
<td>250 none flat board white</td>
<td>5.00 ± 0.002</td>
<td>5.0223</td>
<td>5.0228</td>
<td>21.9</td>
<td>22.8</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>central pixel</td>
<td>250 none flat board white</td>
<td>7.00 ± 0.002</td>
<td>7.0474</td>
<td>7.0465</td>
<td>40.4</td>
<td>46.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>central pixel</td>
<td>250 none flat board black</td>
<td>1.00 ± 0.002</td>
<td>0.9571</td>
<td>0.9564</td>
<td>14.1</td>
<td>-43.6</td>
<td></td>
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<tr>
<td></td>
<td>central pixel</td>
<td>250 none flat board black</td>
<td>3.00 ± 0.002</td>
<td>2.9797</td>
<td>2.9730</td>
<td>83.4</td>
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<td>central pixel</td>
<td>250 none flat board black</td>
<td>5.00 ± 0.002</td>
<td>4.9268</td>
<td>4.9387</td>
<td>209</td>
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<td></td>
<td>central pixel</td>
<td>250 none flat board black</td>
<td>7.00 ± 0.002</td>
<td>5.9881</td>
<td>7.0040</td>
<td>2454</td>
<td>4.0</td>
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<tr>
<td>2</td>
<td>central pixel</td>
<td>250 direct sun flat board white</td>
<td>3.0 ± 0.02</td>
<td>2.9471</td>
<td>2.9396</td>
<td>183.0</td>
<td>-60.4</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>central pixel</td>
<td>250 shade flat board white</td>
<td>3.0 ± 0.02</td>
<td>3.0009</td>
<td>3.0015</td>
<td>19.6</td>
<td>1.5</td>
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</tr>
<tr>
<td></td>
<td>central pixel</td>
<td>250 night flat board white</td>
<td>3.0 ± 0.02</td>
<td>2.9484</td>
<td>2.9485</td>
<td>11.2</td>
<td>-51.5</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>all pixels</td>
<td>250 direct sun flat board white</td>
<td>3.0 ± 0.02</td>
<td>2.9151</td>
<td>2.9104</td>
<td>60.3</td>
<td>-89.6</td>
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<tr>
<td></td>
<td>all pixels</td>
<td>250 shade flat board white</td>
<td>3.0 ± 0.02</td>
<td>3.0018</td>
<td>3.0022</td>
<td>8.5</td>
<td>2.2</td>
<td></td>
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<tr>
<td></td>
<td>all pixels</td>
<td>250 night flat board white</td>
<td>3.0 ± 0.02</td>
<td>2.9496</td>
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<td>4.8</td>
<td>-50.3</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>several pixels</td>
<td>30 shade streamed high ^c</td>
<td>2.5-3.5</td>
<td>-</td>
<td>-</td>
<td>51.9</td>
<td>-</td>
<td></td>
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<tr>
<td></td>
<td>several pixels</td>
<td>30 shade streamed medium ^c</td>
<td>2.5-3.5</td>
<td>-</td>
<td>-</td>
<td>95.8</td>
<td>-</td>
<td></td>
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<tr>
<td></td>
<td>several pixels</td>
<td>30 shade streamed low ^c</td>
<td>2.5-3.5</td>
<td>-</td>
<td>-</td>
<td>179</td>
<td>-</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

^a Independently measured distance with error margins.
^b Defined as median measured distance minus target distance.
^c Reflectivity class, each class indicates the relative strength of the reflected signal (cf. Figure 5).
4 Developing a workflow for RIM field data

In this section we present a workflow for (i) capturing range images in the field with the PMD Camcube camera, (ii) processing the distance data, and (iii) interpolating the 3-D data to a digital terrain model (Figure 7). The test field site is also briefly introduced.

4.1 Field test site

The aim of the present study was to test range cameras in a realistically complex fluvial environment. For our test site we chose the Erlenbach, a small mountain stream located in the northern foothills of the Swiss Alps, (i) because the Erlenbach features a steep and rough streamed surface suitable to test the limits of the range cameras, (ii) because surface topography measurements for mountain streams are generally rare, and (iii) because we have validation data from a terrestrial laser scan for the Erlenbach. The study reach is about 40 m long and the mean bottom width of the channel is 3.5 m. The streamed has a mean slope of 12 % and features a rough surface with a median grain size of 0.07 m and a high boulder concentration (11 % of the bed surface is covered by boulders with b-axis diameter > 0.5 m). For more information on the Erlenbach the reader is referred to Rickenmann [1997], Hegg et al. [2006], and Turowski et al. [2009].

4.2 Fieldwork and field equipment

As with photogrammetric equipment, range cameras can be mounted and positioned using several different platforms, including cranes, balloons and drones. In the present study a commercial lightweight camera crane with an arm length of 5.3 m was employed to provide mobility within a densely forested area, while still achieving a top-down view of the surface to minimize scan shadows (see Figure 8, Model: ABC MiniCrane 520, www.abc-products.de). Adjusting the camera height above ground controls the footprint size and the horizontal resolution of the measurements. We captured images from camera heights between three and four meters with resulting footprint areas between 4.5 and 9 m². In total sixty footprints were taken to scan a contiguous streambed area of approximately 165 m². The footprints were typically overlapped by 30-70 % to increase the point density and to guarantee

![Figure 7. Workflow for capturing and processing range images.](image-url)
seamless merging of the xyz-data point clouds. Additionally, three to six retro-reflective measuring nails with a diameter of 4 cm (see Figure 8) were placed per footprint and their position was surveyed independently with a total station. These control points and their local coordinates in the camera reference system were easily detectible in the camera's amplitude image (Figure 9e). This allowed for the registration of all footprints and the transformation from local camera coordinates to the Swiss coordinate system “LV03”.

4.3 Image post processing

The distance images taken in the field contain noise and errors of various types. While a comprehensive error model for RIM noise is unknown, noise reduction in range images is commonly done by temporal and spatial smoothing [Lindner et al. 2010]. We applied standard image processing methods like median filtering to remove a large portion of the errors. However, finding the optimum of the selected methods was beyond the scope of the present study. The image processing methods were rather chosen to permit a comprehensive and efficient workflow and to demonstrate the potential for data optimization. Processing was done on the distance images, i.e. on the spherical distances \(D\) measured with the range camera (cf. Figure 8). Cartesian coordinates were calculated after processing. Thereby one-dimensional distance errors were prevented from dispersing in the x-, y- and z-directions.

Temporar median

It has been shown that averaging multiple distance image frames significantly reduced the noise and thus the error of a distance image (section 3, Figure 4). Because one frame including distance, intensity and amplitude data produces roughly one megabyte of text data, a compromise between accuracy and data volume had to be made. For each footprint we meas-
ured thirty individual frames and took the median, resulting in a significant noise reduction of the measurements (Figure 9b).

Spatial median filter
The time-averaged distance data still contained random noise, including spiky noise close to water surfaces and at the edges of the high-reflective control points (Figure 9b and 10a). Therefore, we applied a median filter, a nonlinear signal processing technique which is very efficient in noise reduction [Tyan, 1981]. We preferred this filter over other signal processing techniques like classical low pass filtering, because (i) it better preserves the edges of objects, (ii) it is very efficient for spiky noise and (iii), it is easy to calculate [Justusson, 1981]. For each output pixel the filter calculates the median value of the neighbourhood around the corresponding pixel in the input distance image. The larger the neighbourhood (filter window) the more noise is removed, but the less edge detail is preserved. However, to remove the spiky impulses (very large positive or negative values of small spatial extent) while preserving as much edge detail as possible, the filter window has to be larger than twice the width of the impulses. Such impulses span up to three pixels in our images, thus, the optimum filter was theoretically a 7 x 7 pixel window. The effectiveness of the filter was visually evaluated (Figure 10). However, the performance of the chosen filter depends on the noise characteristics; thus the optimal filter size might be case-dependent.

Water surface extraction
The intensity images can be used for the detection of water surfaces. For this purpose we took advantage of the fact that water surfaces have continuously changing slopes. Even if the slope changes are very small, they affect the reflectivity of the water surface. As a result, the intensity values from water surfaces have a significantly larger standard deviation in time than solid rock surfaces (Figure 9f). We found that for our specific measurement setting the intensity standard deviation of solid surfaces was smaller than approximately 50 (16 bit grey scale units). Pixels with a larger standard deviation were classified as water surfaces (Figure 9g). However, the threshold between water and solid surfaces depends on the measured materials and on the light conditions and should thus be adjusted to specific site conditions.

Conversion to Cartesian coordinates
Cartesian coordinates from the processed distance images were obtained by multiplying the spherical distances by the unit vector of each pixel. Unit vectors depend on the optical characteristics of the camera and must be obtained from the internal camera memory or from the camera manufacturer.

Coordinate transformation
The Cartesian point clouds of each footprint were transformed from the local camera coordinate system to the Swiss coordinate system “LV03”. This was achieved by applying a seven-parameter Helmert transformation using the local and the global coordinates of the control points. The coordinate transformation was performed with the triangulation software Bingo.
5.5 [Geoinformatics Photogrammetric Engineering, 2011]. Because of their high reflectivity, the control points and their local coordinates could be visually identified in the amplitude images (Figure 9e).

Cropping and merging point clouds

Nitsche et al. [2010] reported that measurements near the sensor edges are less precise than measurements in the sensor centre. Therefore, we removed 10 % of the rows and columns from each edge on the sensor, which corresponds to the area on the sensor which has a dis-
tance measurement uncertainty of more than 5 mm under optimal laboratory conditions. Each cropped footprint was then merged to a stream-reach-spanning point cloud of 3-D coordinates (Figure 11a).

**Surface modelling**

Finally, a surface model was interpolated from the processed and merged point clouds (Figure 11b) using the natural neighbour interpolation (implemented in ArcGis 9.3) at a grid spacing of 2 cm, which is circa the 2-fold of the mean point spacing of the original point cloud. Among the large variety of interpolation techniques, the natural neighbour method [Sibson, 1981] was chosen because it was found to be an appropriate method for calculating a grid of values from data featuring a combination of regular, sparse, clustered or random distribution of points [Pirotti and Tarolli, 2010]. Moreover, other interpolation or fitting techniques like kriging, splines or polynomial fitting generally result in smoother surfaces, whereas our intention was to preserve as much topographic detail as possible.
5 Analysis of RIM and TLS test measurements

5.1 Field test conditions

The range imaging data presented above was evaluated by comparing to TLS data collected in the same stream reach one week earlier (R. Baran, University of Munich, unpublished data). The TLS data qualifies as validation data, because the general morphology, particularly the position of larger grains and bedforms did not change between the scans. Discharge during both measurement campaigns was very low, amounting to 0.02-0.05 m$^3$s$^{-1}$ for the TLS measurement (3rd Nov. 2009) and 0.01-0.04 m$^3$s$^{-1}$ for the RIM measurement (12th Nov. 2009), and no bedload transport was recorded between the surveys. The wetted area for the TLS and the RIM scans was 29 % and 21 % of the mapped area, respectively (Figure 12a,b). The ambient light conditions were characterized by bright diffuse light through Altostratus clouds accompanied by high contrasts. The illuminance in the visible light spectrum, estimated from global radiation data of a nearby meteorology station, was in the range of 5000-40'000 lx for both the RIM and the TLS measurements.
5.2 Point cloud characteristics

The point clouds of the RIM and the TLS measurements differ for example in total point number and the actual surface each point represents (Table 3). The laser spot size (TLS) and the pixel footprint (RIM) are parameters that define the smallest surface unit for which an integrated distance can be measured. The TLS laser spot has a diameter of circa 6 mm (at a distance of 40 m) whereas the RIM pixel side length is 11 mm (at a typical measurement range of 3 m). While the TLS measurements are made with a single laser beam at a scan rate of 3000 points/s, a single RIM measurement produces a whole distance image including more than 41’000 individual distance values. The nominal point density for TLS can be modulated, whereas point density for RIM needs to be adjusted by the distance between camera and surface or by overlapping of footprints. Points measured with RIM have a rather homogeneous, grid-like distribution over the scanned surface because the view angle is nearly vertical, whereas the point density with TLS is very heterogeneous (Figure 12c,d) owing to the oblique view angle and the wide range of distances between the scanner and the surface. The TLS point density was very high on surfaces perpendicularly facing the laser beam, and became very low on surfaces at shallow angles to the beam. Moreover, with the oblique view
angle of TLS, many areas are in the view shade of the scanner because they are hidden behind larger objects. Due to large boulders, which hid portions of the bed even when scanning with four scan stations, 13 % of the horizontally projected rock surface was effectively unmeasurable. With the range camera, in comparison, only 1 % of the rock surface was in the view shade, which we defined as horizontal areas with a point density of less than 0.3 points/cm$^2$ (Table 3). However, the mean point density for RIM measurements (1.2 points/cm$^2$) was one order of magnitude lower than for TLS (14 points/cm$^2$) (Figure 12c,d; Table 3).

Both the TLS and the RIM points were registered and transformed into the same global coordinate system using independently measured control points (section 4.3). Transformation residuals result from errors in the control point measurements as well as from errors of the point cloud itself. For both the RIM and TLS point clouds the maximum vertical transformation residuals were 15 mm (Table 3). This is of the order of expected errors for the control point measurements itself, which suggests that the point clouds did not introduce significant geometric errors.

To visualize and quantify further characteristics of the RIM and TLS data, profiles (swaths) were taken from the point clouds (Figure 12a,b, bottom). For each sample profile all points within a distance of 1.5 cm from the profile line were analyzed. The profiles of the DEMs along the same line are shown as a reference (Figure 12e,f). Both RIM and TLS point clouds match very well, with a mean elevation of 1112.43 m and 1112.42 m, respectively. However, the RIM points were more scattered around the DEM profile than the TLS points, as indicated by the larger standard deviation of elevations (Table 4). The point elevations were detrended by subtracting the elevations of the respective DEM profile. The resulting standard deviations of the RIM and TLS elevations are 0.026 m and 0.017 m, respectively (Table 4). The discontinuity of TLS points along the profile is a result of view shade, a problem that is insignificant for the RIM measurements due to the vertical view from above.

5.3 DEM characteristics
Digital elevation models were interpolated from the point clouds of the TLS and RIM scans. For better comparison the natural neighbour interpolation method with a grid resolution of 2 cm was applied to both datasets. The DEMs presented as shaded reliefs, feature a similar degree of detail (Figure 12a,b). Grains with a diameter larger than 10-20 cm are distinguishable throughout the RIM model. The TLS model resolves structures of approximately 10 cm in diameter. However, the TLS relief contains various interpolation artefacts, particularly in areas of little or no data (view shade). In the shaded relief of the RIM measurements some naily patterns are present, while the same areas are smooth in the TLS model (Figure 12a,b). These patterns are a result of the varying accuracy achieved for different footprints, visible particularly at footprint overlaps.
Figure 12. Shaded reliefs of DEMs calculated from point clouds of RIM (a) and TLS data (b), corresponding point density maps (c, d) and sample profiles (e, f).
The sample profiles of the DEMs suggest, that the TLS DEM is more detailed in some parts, particularly where the RIM point cloud is very noisy (Figure 12e,f). However, on a centimetre-scale both profiles are approximately congruent. The height offsets of maximal 5 cm and a slight tilt are likely a result of registration and transformation errors (cf. Table 3).

Further quality metrics for the RIM and TLS elevation models were obtained from a DEM detail (indicated in Figure 12a,b). The detail is located in an area where registration and transformation errors are relatively small, and these errors are not part of the comparison. Furthermore the detail covers a part of a concrete plate built in the channel, allowing for a better quality evaluation due to its known surface structure. The contour lines in the elevation...
are smoother in the TLS model than in the RIM model. Smooth surfaces are expected on top of the large boulder (Figure 13a,b, left) and the concrete plate (Figure 13a,b, bottom). These flat or smooth surfaces are better represented by the TLS model, whereas the RIM model shows centimetre scale distortions. While both models have the same average elevation, the RIM model features a smaller minimum elevation, a larger maximum elevation, and a larger standard deviation of elevations than the TLS model, which is again an indication for the somewhat larger uncertainty of the RIM model (Table 5).

The slope maps indicate how the transition from horizontal to vertical surfaces is represented in the models (Figure 13c,d). The narrow bands of steep slopes in the TLS model (Figure 13d, red colours) indicate a rapid transition from flat surfaces to steep grain faces. In the RIM model these transition zones are wider and also less steep. This might be due to the different footprint sizes of the laser beam and the RIM pixels. The large footprint of a RIM pixel might obscure the spatially narrow elevation changes at grain edges, because a footprint with a side length of 11 mm likely covers both grain top and bottom heights. This results in mixed pixel errors and as a consequence the grains are represented by smoother slopes. The model quality can also be evaluated by looking at the elevation variations within a defined region (here, a 3 x 3 pixel matrix). The RIM model on average features larger variations, suggesting the surface contains more small-scale elevation changes (Figure 13e,f). These small-scale changes are particularly implausible on the flat concrete plate at the bottom of the images. Thus they probably represent random errors from the RIM measurements.

### 5.4 Field work

Time and personnel requirements were relatively similar for the RIM and the TLS campaign. The stream reach was measured within ten hours with the RIM camera, which included crane setup, setup and measurement of control points, RIM measurements of the channel, moving the crane and packing. The work routine could probably be sped up, because this was the first attempt at field RIM measurements. The TLS measurements were conducted by experienced users and took seven hours, three hours less than the RIM measurements, but they covered only 90% of the RIM scan area. Both scanners were efficiently operated by two persons.
RIM measurements one person moves and positions the crane, while the other remotely controls the camera and triggers the measurements. In total 60 footprints were taken, whereas half this number would have been enough to cover the entire reach. The TLS measurements were made from four stations, each of which had to be carefully set up. Some 20 minutes are needed to scan control points and to define the scan area for each station. Depending on scan resolution, the automatic TLS scan takes minutes to several hours for each scan station. Power supply is more problematic for TLS than for RIM in remote field use. Both RIM and TLS batteries have a life time of approximately 40 minutes. While the actual measuring time for TLS was approximately four times the battery life time, the RIM camera needs to be turned on only for a few seconds for the measurement of a footprint.

6 Discussion

Range imaging is a method that features principles both of laser scanning and of photogrammetry. The discussion aims at identifying the major differences between the methods and assessing the potential and the limitations of range imaging in comparison to applications of TLS and photogrammetry used in the geosciences.

6.1 Data quality and spatial resolution

The tested range cameras have shown very different data quality for different ambient light conditions and reflectivity of the surface material (sections 3 and 4). In the laboratory experiments (section 3) an accuracy of 2 to 23 mm was determined in favourable conditions (distance < 5 m, no ambient light, white surfaces) (Table 2). This is in the range of values observed for photogrammetric and laser scanning techniques at similar spatial scales. An accuracy of 2-10 mm has been reported for photogrammetric methods [Butler et al., 1998b; Carbonneau et al., 2003; Chandler et al., 2001] and for environmental applications of TLS.

| Table 6. Field equipment and work effort for RIM and TLS test measurements in the same stream reach |
|---------------------------------------------------|-----------------|-----------------|
| Camera/scanner model | PMD CamCube 2.0 | TOPCON GLS-1000 |
| Measured area (m²) | 165 | 148 |
| Number of footprints/stations | 60 | 4 |
| Scan rate (points/s) | 1,040,400 (at 25 frames/s) | 3,000 |
| Field personnel | 2 | 2 |
| Total work time in the field (h) | 10 | 7 |
| Camera/scanner weight (kg) | 1.4 | 16 |
| Tripod weight (kg) | 6.4 | 6.4 |
| Camera crane weight (kg) | 9 | - |
| Netbook weight (kg) | 1.2 | 1.2 |
| Battery weight (kg) | 2 | 0.4 |
| Battery lifetime (min) | 40 (12 V/7Ah) | 40 (7.4V/5Ah) |
| Total equipment weight without crane (kg) | 11 | 24 |
values from 2-25 mm were reported [Vosselmann and Maas, 2010; Hetherington, 2009]. 
Hodge et al. [2009] observed an accuracy of approximately 2 mm for distances measured with TLS in a fluvial environment very similar to the one studied here. Under realistic conditions with shaded ambient light, the RIM accuracy is expected to be lower than observed in the laboratory. This is suggested by experiments 2 and 3 where the standard deviation of repeat measurements was relatively high and the approximate uncertainty ranged up to 52 mm (Table 2). The maximal height difference in the DEM profiles of the TLS and RIM data was also 50 mm (section 5.3), suggesting a realistic upper limit for the RIM distance errors in the field.

Using our test camera PMD CamCube with a 204 x 204 pixel sensor at 3 m above the ground the spatial resolution was 11 mm. Cameras used for photogrammetry can achieve higher resolution due to their larger sensor or film resolution. Bird et al. [2010] for example achieved sub-centimetre resolution taking data from a distance of 10 m above ground with a non-metric film camera. The spatial resolution achievable with laser scanners depends on the distance and the angular precision [Vosselmann and Maas, 2010; Hetherington, 2009], and is limited by the size of the laser footprint. Hodge et al. [2009] reported a minimum footprint size of 4 mm for their TLS measurements. Assuming that an object such as a grain is identifiable when it is represented by nine equally spaced and contiguous measurements, than the smallest grain size measurable with TLS is approximately 12 mm. For our RIM test measurements the smallest grain size would be theoretically 33 mm. However, analyzing the DEM and the DEM profiles (section 5) the smallest identifiable grain size was in fact approximately 100 mm in diameter.

The relative geometrical stability between measured points is guaranteed by the sensor matrix for both RIM and photogrammetry techniques. This is an advantage over TLS, where the laser beam is re-positioned after each measurement [Jansa, 2004]. Thus, the laser beam does not hit the exact same point twice, whereas RIM and photogrammetry measurements always capture exactly the same footprint, as long as the camera is not moved.

6.2 Post processing and optimization

Post-processing is often a major time factor in the workflow from measurement to high quality 3-D coordinates. RIM is capable of delivering 3-D data in real time, without the need of post-processing. To obtain 3-D coordinates in photogrammetry, a typical post-processing workflow includes calculating the orientation parameters of the images [e.g. Lindner, 2009] and measuring corresponding points [e.g. Belhumeur and Mumford, 1992]. Terrestrial laser scanners deliver 3-D data almost immediately after measuring. However, the large amount of data requires specialist software for registration and editing. Due to the relatively small point density in RIM measurements, the data are manageable within software environments like R and Matlab, and in geographical information systems. Nevertheless, standard image processing techniques are useful to optimize RIM data, and relatively little post-processing was required to reasonably reduce random measurement errors. We have shown that temporal averaging (section 3) and spatial median filtering (section 4) were practical and efficient in reducing the distance measurement uncertainty. In contrast, post-processing of TLS data re-
quires somewhat greater effort and more individual filter techniques [e.g. Hodge et al., 2009]. The simple temporal averaging and the spatial median filtering used herein are not necessarily the optimum methods. They were primarily chosen to permit a comprehensive and efficient workflow for data improvement. More sophisticated image processing methods [e.g. Gonzalez and Woods, 2002; Solomon and Breckon, 2011] might yield better results and should be investigated further. The intensity images, for example, can be used as a quality attribute of the range measurements, since higher signal intensities are proportional to measurement accuracy [MacKinnon et al., 2008]. They can be used to detect edges and discontinuities when applying smoothing filters [Reynolds et al., 2011].

The calibration of digital cameras is a standard procedure in photogrammetry [Fraser, 1997]. Recently, various calibration procedures have been developed that can compensate for specific systematic errors of range cameras, for example for the correction of scattering [Jamtsho and Lichti, 2010; Karel et al., 2010], wiggling errors [Lichti and Kim, 2011; Lindner et al., 2010], or errors related to reflectivity [Lindner et al., 2010]. For the present study we calibrated the RIM cameras for interior orientation and range offsets. Other calibrations are possible, but currently there are no widely accepted strategies available.

6.3 Field and practical issues

Range cameras have some unique features that, compared to other range instruments, can facilitate measuring in the field. The 3-D RIM data can be viewed in real time while measuring, which gives unique control over the scan process. Running on video mode allows for a fast collection of distance data. The thirty frames which we used for temporal averaging (cf. section 4) were collected within less than two seconds. Video mode also allows the measurement of rapidly moving surfaces, a task that laser scanners cannot currently achieve. The small size and light weight of the RIM cameras are another advantage compared to TLS. Similarly to photogrammetric cameras, RIM enables the user to mount the devices on cranes or other platforms, achieving a top view of the surface and thus preventing shading effects in many field situations.

However, the RIM method has some important practical drawbacks compared to other methods. One of the major constraints is the sensitivity to strong ambient light in the field. While it is often difficult to control the light conditions in the field (e.g. by setting up a tent over the scan area), one can compensate somewhat for the effects of strong ambient light and dark surfaces by adjusting the camera-surface distance and the integration time of the sensor, leading to a stronger signal. Laser scanners are much less sensitive to ambient light and distance, however, direct sunlight can also affect the reflectance and lead to an erroneous signal or missing data [Charlton et al. 2009]. While low-light conditions are desirable for RIM and TLS measurements, photogrammetry is only possible when the surfaces are well illuminated [Jansa et al. 2004]. Low surface texture, shadows and severe brightness contrasts are problematic in photogrammetric applications, but have only a relatively small effect on laser scanning or RIM. Moreover, the 3-D point density for photogrammetric techniques depends on the surface texture; for low-textured surfaces measurements can fail [Jansa et al. 2004]. In con-
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Contrast, data quality is relatively independent of texture in RIM and laser scans. The range limitation of approximately 10 m restricts RIM cameras to close-range applications. Medium-range TLS scanners can measure over distances up to a few hundred meters [Charlton et al. 2009], and photogrammetric cameras are generally not range-limited.

7 Conclusions

In the present study, RIM cameras were tested to quantify major measurement errors and to evaluate their suitability for small- to medium-scale field measurements. In addition to controlled experiments, a reach of a small, steep mountain river was measured using a RIM camera mounted on a crane. A comprehensive workflow was developed including scanning, post-processing and the calculation of a digital elevation model. Ambient light and surface reflectivity were identified as the main sources of distance measurement error. The standard deviation of repeat measurements was in the range of 9-52 mm for favourable field conditions, i.e. distance ≤ 5 m, shade and highly reflective flat surfaces. Higher precision was achieved when measuring without ambient light. Taking the median of repeat measurements was shown to effectively reduce random noise in the single measurements, resulting in significantly reduced distance errors. In the laboratory experiments a distance accuracy of 2-23 mm was determined for measurements on a highly reflective surface. For favourable field conditions the distance accuracy can be worse by a factor of 2-3. However, the fast and real-time acquisition of 3-D data is a main advantage compared to other available methods like laser scanning and photogrammetry. Furthermore, post-processing of RIM data, if desired, is relatively fast and straightforward. Major drawbacks of RIM include the limited range of only up to ten meters and the relatively low distance accuracy in the field due to several error sources. TLS and some photogrammetric methods are better suited for obtaining highly accurate data over long ranges. But RIM cameras are in development: with stronger signal emitters and more effective backlight suppression, range cameras will improve their target survey performance and larger sensors will allow higher horizontal resolution. Our field measurements of a river reach allowed the creation of a high-resolution (2 cm) DEM, featuring a similar degree of detail as a DEM created from TLS data for the same site. RIM could be considered as a substitute for terrestrial laser scanners or photogrammetric approaches in small-scale applications such as grain size diameter calculations and micro-topography measurements. Operating on video mode opens up new possibilities to study debris flows, the collapse of sand piles, or other phenomena in which surfaces evolve quickly. Positioning techniques like differential GPS could be exploited and combined with range camera measurements to obtain real-time referenced global coordinates. In principle, range cameras can also be employed on a number of different platforms; for example, first experiences with RIM cameras on an unmanned helicopter have been reported by Eisenbeiss et al. [2011].
Chapter IV

Acknowledgements

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Chapter V

Conclusions

Sediment transport in steep streams is a major natural hazard in mountainous regions. To reduce the risk to human life and infrastructure, it is crucial to accurately predict transport rates. However, there is a lack of widely applicable methods to predict realistic values of sediment transport capacity in steep and rough mountain streams. For this reason, this study aimed at creating a basis for future methods that can better account for the characteristics of steep streams. The thesis was driven by the hypothesis that macro-roughness (as generated, for example, by large boulders, step-pool bedforms and woody debris) is an important factor that needs to be considered in flow resistance and sediment transport equations. Consequently, the aim was to identify and analyze the connection between macro-roughness, flow resistance and sediment transport.

The first study tested how macro-roughness can be measured in the field and how different parameters of macro-roughness are related to channel-bed slope. Water discharge, flow velocity and channel geometry were measured in six streams with different roughness characteristics, and the between-site differences were analyzed across a wide range of flows. It was found that both channel slope and macro-roughness are important factors explaining the variation of flow resistance between different sites. A collapse of the data was achieved by non-dimensionalizing the parameters flow velocity and unit discharge, using non-dimensional variables previously introduced by Rickenmann and Recking [2011]. In my thesis, an empirical and dimensional justification for the dimensionless velocity and discharge was given. Instead of using a characteristic grain size, measures of macro-roughness, including the standard deviation of profile elevations, boulder protrusion, and step height, were introduced in non-dimensional form. Applying these dimensionless variables resulted in a similarity collapse of the data for all study sites around a simple power-law relationship, in which the dimensionless velocity was approximately proportional to the 0.6 power of dimensionless discharge. Because the non-dimensionalization did not perfectly explain the between-site variation of flow velocity, it was examined whether additional non-dimensional parameters of macro-roughness could further collapse the data. Among these parameters, the boulder concentration correlated best with the remaining between-site variation of flow resistance. Including the boulder concentration in a simple regression-based equation further improved the prediction of flow velocities slightly compared to predictions with the variable power-law equation proposed by Ferguson [2007] and used by Rickenmann and Recking [2011].
The study was based on only a few sites, thus the observed empirical relations between macro-roughness and flow resistance may not be valid for all streams. However, the trends confirmed the predictions of theoretically-based flow resistance equations by Yager [2006] and Egashira and Ashida [1991]. These equations, both of which explicitly include macro-roughness measures, performed better for streams with high concentrations of macro-roughness elements. Moreover, the equation of Yager [2006], which uses boulder spacing as a roughness measure, performed better overall than the equation by Egashira and Ashida [1991], which uses step height as a roughness measure. This indicates that these roughness parameters are not interchangeable, and each parameter may represent a different type of flow resistance. Overall, the study has shown that macro-roughness, and boulder concentration in particular, is an important variable for better predicting flow velocities in steep streams. However, more field measurements should be conducted to verify the connection between macro-roughness and flow resistance found in this study.

In the second study it was tested how various measures of macro-roughness affect the calculation of flow resistance and sediment transport. Therefore, several flow resistance equations were tested, which explicitly include a measure of macro-roughness to account for the increased channel-bed roughness in steep streams. These equations were combined with bedload transport equations, and the predictions were compared to field measurements of discharge, transported bedload volumes, and channel characteristics in 13 Swiss mountain streams. The flow resistance equations are employed to calculate the partitioning between total flow resistance and the resistance due to macro-roughness. The partitioning is then used to estimate a reduced energy slope, assuming that energy dissipated by the macro-roughness elements is not available for sediment transport. Finally, the reduced energy slope is used as a basis for modified bedload transport calculations. This chosen procedure significantly reduced the over-prediction of observed bedload volumes compared to the predictions with the reference transport equation of Rickenmann [2001], which did not account for macro-roughness effects.

The accuracy of bedload transport predictions was better for streams with a high concentration of macro-roughness elements. The approaches which account for the effects of large boulders [Pagliara and Chiavaccini, 2006; Whittaker et al., 1988; Yager, 2006] generally performed better in streams featuring a high boulder concentration or a step-pool system. These equations that take into account a measure of macro-roughness resulted in bedload transport predictions that were up to an order of magnitude closer to observed transport rates than predictions from equations that did not account for additional flow resistance effects. The relatively good performance of the stress-partitioning approach of Yager [2006] for streams with higher boulder concentrations indicates that this physically based correction for additional flow resistance is a step forward in better characterizing such stream conditions from a theoretical point of view. For practical applications, if no detailed roughness information is available for a given stream, the approach of Rickenmann and Recking [2011] represents a simple way to account for additional flow resistance in steep streams with small
relative flow depths. The approach by *Rickenmann and Recking* [2011] generated the best average performance for all study streams, including a large range of streambed characteristics and flow conditions. This suggests either that the more physically based approaches in steep streams may still be insufficient in predicting the influence of macro-roughness on total flow resistance, or that the identification and measurement of macro-roughness and flow conditions in these streams are not accurate enough. Overall, this study has shown that macro-roughness has a significant influence on bedload predictions and thus, it should be accounted for in bedload transport equations.

In the third study, range imaging is evaluated as an alternative method for obtaining surface data in complex environments such as the steep streams studied in chapters II and III. Range imaging cameras are a new 3-D technology based on time-of-flight measurements. In this study, these cameras were tested to quantify major measurement errors and to evaluate their suitability for small- to medium-scale field measurements. In addition to controlled experiments, a reach of a small, steep mountain river was measured using a range imaging camera mounted on a crane. A comprehensive workflow was developed, including scanning, post-processing, and calculation of a digital elevation model. Ambient light and surface reflectivity were identified as the main sources of distance measurement error. In laboratory experiments with no ambient light, distance accuracies of 2-23 mm were obtained for measurements on a highly reflective surface. For field measurements on a white board under illumination ranging from nearly dark to full sun, the measurement accuracy was 2-90 mm.

The field measurements of a river reach were suitable to generate a high-resolution (2 cm) digital elevation model, featuring a similar degree of detail as a model obtained from terrestrial laser scans of the same site. Therefore, range imaging was considered a substitute for terrestrial laser scanners or photogrammetric approaches in small-scale applications such as grain size diameter calculations or micro-topography measurements. Furthermore, the fast and real time acquisition of 3-D data is a main advantage of range imaging. Post-processing of range imaging data, if desired, is relatively fast and straightforward. Major drawbacks of range imaging include the limited measurement range of up to ten meters, and the relatively low distance accuracy in the field due to a multitude of error sources. However, operating on video mode opens up new possibilities to study events such as debris flows or the collapse of sand piles, or other phenomena in which surfaces evolve quickly. Positioning techniques like differential GPS could be exploited and combined with range camera measurements to obtain real-time referenced global coordinates. In principle, range cameras can be employed on a number of different platforms. First experiences with range imaging cameras on an unmanned helicopter were reported by *Eisenbeiss et al.* [2011].

Altogether, the three studies conducted in the framework of this dissertation added to both the physical understanding of sediment transport processes and practical aspects of measuring relevant field parameters. Macro-roughness has shown to be an important factor in explaining the differences in flow resistance among different sites (chapter II). It was further demonstrated that accounting for macro-roughness in bedload transport equations significantly improves the accuracy of the predictions. The presented method (chapter III) is feasible for sediment
transport modeling in various fields, such as water management, aquatic ecology, and natural hazard assessment. Finally, I presented a new method that can be used to measure roughness in steep mountain streams (chapter IV). In a next step, this data can be used to further study the characteristics and scales of macro-roughness, although a comprehensive definition of roughness in steep streams is still lacking.

Developing bedload transport models for steep streams that predict transport rates with reasonable accuracy, say, within a factor of three to five, will require much more fundamental research. First of all, a larger number of bedload measurements is needed, including both long-term and event-based data, to constitute a more reliable empirical basis from which theories can be tested and developed. Furthermore, detailed flow velocity measurements for a wide range of discharges are essential to investigate flow transitions and the relevant roughness scales at specific flows. The study of fractional bedload transport, initiation of bedload motion, and patch organization in steep streams will help in gaining further insight into transport processes. Additionally, the long-term organization of step-pool systems and the variability of channel roughness in time are important factors that have to be assessed for a better understanding of sediment transport in steep mountain streams.

References


**Publication list**

*Thesis papers:*


*Additional publications:*


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