Identification of Debris-Flow Channels Using High-Resolution Topographic Data: A Case Study in the Quebrada del Toro, NW Argentina

A. Mueting1, B. Bookhagen1, and M. R. Strecker1

1Institute of Geosciences, University of Potsdam, Potsdam, Germany

Abstract Resolving Earth’s surface at the meter scale is essential for an improved understanding of the dynamics of mass-movement processes. In this study, we explore the applicability and potential of digital elevation models (DEMs) derived from stereophotogrammetry to detect debris-flow channels in the Quebrada del Toro in the northwestern Argentine Andes. Our analysis relies on a high-resolution (3 m) DEM created from SPOT-7 tri-stereo satellite data. We carefully validated DEM quality with ~6,000 differential GPS points and identified optimal parameters for DEM generation in high-relief terrain. After multiple processing steps, we achieved an accuracy of 0.051 ± 1.915 m (1σ) using n = 3,139 control points with cm precision. Previous studies have used the drainage area and slope framework to identify topographic signatures of debris flows within a catchment. We built upon this and investigated individual river-channel segments using connected-component (CC) analysis on meter-scale topographic data. We define CC as segments of similar slope along the channel profile. Based on seven manually identified debris-flow catchments, we developed a debris-flow similarity index using component length and mean channel-segment slope and identified channel segments that have likely been shaped by debris flows. The presented approach has the potential to resolve intra-catchment variability of transport processes, allows to constrain the extent of debris-flow channels more precisely than slope-area analysis, and highlights the versatility of combined space- and field-based observations for natural-hazard assessments.

Plain Language Summary Debris flows are potentially destructive mass movements that involve a mixture of water and sediment. They regularly disrupt infrastructure and threaten local populations in mountainous regions worldwide. For hazard assessment, it is important to locate areas where debris flows occur. Debris flows carve into bedrock, forming continuously steep channels for long distances of several hundred meters. This research locates channels that were shaped by debris flows using gridded elevation models of the Earth's surface. These models are generated using overlapping satellite-image pairs that show the study area from different viewing angles. Similar to what the human brain does by merging two images from our eyes to produce depth perception, we use algorithms to turn pairs of satellite images into height information. From the surface model, we can derive individual river channels and dissect these into segments that have a common channel slope. In a following step, we compare all channel segments to known debris-flow channels in the landscape and evaluate how similar they are. We detect the signature of debris flows primarily in regions near geologic faults where sufficient loose material is available to fuel a debris flow and steep hillsides provide enough gravitational energy to transport this material downstream.

1. Introduction

Mountainous high-relief terrains stretching across several climatic zones are often subjected to natural extreme events such as debris flows and landsliding (e.g., Bookhagen et al., 2005; Marchi et al., 2002; Olen & Bookhagen, 2018, 2020; Stock & Dietrich, 2003). With populations and infrastructure at risk, it is important to identify, measure, and comprehend the driving forces and mechanisms of slope movements in these environments at regional scale. Debris flows are gravity-induced mass movements of water-saturated sediment (Iverson, 1997). In steeply sloping catchments, debris flows have been identified to be a key erosive agent (Anderson et al., 2015; Stock & Dietrich, 2003, 2006). Due to their hazard potential and impact on erosion rates, there has been a long-standing interest in constraining debris-flow-prone regions. In this study, we aim to spatially constrain channels shaped by debris-flow activity using their distinct topographic signature as first described by Montgomery and Foufoula-Georgiou (1993) and Stock and Dietrich (2003).
Debris-flow and landslide-identification techniques often rely on topographic data which is why the results are strongly influenced by the quality and resolution of the underlying digital elevation model (DEM) (Tarolli & Dalla Fontana, 2009) (Figure 1). Although there has been an increase in publicly available DEM data (Abrams et al., 2020; Farr et al., 2007), there is a need for high-quality DEMs at scales of 1–5 m to better recognize local morphology and to detect the topographic signature of debris-flow incision (Purinton & Bookhagen, 2017; Röering et al., 2013; Tarolli & Dalla Fontana, 2009) (Figures 1 and 2). Highly accurate elevation information, including that of vegetated terrain, is usually obtained from airplane-based light detection and ranging (lidar) data. Numerous studies have also relied on terrestrial laser-scanning data to assess surface changes caused by debris flows (e.g., Bremer & Sass, 2012; Schuerch et al., 2011; Staley et al., 2014). However, the acquisition of lidar data is costly and requires complex infrastructural logistics, which limits the size of the target area to individual channels (e.g., Schuerch et al., 2011), single drainage basins (e.g., Staley et al., 2014; Tarolli & Dalla Fontana, 2009), or a limited number of catchments (e.g., Bremer & Sass, 2012; Tseng et al., 2015).

Finding suitable, economical alternatives for creating well-resolved DEMs that cover extensive regions is essential for the study of geomorphic processes at regional scale, which may enable the detection of their spatial variations, clustered occurrence, and trends. With the advent of high-resolution optical satellite imagery, this gap can potentially be closed for some areas through using DEMs derived from stereophotogrammetry (e.g., Porter et al., 2018; Shean et al., 2020). Stereophotogrammetry is a technique that identifies common markers on two or more optical images taken from different angles to extract 3D spatial information. Especially in areas with sparse vegetation, stereophotogrammetry has proven to be a viable tool for creating DEMs with spatial resolutions in the range of a few meters. Optical satellite imagery with spatial resolutions between 1 and 5 m can cover larger areas and costs a fraction of a lidar acquisition for a comparable spatial coverage. Thus, stereophotogrammetry has the
potential to bridge the gap between coarser-gridded radar and high-precision lidar-derived surface morphology in terms of resolution and feasibility.

With the increasing capabilities to obtain meter-scale resolution topographic data for large areas, new opportunities are opening up to study earth-surface processes. This, however, also requires a rethinking of traditional methods for the analysis of topographic data. A common tool in geomorphology for evaluating how debris flows and other processes that have shaped the landscape is the study of slope and drainage-area relationships. This technique involves averaging topographic slope across different drainage areas to provide information on the dominant transport processes. The need to average slope measurements arises from the low spatial resolution of many elevation models and their inherent uncertainties but introduces an averaging bias, which may blur the transition between debris-flow and fluvially dominated parts in catchments that are shaped by both processes.

With meter-scale elevation models, the analysis of topographic signatures can be shifted to individual channels instead of entire catchments. In this study, we introduce connected-component (CC) analysis along individual channels to isolate parts of the channel profile that show the topographic signature of debris flows. We thus can segment valleys according to dominant transport processes, better constrain debris-flow activity, and demonstrate the unique potential of stereo-derived DEMs for geomorphic applications.

Our study area is the Eastern Cordillera of the northwestern Argentine Andes where debris flows and landslides are a common phenomenon (e.g., Cencetti & Rivelli, 2011; Hermanns et al., 2001; Olen & Bookhagen, 2018, 2020; Purinton & Bookhagen, 2020; Tofelde et al., 2017; Wayne, 2011). Active tectonic deformation (Figueroa et al., 2021; Marrett & Strecker, 2000) and hydro-meterological extreme events (Castino et al., 2017) promote slope instabilities and frequently trigger debris flows that can threaten local populations and infrastructure. The high debris-flow density together with steep gradients of topography, rainfall, and erosion make the Eastern Cordillera representative of many high-relief regions worldwide and an ideal natural laboratory in which to study the topographic signature of debris flows. A better understanding of the occurrence and characteristic signature of debris-flow activity will not only allow an improved debris-flow hazard and risk assessment in this region but also help to understand the generation of large volumes of sediment in this semi-arid, mountainous environment that is derived from high elevations and aggraded within the intermontane basins.

Figure 2. Characteristic relationship between topographic slope and drainage area for a debris-flow-rich (red; the lower part of the Río Capilla, a tributary of the Río Toro) and a more fluvially dominated region (blue; main gorge of the Quebrada del Toro) derived using different topographic data sets: (a) 12 m TanDEM-X and (b) 3 m SPOT-7 stereo DEM (cf., Figure S1a in Supporting Information S1). The 3 m stereo DEM shows greater differences in slope for the same drainage areas and thus can better discriminate between different channelized processes. Also, the inherent scatter is much lower for the stereo-derived DEM than for TanDEM-X (NASADEM plot is shown in Figure S1b of Supporting Information S1). Flow accumulation was calculated with the D8 algorithm (Tarboton, 1997) after eliminating depressions through filling with a minimum slope value of 0.001 (Barnes et al., 2014) and multiplied by pixel area to retrieve the drainage area. Slopes were determined following Horn (1981). Median slope and mean drainage-area values are calculated for 200 logarithmically spaced drainage-area bins.
2. Study Area

The Eastern Cordillera of northwestern Argentina is characterized by steep gradients in topography, rainfall, erosion, and seismicity (Figure 3). The mountain range connects the arid plateau in the interior of the Andean orogen (Altiplano-Puna plateau) at an average elevation of 3,700 m with the more humid foreland at about 1,100 m above sea level (Allmendinger et al., 1997; Strecker et al., 2007). The Eastern Cordillera is a Cenozoic thick-skinned fold-and-thrust belt differentiated by several fault-bounded intermontane basins, which constitute essential infrastructural pathways. One of the two main routes linking the Puna plateau with the densely populated lowlands in this area traverses the deeply incised Quebrada del Toro in the vicinity of the town of Salta. High relief, recurring seismicity, and frequent rainstorm events associated with the South American Summer Monsoon make the intermontane valleys of this region particularly susceptible to flooding and debris-flow activity as well as other types of mass movements (e.g., Bookhagen & Strecker, 2012; Castino et al., 2016, 2017; Wayne, 2011).

The Quebrada del Toro is a reverse-fault-bounded basin located at ~24.5° S that has been actively deforming since the Miocene (Garcia et al., 2019; Hilley & Strecker, 2005; Marrett & Strecker, 2000; Schwab & Schäfer, 1976) (Figure 3). To the north, the upper sectors of the valley exhibit relatively flat terrain that consists of highly erodible Tertiary and Quaternary conglomerate terrace deposits (Hilley & Strecker, 2005; Tofelde et al., 2017) (Figure S2 in Supporting Information S1). Farther south, the valley narrows and is dominated by Precambrian through Paleozoic basement rocks (Escayola et al., 2011; Jezek et al., 1985). In this lower sector, the incision of the Toro river has created a steep, narrow gorge that is frequently affected by debris-flow activity (e.g., Cencetti & Rivelli, 2011; Olen & Bookhagen, 2020; Purinton & Bookhagen, 2020; Tofelde et al., 2017; Wayne, 2011) (Figure 4). Repeated mass wasting from the steep hillslopes and contributing catchments has led to riverbed aggradation, which is associated with the risk of flooding, loss of agricultural land, and temporary blockage of the main valley. Due to the sustained sediment input, the main route leading through the Quebrada del Toro toward the plateau region requires permanent, costly maintenance in the form of longitudinal defense work or excavation of the riverbed.
Climatically, the Quebrada del Toro is situated in a semi-arid region. Like the entire Eastern Cordillera, a pronounced orographic rainfall gradient characterizes the basin and adjacent mountain flanks (Bookhagen & Strecker, 2008, 2012; Castino et al., 2016, 2017, 2020). Rainfall ranges from \( \sim 900 \) mm/y at the outlet of the basin to \( \sim 200 \) mm/y in the interior of the catchment (Castino et al., 2017), leading to a distinct shift in vegetation cover: While a dense subtropical forest covers the eastern flank of the ranges that delimit the basin, the vegetation cover rapidly decreases westward (Cabrera, 1976), offering ideal conditions for stereophotogrammetric surface reconstruction.

3. Data and Methods

3.1. Stereophotogrammetry as a Tool for DEM Generation

The 3D structure of any object, including the land surface, can be determined by matching corresponding pixels of two or more photographs from different camera locations in a process called stereophotogrammetry. Stereophotogrammetry is a cost-efficient method for capturing high-resolution topographic information over large areas and has gained popularity in recent years due to the availability of high-resolution satellite imagery (Shean et al., 2020). Stereophotogrammetric surface reconstructions are used in geomorphology (e.g., Dewitte et al., 2008; Koci et al., 2017), in glaciology for mass-balance estimation (e.g., Berthier et al., 2004; Porter et al., 2018; Shean et al., 2020), for measuring canopy height in forestry (e.g., St-Onge et al., 2008), and for monitoring urban areas (e.g., Alobeid et al., 2010). Stereophotogrammetry has the great advantage to provide near real-time information on surface elevation and to potentially better depict steep topography due to the multiple view angles (Purinton & Bookhagen, 2017). Limitations include the inability of optical sensors to penetrate cloud cover and to illuminate steep terrain if only a single stereo pair with oblique viewing angle is available. Stereo images will furthermore capture natural and anthropogenic structures such as vegetation and houses so that a digital surface model (DSM) will be generated. For the investigation of geomorphic processes, a digital terrain model (DTM) representing the bare earth is better suited, which is why we are locating our studies in a semi-arid, sparsely vegetated and populated area. In our semi-arid study area, the effects of surface cover are negligible and our stereo-derived DSM is comparable to a DTM.
3.2. Satellite Data

For DEM generation we used two sets of SPOT-7 tri-stereo data with a spatial resolution of 1.5 m covering the Quebrada del Toro (scene area: 349 km²) and the lower part of the Río Capilla (scene area: 262 km²), which is a tributary to the Toro river from the west (Olen & Bookhagen, 2020; Tofelde et al., 2017) (Figure 4a). Each data set was processed individually, as the extension to the Río Capilla catchment was acquired at a later date. Yet, both data sets belong to the same scene, which was recorded during October 2014 (Table 1).

3.3. DEM Generation With Ames Stereo Pipeline

Stereo correlation was carried out using Ames Stereo Pipeline, a collection of free and open-source geodesy and stereophotogrammetry tools designed for processing stereo images (Beyer et al., 2018). Obtaining optimal results included several pre- and post-processing steps:

1. Through bundle adjustment, satellite position and orientation errors are minimized. In this step, we employ 23 static differential GPS points (mean of 1σ values in X, Y, Z direction: 3.138e-07, 2.388e-07, 0.055 m) as ground-control points (GCPs). These were sampled at distinct locations such as bridges, road intersections, or railroad crossings along the principal route traversing the Quebrada del Toro during a field campaign in March 2019. The points are well recognizable on the aerial imagery, allowing us to assign the GCPs to the corresponding pixel coordinates manually. GCPs have the potential to improve the internal consistency of the output DEM and align it to the measured ground truth (Beyer et al., 2018).

2. Map projection of the stereo imagery onto a pre-existing DEM is a vital step to minimize errors. Steep terrain makes the matching process between two images more difficult due to the distortion associated with the different view angles. Projecting both images onto a common surface enhances similarity. Thus, the neighborhood of a pixel in the primary image is more likely to be matched with a neighborhood in the secondary image during stereo correlation, which significantly improves the outcome (Beyer et al., 2018). Selecting a smooth, void-free DEM is crucial for obtaining good results, as errors in the reference DEM will directly translate to the output. Among 12 and 90 m TanDEM-X, 30 and 90 m SRTM DEMs (NASADEM and CGIAR DEM), and a smooth, 90-m-resolution DEM created with Ames Stereo Pipeline itself, we find that projecting the SPOT-7 data onto a 90 m void-filled CGIAR SRTM DEM (Jarvis et al., 2008) generates the smoothest surface with least artifacts. The key factor for a successful output is not the resolution, but rather the surface smoothness and the absence of voids.

3. Stereo correlation is the main process during which the correspondence between a primary and a secondary image is calculated and translated into a 3D surface. Since we are working with tri-stereo data, we use one primary image to which the other two secondary images are adjusted. Stereo correlation is carried out three times with the forward, backward, and nadir images as a primary image to ensure that our choice of reference image does not influence the final DEM and to increase point density. Merging the resulting point clouds constitutes the final 3D surface.

4. Through comparison of the inferred elevation model with 6,279 collected kinematic dGPS points (mean uncertainty in X, Y, Z direction: 0.037, 0.047, and 0.127 m) measured during the 2019 field campaign, we observed an offset of about 2 m between the generated DEM and kinematic GPS points. We mitigated this problem by aligning the 3D surface to the kinematic ground-control data, using 50% randomly selected kinematic dGPS points (n = 3,140). The remainder was reserved for DEM validation. After the initial alignment of the Quebrada del Toro segment to the kinematic ground-control points, the 3D point cloud covering the Río Capilla was aligned to this adjusted point cloud, because limited accessibility prohibited extensive collection of GCPs within the Río Capilla catchment. A generous overlap between the two data sets allowed us to align and merge both products without difficulty. As a final step, the merged and aligned point clouds were gridded.
to a resolution of 3 m, which is equivalent to two times the resolution of the aerial imagery (e.g., changing from 10 to 20 m). Beyer et al. (2018) suggested a final DEM resolution of three times the initial image resolution as a rule of thumb, yet, the quality of our final product and subsequent filtering step support a slightly higher, 3 m spatial resolution.

5. A low-pass filter with a kernel size of $3 \times 3$ pixels (i.e., $9 \times 9$ m) was applied to the final DEM to smooth out small irregularities and artifacts persisting after the stereo correlation. We masked the filtered surface by selecting only pixels with a triangulation error greater than the 75th percentile calculated from all pixels. This allowed us to keep more reliable points while smoothing less reliable regions. We experimented with weighted filtering methods, but deem this masking procedure to be solid and less complex. The triangulation error (distance between rays from different cameras to a common observation) is a metric estimated during the triangulation stage of the stereo correlation and is an indirect measure of DEM quality. High values indicate a low self-consistency of the DEM. Small areas with high triangulation error result from correlation mismatches, which are common in steep terrain. Larger erroneous areas can point to camera model or position inadequacies (Beyer et al., 2018).

The smoothing of steeply sloping areas might moderately alter the results of subsequent geomorphic analyses, especially since these are often prone to debris-flow activity. Despite this problem, it is to be expected that erroneous regions are not of great importance for any analysis and can thus be smoothed with reasonable confidence.

3.4. Using High-Resolution Stereo DEMs for Detecting the Geomorphic Signature of Debris-Flow Incision

3.4.1. Slope-Area Approaches as a Tool to Distinguish Between Different Geomorphic Processes

Morphometric analyses of catchments are often based on the relation between drainage area and local slope, usually shown in log-log space (e.g., Dietrich et al., 2003; Tarolli & Dalla Fontana, 2009; Tucker & Bras, 1998). Slope-area approaches are a fast and efficient tool to distinguish signatures of different transport processes, including hillslopes and debris-flow dominated or fluvial channels (Montgomery & Foufoula-Georgiou, 1993) (Figure 5a). The partitioning of the slope-area diagram as proposed by Montgomery and Foufoula-Georgiou (1993) is characterized by two distinct inflection points that mark the transition between hillslope (diffusive) and channelized processes as well as between debris-flow and fluvial processes (Montgomery & Foufoula-Georgiou, 1993; Stock...
& Dietrich, 2003). Other studies have related further points of reversal of the slope-area relation with large-scale landsliding (e.g., Booth et al., 2013; Tarolli & Dalla Fontana, 2009; Tseng et al., 2015). Breaks in the slope-area diagram of a landscape have been successfully used to spatially distinguish between the dominating geomorphic processes and to identify transitions (e.g., Booth et al., 2013; Montgomery & Foufoula-Georgiou, 1993; Staley et al., 2014; Stock & Dietrich, 2003; Tarolli & Dalla Fontana, 2009; Tseng et al., 2015). Stock and Dietrich (2003) in particular have investigated differences in the signature of debris-flow and fluvial-transport processes: Channels dominated by debris flows have a less steep slope-area relationship than fluvial channels, which does not follow the common stream power law and is best fitted by a curvilinear function (Stock & Dietrich, 2003, 2006).

Plots of slope against drainage area are usually obtained by assigning slope values to logarithmically spaced bins of drainage area, and calculating the median or mean slope. This approach is partly motivated by improving signal strength through integrating multiple measurements from a DEM because individual channels could not be resolved using lower-resolution (≥30 m) elevation data. However, jointly analyzing topographic signatures across an entire catchment may result in an averaging bias, potentially obscuring trends and transitions. We note that debris-flow distribution can be highly stochastic. Integrated catchment approaches mix debris-flow signatures with fluvial signatures because debris flows do not extend to the same drainage area or flow distances for every part of the catchment. This is demonstrated by analyzing the slope percentiles of a characteristic catchment in the Quebrada del Toro shaped by both debris-flow and fluvial processes (Figure 5b). In the given example, the median slope-area relationship exhibits a distinctive curved trend, marking the transition between different channelized processes. Yet, any clear sign of transition is absent from the highest and lowest percentiles. Identifying a single point of inflection as the transition between debris-flow and fluvial processes for this characteristic catchment is not representative. While DEMs with a 1–5 m spatial resolution are capable of better depicting local morphology and topographic signatures (Tarolli & Dalla Fontana, 2009), we want to avoid the pitfalls of mixing fluvial and debris-flow signatures by identifying individual channels and their signatures.

3.4.2. Extracting Debris-Flow Signals From Individual Channels

A single channel at 3 m resolution offers not enough data points to accurately identify the dominating transport regime in area-slope space. Thus, we turn to the analysis of debris-flow signatures in channel profiles (elevation vs. downstream distance) to distinguish between debris flows and fluvial signals. The channel network in the Quebrada del Toro was extracted with LSDTopoTools and the chi mapping tool (Mudd et al., 2014, 2019), setting a minimum threshold of 1,000 contributing pixels (9,000 m²). Since we aim to study channelized processes only, this minimal area threshold should eliminate any signature of hillslope processes that typically only applies to drainage areas of 100–1,000 m² (Montgomery & Foufoula-Georgiou, 1993; Staley et al., 2014; Tarolli & Dalla Fontana, 2009). Alluvial sectors of the Toro river were manually mapped and clipped from the DEM to avoid the erroneous detection of small, flat channels and catchments in the area of the braided main stream.

A less steep relationship between topographic slope and drainage area (low concavity index $\theta$) indicates the presence of debris-flow deposits in area-slope space (Stock & Dietrich, 2003). This implies that debris-flow channels must exhibit constant steep slopes with increasing drainage area (no channel curvature). Channel profiles extracted from debris-flow sample regions in the Quebrada del Toro, which were selected based on the presence of prominent debris-flow deposits, confirm this phenomenon (Figure 6). Extracted profiles have a very linear appearance that can well be described by a linear regression fit, in contrast to fluvial channels, which show a characteristic curved profile. All sample regions were mapped based on field observations and Google Earth imagery (Figure S3 in Supporting Information S1).

The signature of fluvial processes and debris flows differs primarily in channel gradient (steep vs. gradually declining) and channel curvature (straight vs. concave). Based on these two measures, we introduce the concept of CCs to detect differences in slope and changes in channel curvature. CC characteristics are then used to distinguish between different channelized processes. We define a single CC as a segment of a river profile with continuous, similar channel-slope values. An ideal channel shaped by debris flows would constitute a single CC, while channel parts with higher curvature would be segmented into shorter CCs of gradually decreasing slopes (Figure 7). From upstream to downstream areas, we identify CCs by comparing slopes of adjacent pixels and longer distances: A CC increases in length when the next downstream pixel is within a slope threshold compared to the mean (upstream) CC slope. As slope and slope-change (curvature) are the factors constraining the extent of a CC, it is important to accurately determine the channel slope at every pixel attributed to the stream network. A DEM-derived slope, however, is often affected by noise related to DEM errors, gridded data structure, or
slope-calculation algorithms (e.g., Clubb et al., 2019; Florinsky, 1998; Smith et al., 2019; Zhou & Liu, 2004). We apply a low-pass slope smoothing approach for river channels to reduce DEM-related noise based on the following assumption: Large changes in channel slope at the inter-pixel scale are related to noise, while multi-pixel changes are signals caused by variations in the dominating transport regime. Moving downstream, a linear regression is fitted through 7 pixels up- and downstream of the current cell (total 15 pixels), which corresponds to a length of 45 m. A similar approach to calculate channel slope was applied by Clubb et al. (2019). The optimal slope-integration length was determined through identifying the knee point of a function of pixel-to-pixel slope change against regression length (Figure 8) of 1,000 randomly selected channels throughout the study area. Incorporating short up- and downstream portions into the slope calculation will cause the pixel-to-pixel slope change to be as gradual as possible while using a minimal number of pixels for regression fitting to avoid over-smoothing. At the beginning and end of each stream, the integration length is shortened to at most 7 pixels downstream (channel head) or upstream (outlet).

A CC is terminated when the slope change between the current component and the subsequent pixel exceeds a certain slope threshold. We additionally allow bridging of up to 5 pixels (15 m) to bypass small bumps and artifacts in the DEM and require a minimum component length of 10 pixels (30 m). At a channel junction, we continue with the current segment until the critical threshold is reached, but do not continue further downstream, if the channel has already been processed. In this way, we are certain to obtain representative segment lengths whilst not counting segments multiple times. The component-constraining slope threshold should be sensitive enough to detect changes in channel morphology, while not being overly susceptible to small slope variations that would break a channel into many short components. We have experimented with various slope-change thresholds and find that there is not a single optimal threshold, but rather a suitable range between ~0.15 and 0.25 m/m. An estimate of a good slope-change threshold can be obtained by investigating channels retrieved from debris-flow sample regions. An ideal, easy-to-identify debris-flow channel should form a single CC only. In the natural environment, stochastic processes and DEM noise complicate this expectation and we postulate that a suitable threshold identifies at least 50%
of the given debris-flow channels as a single component. For our sample data, this would be the case for a threshold of 0.23 m/m (Figure 9a). Alternatively, if no reference data set is available, one could investigate the slope change over any given number of pixels along the channel, creating artificial CCs of fixed length. Assuming that a change in the dominant transport process will occur at the scale of tens of meters (e.g., 10 pixels = 30 m), the majority of a channel will show a very low degree of slope variation over the given integration length while changes in the transport regime and regions of high channel curvature mark the extremes (5th and 95th percentile) of the slope-change distribution. For 1,000 randomly selected streams within our study area, these correspond to ~0.22 (5th percentile) and 0.2 (95th percentile) m/m, respectively (Figure 9b). Given this range of appropriate threshold values, we choose a threshold of 0.21 m/m to constrain CCs in this study, which represents the mean of the absolute 5th and 95th percentile of slope change over 30 m channel segments. The distribution of CCs determined using other slope-change thresholds can be found in Figures S9–S11 of Supporting Information S1.

3.4.3. Classification of Connected Components

Using the CC framework, we aim to distinguish between channel segments dominated by debris flows and fluvial processes. While at the catchment scale the topographic signature of debris flows is expressed through the relationship between slope and drainage area, we use the parameters CC mean slope and length (defined as the cumulative three-dimensional distance between two points along the channel network) to determine debris-flow signatures of individual channels. We measure three-dimensional distance instead of two-dimensional (planar) distances because at 3 m spatial resolution the vertical offsets are much better resolved and pixel-to-pixel flow distances for steeper slopes will differ significantly from lower slope distances. Within the framework of CC slope and length, we find that components extracted from debris-flow sample regions are mostly characterized by slopes of ∼0.65 m/m and lengths between 200 and 1,000 m (Figure 10a). We use these characteristic measures to define a debris-flow similarity index (DFSI) that expresses how similar any given CC is with respect to the designated
debris-flow samples. The DFSI normalizes CC mean slope and length using scaling factors derived from debris-flow sample regions and is defined as

\[
DFSI = L_{CC_{norm}} \times l + S_{CC_{norm}} \times s - 1, \quad l + s = 2
\]  

where \( L_{CC_{norm}} \) is the length of a CC normalized using the mean and minimum length of CCs derived from debris-flow sample regions and \( S_{CC_{norm}} \) is the mean slope of a CC normalized using the mean and minimum slope of CCs derived from debris-flow sample regions. \( l \) and \( s \) are optional weighting factors that can determine the relevance of the slope and length components and should sum up to 2. In this analysis, we weigh component mean length and slope equally and therefore set both \( l \) and \( s \) to 1.

Both \( L_{CC_{norm}} \) and \( S_{CC_{norm}} \) are calculated through normalization steps comparable to a minimum-maximum normalization, with scaling factors derived from the debris-flow sample regions. They are defined as:

\[
L_{CC_{norm}} = \begin{cases} 
1 & \text{for } L_{CC_{norm}} > 1 \\
L_{CC_{norm}} & \text{for } 0 \leq L_{CC_{norm}} \leq 1 \\
0 & \text{for } L_{CC_{norm}} < 0
\end{cases}
\]

\[
S_{CC_{norm}} = \begin{cases} 
1 & \text{for } S_{CC_{norm}} > 1 \\
S_{CC_{norm}} & \text{for } 0 \leq S_{CC_{norm}} \leq 1 \\
0 & \text{for } S_{CC_{norm}} < 0
\end{cases}
\]  

where \( L_{DF_{min}} \) and \( S_{DF_{min}} \) represent the minimal length and slope of a CC from the debris-flow sample regions. To exclude outliers, we have chosen to work with the fifth percentile of slope and length values from debris-flow CCs. \( L_{DF_{mean}} \) and \( S_{DF_{mean}} \) are the weighted averages of length and slope values derived from debris-flow samples. Sample weights are based on the kernel density of all debris-flow components to account for outliers and uncertainties inherent to manual mapping (Figure 10a). For a slope-change threshold of 0.21 m/m these scaling factors correspond to 54.975 and 421.367 m (\( L_{DF_{min}} \), \( L_{DF_{mean}} \)), and 0.327 and 0.659 m/m (\( S_{DF_{min}} \), \( S_{DF_{mean}} \)). See Table S1 in Supporting Information S1 for scaling factors estimated for other slope-change thresholds.

Because the slope and length of a CC can be below or above the scaling factors derived from the debris-flow sample regions, the resulting values for \( L_{CC_{norm}} \) and \( S_{CC_{norm}} \) range not exclusively between 0 and 1 (as is the case for conventional minimum-maximum normalization), but are set to 0 and 1, respectively, when these limits are exceeded:
The resulting DFSI, ranging between $-1$ and 1, assigns channel segments to one of three groups: CCs whose slope and length are similar to previously mapped debris-flow samples (DFSI $> 0$), components that are either too short or too gentle to be related to debris-flow activity (DFSI $= 0$) and components that are completely dissimilar to the given debris-flow samples (DFSI $< 0$) (Figure 10b). We postulate that these groups can be associated with different geomorphic conditions: debris-flow activity, the presence of knickpoints, and the occurrence of fluvial processes.

4. Results

4.1. Best Practices for SPOT-7 DEM Generation in High-Relief Terrains

Various parameters were tested during the DEM-generation process from SPOT-7 stereo data and we determine the adjustments necessary for creating optimal surface models in mountainous regions with high relief. We evaluate DEM quality based on (1) visual assessment (smoothness, absence of voids, and artifacts); (2) the triangulation error estimated during the triangulation stage of the stereo correlation; and (3) the elevation difference between the generated 3D models and the dGPS ground-control data (Table 2). For comparison with the dGPS measurements, we only use points for validation that were not used for the DEM alignment. We collected 6,279 kinematic dGPS points of which 3,140 were used for DEM alignment and 3,139 for DEM validation.

One of the key findings regarding optimal DEM generation, which was also emphasized by Beyer et al. (2018), is that considerable pre-processing of the raw data product significantly improves the outcome of the stereo correlation. Bundle adjustment and the number of GCPs employed during this step particularly affect DEM heights and triangulation errors while the obtained surfaces appear very similar (Table 2, Figure S5 in Supporting Information S1). We observe that using very precise static dGPS points ($n = 23$) as GCPs during bundle adjustment produces a DEM that is further offset from the kinematic ground control ($\Delta h = -2.666 \pm 2.11$ m) than a surface generated without providing any GCPs ($\Delta h = -0.297 \pm 2.19$ m) (Figure 11a). However, while the absolute offset to the ground control is larger, the standard deviation of elevation differences between kinematic ground control and DEM adjusted with GCPs is slightly lower (= more consistent offset). Generally, we find that the offset

| Varied parameter                          | Value/data set employed                | $\mu$ $\Delta h$ (m) | $\sigma$ $\Delta h$ (m) | $\mu$ TE (m) | $\sigma$ TE (m) |
|-------------------------------------------|----------------------------------------|-----------------------|--------------------------|--------------|-----------------|
| Optimal DEM                               | Optimal parameters                     | $-2.666$              | 2.11                     | 0.446        | 0.211           |
| Number of GCPs used for bundle adjustment | No GCPs                                | $0.297$               | 2.19                     | 0.452        | 0.228           |
| Number of GCPs used for bundle adjustment | 1 GCP                                  | 5.522                 | 2.02                     | 0.899        | 0.283           |
| Number of GCPs used for bundle adjustment | 4 GCPs                                 | 0.366                 | 3.459                    | 0.449        | 0.226           |
| Number of GCPs used for bundle adjustment | 12 GCPs                                | 1.169                 | 2.344                    | 0.904        | 0.287           |
| Bundle adjusted                           | No                                     | $-3.564$              | 1.914                    | 1.266        | 0.349           |
| DEM employed in map-projection            | 12 m TanDEM-X                          | $-2.633$              | 2.248                    | 0.454        | 0.233           |
| DEM employed in map-projection            | 90 m TanDEM-X                          | $-2.852$              | 2.178                    | 0.455        | 0.232           |
| DEM employed in map-projection            | 90 m self-created DEM                  | $-2.679$              | 2.107                    | 0.463        | 0.227           |
| DEM employed in map-projection            | 30 m NASADEM                           | $-2.65$               | 2.118                    | 0.457        | 0.228           |
| DEM employed in map-projection            | None                                   | $-2.873$              | 2.148                    | 0.548        | 0.282           |
| Subpixel-mode                             | Parabola fitting                       | $-2.6$                | 2.34                     | 0.507        | 0.257           |
| Subpixel-mode                             | Affine window                          | $-2.679$              | 2.243                    | 0.466        | 0.248           |
| Subpixel-kernel size                      | 11 $\times$ 11                         | $-2.738$              | 2.355                    | 0.582        | 0.291           |
| Subpixel-kernel size                      | 21 $\times$ 21                         | $-2.556$              | 2.057                    | 0.384        | 0.193           |

Note: These values represent error estimates before selective filtering and alignment to the ground control. We evaluate the influence of one parameter at a time, i.e., the other parameters were left at optimal settings: all 23 static dGPS GCPs were employed during bundle adjustment, images map-projected onto the 90 m CGIAR DEM (Jarvis et al., 2008), stereo correlation carried out with an affine adaptive window with Bayes expectation maximum weighting during subpixel refinement, and a 15 $\times$ 15 pixel correlation kernel size.
between a DEM and kinematic dGPS points is not evenly distributed, but more pronounced in the north of the study area (Figure S4a in Supporting Information S1). Similarly, the GCPs that were included in the DEM-generation process tend to fall below the final surface. In contrast, the interest point matches (tie-points in overlapping regions of 2 or 3 images) found during bundle adjustment are generally well aligned with the output DEM (Figure S4b in Supporting Information S1). We acknowledge that (1) our static dGPS GCPs were not evenly distributed throughout the image and were focused on low elevation, low slope, and easily accessible sites; (2) all GCPs are located nearly along a single NW-SE-oriented axis with barely any lateral spread; and (3) that the number of GCPs may not be sufficient for the size of the study area. We observe that GCPs may introduce a significant bias, if not selected carefully and distributed through the entire image. For example, median and interquartile range (IQR) of height differences between calculated DEMs and the control data set vary widely, depending on the number of GCPs used for bundle adjustment (Table 2). Ground-control picking is generally error-prone, and thus, aligning the DEM with a significantly larger ground-control data set after stereo correlation appears to be a more robust method to ensure spatial coherence of the final product (Figure 11b). We thus use two sets of GCPs: One set of \( n = 23 \) static dGPS GCPs used during the bundle adjustment and a second set of \( n = 3,140 \) kinematic dGPS GCPs to perform an additional alignment step. The post-aligned surface shows a mean elevation difference of 0.051 ± 1.915 m to our validation data set. With or without GCPs, bundle adjustment is nevertheless an important step in obtaining DEMs that are more internally consistent.

As an indirect measure of DEM quality, the triangulation error indicates how internally consistent an image is (Beyer et al., 2018). We observe that higher triangulation errors often correspond to either hilltops (gently sloping, similar-looking surfaces), or steep sections, where an observation might not appear in all three stereo images (Figure 12). Across all parameters studied, skipping bundle adjustment leads to the highest triangulation error (1.266 ± 0.349 m) and is therefore not recommended.

The effects of map projection become most apparent when examining the surface characteristics of the generated elevation models (Figure S6 in Supporting Information S1). Without a reference DEM, the resulting surface exhibits a rippled texture, especially in sloping areas. Projecting the stereo images onto an existing reference DEM produces a considerably smoother surface. However, the reference DEM needs to be selected with great care, as problems in the reference DEM directly translate to the final data product. This ruled out the use of the 12 m TanDEM-X data as a reference model as it is associated with problems in steep regions due to radar shadowing and overlay effects in our study area (Purinton & Bookhagen, 2018), which affects stereo correlation when stereo images are projected onto these erroneous regions. The 30 m NASADEM induced less, but still recognizable artifacts and small errors. Results obtained using the 90 m TanDEM-X, 90 m CGIAR, and a 90 m self-created DEM from the stereo data itself, as suggested by Beyer et al. (2018), are comparable. Regarding the self-created surface, it should be noted that it must be free of voids and of reasonable quality to achieve meaningful results. Using a self-created DEM as a reference furthermore entails a slight loss of pixels along the edges where triangulation

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**Figure 11.** Elevation difference between \( n = 3,139 \) kinematic dGPS points and a DEM bundle adjusted with and without GCPs (a) before and (b) after alignment. Mean and standard deviation units are in m.
is less precise. We decided to choose the 90 m void-filled CGIAR DEM (Jarvis et al., 2008) as a reference, as it represents the smoothest surface and minimal triangulation error. As for the height of the DEM, the elevation of the reference DEM should not affect the elevations of the output DEM. Most of the resulting surfaces show a similar offset to ground control with Δh between −2.633 and −2.852 m.

Next to careful pre-processing, we find that picking optimal processing parameters for stereo correlation can further enhance DEM quality, mostly in terms of internal consistency and visual appearance. The subpixel mode determines the subpixel-refinement method. In accordance with Beyer et al. (2018), we find that the use of an affine adaptive window with Bayes expectation maximum weighting during subpixel refinement produces the best results, but is slower. Nevertheless, a compromise in runtime usually implies a reduction in DEM quality: The fast, parabola-fitting algorithm produces an unnatural laminated-like surface, while the simple affine correlator performs better, but the obtained surface still contains a considerable amount of artifacts (Figure S7 in Supporting Information S1).

The subpixel-kernel parameter sets the size of the subpixel-correlation kernel in units of pixels. Keeping the kernel size slightly larger when using Bayes EM methods is beneficial, yet, smaller kernel sizes are better capable of depicting more complex high-relief features which can be found in the Quebrada del Toro (Beyer et al., 2018). Based on visual assessment, we favor a kernel size of 15 × 15 pixels, which appears to be a good compromise between surface smoothness and accurate representation of incision features. Smaller kernel sizes produce a rougher surface, while a larger kernel size of 21 × 21 pixels results in the lowest triangulation error. However, the obtained surface appears overly smooth and may not resolve any finer details (Figure S8 in Supporting Information S1). Concerning the elevation difference between the DEM and our ground-control points, neither subpixel mode nor correlation-kernel size shows any significant impact.

Overall, we find that bundle-adjusting images with all 23 GCPs, map projecting onto the 90 m CGIAR DEM, using Bayes expectation maximum weighting for subpixel refinement and a subpixel-kernel size of 15 × 15 pixels and aligning the final result to a larger set of 3,140 kinematic dGPS points represent the optimal parameters and processing steps for DEM generation from tri-stereo SPOT-7 data in high-relief terrains.

Figure 12. (a) Spatial variation of the triangulation error (TE) of a DEM generated with optimal processing parameters over a small section (∼10 km²) within the study area. (b) Relationship between triangulation error and topographic slope (m/m) throughout the entire study area (errorbars indicate interquartile range). We observe that triangulation errors are particularly high along very high, as well as gently sloping, uniform areas (hilltops), because steep terrain impedes accurate matching of features within all three SPOT-7 images, while on unvegetated hilltops, low image texture due to similar pixel reflectances may evoke mismatches.
4.2. Debris-Flow Activity in the Quebrada del Toro

In total, 21,609 CCs from 12,814 streams in 527 catchments were extracted for the study area constraining components using a slope-change threshold of 0.21. Within the framework of mean slope and length, we find that CCs extracted throughout the entire study area can generally be attributed to four main types: short and moderately sloping or very long and gentle, long and steep, and short and very steep. We suggest that these types are related to different channelized processes and conditions: fluvial processes (short and moderately sloping, very long and gentle), debris flows (long and steep), and knickpoints (short and very steep) within the channel profile. This hypothesis is backed by components extracted from debris-flow sample regions, which cluster at steep slopes of $\sim 0.65$ and form components with lengths in the range of a few hundred meters. The great majority of these components represent the first segment along the profile or are situated between two other CCs (Figure 13a). This is consistent with the notion of debris flows dominating most of the upstream parts of a catchment where drainage areas are small (Figure 5). In contrast, concave fluvial river profiles with gradually decreasing slopes are decomposed into moderately sloping, short segments and very long and gentle components toward the basin outlet. This gradual decrease in slope is well illustrated by comparing the mean slope of a CC with that of the previous one (Figure 13b): In the postulated fluvial region of the slope-length diagram, components generally show lower slopes than the preceding segment. These components are also characterized by particular positions along the river profile. For example, shorter segments from the concave part of a fluvial river profile are mostly located in between two other components, while very long and gentle components are typically found at the end of a channel or form one component per channel only (Figure 13a).

The back-transformation of the debris-flow similarity of individual components into map view reveals areas in the Quebrada del Toro with very high DFSI values that are consistent for various slope-change thresholds (Figure 14a). These include large parts of the Río Capilla catchment, the steep western slopes of the Toro gorge, and hillsides to the northeast of our study area. Some portions of these areas were previously included within the debris-flow sample regions, but channels throughout the entire Quebrada del Toro show very similar signatures. The longest segments associated with debris flows (>1,000 m) are found predominantly within the Río Capilla catchment along the more interior parts of individual basins (Figure 14b). Shorter segments with a less pronounced signal of debris-flow similarity are present throughout the study area, also toward the more vegetated southern part where a fluvial signature dominates the log-area versus log-slope diagram. We posit that channels with high DFSI values have been shaped by debris flows in the past and could potentially be source areas for further debris flows in the future, provided there is sufficient water and sediment supply. Many potential debris-flow channels are located directly along the main road through the Quebrada del Toro and pose a threat to local infrastructure. More remote areas of the river network with high debris-flow similarity could also become hazardous to the infrastructural network if a debris flow reaches a high level of fluidity, causing it to inundate large areas farther downstream.

Figure 13. Plot of connected component (CC) length and CC mean slope of all components extracted throughout the study area. (a) Segments are colored by their location within the channel and (b) the slope change of a component with respect to the preceding one.
The locations of areas with a strong debris-flow signal remain consistent over a variety of slope-change thresholds. A change in threshold mostly affects the component-length parameter (Figure 15a). More generous thresholds are less sensitive, particularly to gradual slope changes, and thus generate fewer and longer segments: Concave sections of river profiles are combined into a single CC, resulting in increasingly longer components with lower average slopes at the expense of higher slope components (Figure 15b). Potentially, even debris flow and fluvial segments may merge into one component if the transition is not pronounced enough. In addition, the number of channel pixels contained in multiple components increases, because CCs are less likely to end shortly

Figure 14. (a) Channel network of the Quebrada del Toro colored by the maximum DFSI estimated for a stream pixel using a slope-change threshold of 0.21 to constrain individual connected components (CCs). (b) CCs with a DFSI ≥0.5 colored by segment length.

Figure 15. (a) Scaling factors for DFSI assignment derived from hand-mapped debris-flow sample regions using different slope-change thresholds. A change in slope-change threshold predominantly affects the $L_{DF}$ parameter as components become increasingly longer. (b) Change of connected component (CC) length (25th, 50th, and 75th percentiles) and number of components using a strict (0.1) and generous (0.3) slope-change threshold to constrain CCs within the study region. Components were binned by common slopes using breaks of 0.05 m/m. The change in component length and number of components in each group was calculated by subtracting low-threshold from high-threshold estimates. Component length generally increases with higher slope-change thresholds, especially at slopes < 0.3. As components become longer, the overall number of detected components decreases. This decrease particularly affects moderate to high-sloping components which are incorporated into longer and on average gentler components.
after an intersection. On the other hand, stricter slope-change thresholds divide a channel into more and overall shorter components. This results in a more distinct separation of long segments at high and low slopes and shorter segments of intermediate slope (Figure S9–S11 in Supporting Information S1). A more sensitive threshold could, however, underestimate a channel’s potential to generate debris flows by reducing overall connectivity. This could be compensated for by increasing the minimum required component length and the allowance to bridge pixels. Also, the scaling factors derived from the debris-flow sample regions adjust as a function of the given threshold, so that at stringent values, a smaller component length is required to assign high debris-flow similarity than at higher thresholds. We argue that a range of moderate slope-change thresholds between \( \sim 0.15 \) and 0.25 is optimal to distinguish between individual channel processes without considering large portions of the stream network multiple times. In case of doubt, we advise choosing a lower threshold and increasing the number of pixels that can be bridged to avoid diffuse transitions and generating overly long segments.

5. Discussion

5.1. Potential and Implications of Connected-Component Analysis for Mapping Topographic Signatures

An approach to detect debris-flow channels based on their topographic signature has the great advantage that it requires only a single DEM. While it is not possible to determine the volume of a single debris-flow event, as is the case when a pre- and post-event elevation data are available, it does allow for rapid identification of channels formed by debris-flow activity across multiple catchments. The use of a connected-component framework has the potential to constrain debris-flow-prone sectors of the landscape more precisely than slope-area analysis. By segmenting channels into components shaped by different transport processes, the beginning and end of a debris-flow-prone channel segment can be determined with an accuracy close to the resolution of the underlying elevation model. The averaging bias inherent in the slope-area framework is avoided, as topographic signatures are no longer averaged over entire catchments but mapped along individual channel profiles. This allows much finer details to be constrained in the channel and the identification of spatially variable extents within catchments shaped by mixed processes. Assessing debris-flow similarity based on the two parameters of CC mean slope and CC length offers a straightforward framework for identifying regions characterized by continuous, long, and steep channel segments where debris flows have shaped topography and may continue to do so in the future.

An additional capability of connected-component analysis can be the detection of knickpoints, if the imposed constraints on minimum component length, bridging extent, and slope change are exceeded. The segmentation of longitudinal river profiles in \( \chi \)-elevation space (Mudd et al., 2014) has already been used for knickpoint detection based on changes in channel steepness \( (k_m) \) (Gailleton et al., 2019). Within the CC framework, knickzones in the channel profile are generally characterized by an increase in channel slope compared to the previous CC (Figure 13b). Components with this behavior cluster at very high slopes \( (\sim 1 \text{ m/m}) \) and have very low component lengths. However, the detection of knickpoints is not the main objective of this work, and parameters are therefore optimized to identify long debris-flow components. The presented setting and identified high-sloping segments may only represent very prominent breakpoints along a channel because more gentle knickpoints are bridged and merged with the encompassing segments.

5.2. Caveats: Accuracy Assessment and Constraints of the Connected-Component Framework

Inevitably, the hand-mapped reference regions used for assigning similarity indices (DFSI) add a subjective component. Furthermore, the reference data set has been taken from the southern Central Andes, and other geographic regions may exhibit different signals. We assess the quality of our sample data set and its influence on the assigned DFSI by selecting random sub-samples of 75% of all CCs extracted from debris-flow sample regions \( (n = 178) \) and calculating mean slope and length scaling factors 1,000 times. The obtained scaling factors range between 50 and 72 m \( (L_{DF_{max}}) \), 369–471 m \( (L_{DF_{mean}}) \), 0.286–0.415 m \( (S_{DF_{max}}) \) and 0.641–0.672 m \( (S_{DF_{mean}}) \). The assigned DFSI values using minimum and maximum values obtained throughout the 1,000 random sampling steps naturally exhibit some differences, mostly at lower similarity values. Components with particularly high-debris flow similarity remain well constrained (Figure S12a in Supporting Information S1). The overall low variance of the assigned DFSI values suggests a reasonable quality of our selected reference data set, indicating that channels shaped by debris-flow activity can be distinguished with high confidence.
But what constitutes a high-quality reference data set? Since we identify similarity, the given sample data should represent natural variance, while not being too dissimilar. To simulate the difference between very similar and very dissimilar sample data sets, we subdivide the components of the debris-flow samples based on quartiles derived from the kernel-density estimation (Figure 10a). Using a very dissimilar data set (lowest quartile), we obtain many components that are potentially similar to the provided components (likely an overestimation), while samples from the highest quartile result in a very narrow range of possible debris-flow candidates (possible underestimation) (Figure S12b in Supporting Information S1). We conclude that a carefully selected debris-flow calibration data set is important to identify similar channels. While debris flows inherently require a high channel gradient, the component-length parameter in particular can vary depending on local morphology. Component length is further largely influenced by the slope-change threshold selected to define individual CCs and may also vary with more advanced approaches to channel-head detection (Clubb et al., 2014) than the area-based threshold used in this study.

5.3. Independent Validation of Sample Data Using SAR Coherence

We validate our results against a time series of SAR coherence images from the Quebrada del Toro between 2014 and 2018 (n = 150) (Olen & Bookhagen, 2020) and explore interferometric coherence as an option to independently calibrate the scaling factors used to assign debris-flow similarity. In the absence of vegetation, a loss of coherence between two acquisitions can be attributed to surface change or movement, possibly related to debris-flow activity in an area that is generally predisposed to slope instabilities. We emphasize that the connected component-based analysis for the detection of debris-flow channels is controlled by past occurrences of channel-forming processes recorded in the digital topography. In contrast, the SAR-based analysis is sensitive to recent changes of the past years and thus indicates which of these debris-flow channels experienced a debris flow during the monitoring period.

To compare the debris-flow similarity of CCs along the channel network, we take the SAR coherence time series for the Toro basin from Olen and Bookhagen (2020) with 30 m resolution, mask areas with vegetation defined by a greenest-day average normalized difference vegetation index (NDVI) ≥ 0.5, and identify the lowest coherence (tenth percentile) in every pixel observed throughout the investigated period. Comparing these values to the corresponding DFSI value within the same grid cell, we find that areas that exhibit particularly low coherence throughout the study period correspond well with a high DFSI (Figure 16). We also observe that CCs that fall within the area of lowest coherence (lowest quartile) over the observed time period often exhibit a characteristic debris-flow signature: high slope and higher connectivity (= longer segments) (Figure 17a). Although these components are more scattered than components from carefully selected debris-flow example regions, they could potentially serve as a debris-flow sample data set if no other reference is available. To improve the quality of such a sample data set, further refinement steps can be taken. For example, we assess the IQR of SAR coherence for components within active areas coherence throughout the observation period (Figure 17a), as we find that this is particularly high for components located within the fluvial realm of the CC mean slope and length framework. A high variation of coherence measurements could point to an overall stable terrain that just occasionally exhibits low coherence, such as during the rainy season or times of increased rainfall due to climate variability (Castino et al., 2017). Highly active areas (narrow IQR), on the other hand, would be more reliable indicators of debris-flow activity and should thus be preferred for deriving DFSI scaling factors. By selecting only components below the median IQR as debris-flow samples (n = 1,311), we obtain estimates of regions prone to debris flows throughout our study area that are very similar to those based on manually mapped sample data (Figure 17b).

5.4. Comparison to Approaches Based on Drainage Area

Commonly, the identification of debris-flow topographic signatures is carried out through the analysis of drainage area and slope relationships. Here, we compare our approach to approaches examining channel curvature and channel steepness, which are both derived from log-area and log-slope space. In a subsequent step, we identify breakpoints within the same framework.

5.4.1. Curvature

In the log-area log-slope space, the signature of debris flows is commonly expressed by low concavity indices (θ), which translates to the CC framework in the sense that low-curvature sectors of a channel will form long
components, while highly concave sections are split into multiple short segments. We estimate the average $\theta$ values for 55 catchments (sizes from 1 to 30 km$^2$) throughout the study area by binning slope in logarithmically spaced bins of drainage area and fitting a linear regression through the 75th percentile of slope. We select the

![Figure 16](image1.png)

**Figure 16.** (a) Map view of the tenth percentile SAR coherence between 2014 and 2018 ($n = 150$) from ascending and descending data (see Olen and Bookhagen [2020]), binned into quartiles to enhance visibility. Vegetated areas with an NDVI $\geq 0.5$ were masked to exclude low coherence measurements associated with vegetation changes. Remaining pixels with low coherence estimates could potentially be attributed to surface movement related to debris-flow activity, while stable areas are characterized by higher SAR coherence. Comparing coherence values to the average DFSI within 30 x 30 m cells (b) we observe a negative correlation between debris-flow similarity and SAR coherence, indicating that interferometric coherence time-series could potentially be employed as an independent measure to constrain debris-flow prone areas.

![Figure 17](image2.png)

**Figure 17.** (a) Connected components (CCs) that are 75% or more within active regions defined as the lowest quartile of SAR coherence (see Figure 16) within the framework of CC mean slope and length. While most of the extracted components fall within the debris-flow and knickzone areas (cf., Figure 10), active areas also include a handful of long, shallow components. However, we find that these components within the fluvial zone are further defined by a broad interquartile range (IQR) of SAR coherence measured over the entire observation period between 2014 and 2018 (as indicated by size and color). This could be related to an occasional loss of coherence, for example, during the rainy season, while stable conditions prevail during the rest of the year. Segments in the debris-flow area of the CC slope and length plot, on the other hand, are mostly characterized by a narrower IQR, conceivably due to frequent loss of coherence associated with recurrent debris-flow activity. A potential debris-flow sample data set could be made up of components that (1) fall within zones of low SAR coherence and (2) exhibit low coherence over a larger duration. Panel (b) shows the DFSI values assigned using the lower half ($n = 1,311$, red circled dots) of components from (a) based on the IQR of coherence. The obtained DFSI values are close to the results using a much smaller sample data set ($n = 178$) of components from hand-mapped debris-flow areas.
third quartile instead of the commonly chosen mean or median, as we find that debris-flow signature is better represented in the higher percentiles, especially for larger drainage areas (Figure 5b). We observe clear spatial differences: Catchments in the southern part of our study area are characterized by lower values of \( \theta \) than basins farther north and especially in the lower part of the Río Capilla catchment (Figure S13a in Supporting Information S1). Comparing the curvature estimated over an entire drainage basin with individual segments defined along the catchment’s channel network, we find that the CCs with the highest debris-flow similarity are mostly observed within drainage basins characterized by low curvature (Figure S13b in Supporting Information S1). This implies a general correspondence between \( \theta \) and DFSI, suggesting that the value of \( \theta \) is a good indicator of debris-flow activity at the catchment scale.

### 5.4.2. Channel Gradient

The normalized steepness index \( (k_{sn}) \) is a metric widely used to assess the geometry of channel profiles (e.g., Harel et al., 2016; Lague, 2014; Wobus et al., 2006). It is derived from the slope-area regression by normalizing the drainage area using a reference concavity \( (\theta = 0.4 \text{ for the Quebrada del Toro}) \). While the \( k_{sn} \) is often employed in knickpoint detection and in the study of active tectonics, it can also reveal debris-flow channels as these are characterized by particularly high gradients at larger drainage areas, which should result in elevated \( k_{sn} \) measurements. We compare \( k_{sn} \) values calculated throughout the channel network to our results by (a) investigating \( k_{sn} \) values averaged over an entire CC (Figure S14a in Supporting Information S1) and (b) performing a pixel-wise comparison between DFSI and \( k_{sn} \) values (Figure S14b in Supporting Information S1). We find that there is an overall positive correlation between \( k_{sn} \) and DFSI as both measures are related to channel slope. By averaging \( k_{sn} \) values over the length of a CC, we observe that higher \( k_{sn} \) measurements correspond to very steep and short, long and steep, but also very long, gentle components. This last observation in particular highlights the dependence of the \( k_{sn} \) on drainage area: In the case of very high drainage areas, even slightly elevated slope values will raise the \( k_{sn} \) while steep sections in the most upstream parts of a catchment are assigned lower values \( k_{sn} \). This makes it difficult to precisely constrain to what extent a debris-flow signature exists within a channel. We conclude that a method independent of drainage area, such as the DFSI, will provide a more precise assessment of steep sloping, low-curvature channel segments that could potentially be a source area for debris flows.

### 5.4.3. Breakpoint Detection to Decipher Debris-Flow Signals

Following the interpretation of the slope-area diagram by Montgomery and Foufoula-Georgiou (1993) and Stock and Dietrich (2003), debris-flow processes are dominant between the first and second reversal points. Limiting our analysis to drainage areas \( \geq 900 \text{ m}^2 \), we disregard the hillslope-valley transition and focus on the transition between fluvial and debris-flow processes in area-slope space, which we determine through breakpoint-detection (Muggeo, 2008). We then find the estimated point of transition within the extracted channel network for various basins by identifying the minimum difference between the estimated breakpoint and the drainage area of every channel pixel. Figure 18 shows the estimated point of transition between debris-flow and fluvial processes for 10 randomly selected streams within fluvially, mixed, and debris-flow-dominated catchments.

The estimated point of transition seems to be a good fit when the overall slope spread within individual bins of drainage area is small and a clear curved relationship is observed in all slope percentiles for similar drainage areas. This is the case for catchments primarily dominated by debris flows (Figures 18a and 18b) and catchments exhibiting signatures of multiple channel-forming processes (Figures 18c and 18d). Here, with a few exceptions, the estimated breakpoint corresponds well with a change in DFSI. We emphasize that in this comparison, most upstream regions show evidence for debris-flow activity and hence have low upstream curvatures. A channel-based debris-flow assessment additionally allows the separation of short, gently inclined sections at small drainage areas that would not be considered in a catchment-wide approach. For the selected fluvially dominated catchment (Figures 18e and 18f), the estimated extent of debris-flow activity varies widely. In this basin, the presence of greatly variable slopes at lower drainage areas makes it difficult to determine a universally valid point at which fluvial incision replaces debris-flow activity. The estimated breakpoint at 3,758 \text{ m}^2 seems to be accurate for some channels, while others exhibit considerably steeper segments with high debris-flow similarity in upstream parts of the catchment. Debris flows generated in these sectors could very well be missed when assessing debris-flow activity based on the slope-area relationship.

From these observations, we conclude that using the log-area and log-slope framework is a viable tool to obtain a synoptic view of the dominant transport processes in high-mountain terrain. If the slope variations at similar
Figure 18. Location of breakpoints (BP) estimated from log-area and log-slope plots compared to the DFSI derived for individual connected components within the channel network (showing ten randomly selected channels per basin only). Blue parts indicate channel segments that were unlikely shaped by debris flows (DFSI ≤0). The breakpoint was matched to the river profiles by selecting the point that had the lowest drainage-area difference. Example of a debris-flow dominated catchment (a and b), a catchment shaped by both fluvial and debris-flow processes (c and d), and a more fluvially dominated basin (e and f). For the location of the individual catchments within our study area see Figure S15 in Supporting Information S1.
drainage areas throughout the catchment are small (uniform catchment with debris flows in all upstream areas), the slope-area relationship will provide good estimates on the areal extent of debris-flow-dominated regions. Steady-state conditions, however, do not apply to all drainage basins within our study area where the IQR of slope values per drainage-area bin can be as high as 0.4 m/m on average (Figure S15 in Supporting Information S1). In a transient landscape (i.e., adjusting to a wave of incision or increased erosion rates) or in catchments traversing different lithologies, a drainage-area-based approach alone will likely not be capable of reliably identifying all areas susceptible to debris flows. For a precise assessment of debris-flow activity and possible differentiation between individual channel segments, we suggest the investigation of channel segments using meter-scale resolution topographic data.

5.5. Factors Triggering Debris-Flow Activity in the Quebrada del Toro

The slopes bordering the intermontane Quebrada del Toro basin offer ideal conditions to generate debris flows. These include steep topographic gradients, pervasively fractured bedrock in the steep hanging walls of basin-bounding faults, frequent rainstorm events during summer, and ongoing tectonic activity. In addition, the strongly deformed and cataclasized Proterozoic phyllites of the Puncoviscana Formation predispose this region to debris flows (e.g., García et al., 2019; Olen & Bookhagen, 2018; Purinton & Bookhagen, 2020; Tofelde et al., 2017). Sudden rupture events along basin-bounding faults in this environment can also trigger rockfalls and landslides (Strecker & Marrett, 1999) or generate pervasive rock fractures that supply large volumes of unconsolidated material to debris flows, similar to tectonically active high-relief environments elsewhere (e.g., Tang et al., 2009). The Quebrada del Toro is dissected by several fault strands, of which the west-dipping Solá Fault and the east-dipping Gólgota Fault traverse our study area and bound the margins of the upper basin (Marrett & Strecker, 2000). Principal deformation along the Gólgota Fault occurred before 0.98 Ma, while the Sóla fault segment has been active since the Pliocene (Marrett & Strecker, 2000). Channels with high debris-flow similarity are found more frequently along the hanging walls of these structures (Figure 14, Figure S2 in Supporting Information S1). In between these fault strands, where Cretaceous sandstone and Tertiary conglomeratic and sandstone units are exposed, we find only few signs of debris-flow signatures, which clearly suggests a close relationship between the occurrence of debris flows and the proximity to geological structures, but also with the exposed highly deformed lithological units.

The most commonly exposed rock type on the higher flanks of the Toro basin is the Puncoviscana Formation. These pervasively sheared phyllites have been thrust over the conglomerate and sandstone units in the northern part of the basin (Hilley & Strecker, 2005; Jezek et al., 1985). These phyllites appear to be ideal for debris-flow generation as their cataclasized character offers sufficient surface area and incohesive material for weathering and erosion that can be dislodged during infrequent heavy rainstorms. In addition, active uplift and deformation maintain a significant topographic gradient and result in steep, gravitationally unstable slopes (García et al., 2019; Hilley & Strecker, 2005). Conversely, the medium- to coarse-grained Alfarcito conglomerate and the Aguas sandstone and conglomerate (Marrett & Strecker, 2000) could potentially be sources to fuel debris flows, but they are only exposed in the lower sectors of the basin, in regions characterized by deeply incised slot canyons that lack the necessary catchment areas and rainfall during summer storms (Castino et al., 2017) to initiate gravity-driven movements.

Previous regional studies have revealed high erosion rates based on 10Be cosmogenic nuclide dating of sands from the Río Capilla subcatchments (Bookhagen & Strecker, 2012; Tofelde et al., 2017). In addition, grain-size measurements indicate a significant increase in pebble sizes downstream of the confluence of the Río Capilla with the Río Toro mainstem (Purinton & Bookhagen, 2020, 2021). These observations are consistent with the distribution of channels with high debris-flow similarity, which are widespread within the Río Capilla catchment (Figure 14). The Río Capilla catchment is also dominated by exposure of the Puncoviscana formation and receives rainfall during summer storms. The lack of ground-stabilizing vegetation, the presence of fractured bedrock, and proximity to the active Sóla fault appear to provide ideal conditions for debris-flow generation in this region.
6. Conclusion

Accurate debris-flow assessment in high-relief mountain landscapes is important for minimizing hazards and risks for human lives and infrastructure. The increasing availability of high-resolution satellite data enables precise investigation of debris-flow activity at large scales in remote areas and may help to alleviate their potential impact. Stereophotogrammetry is a viable tool for obtaining topographic information for geomorphologic analysis in steep terrains. Current SPOT-7 tri-stereo satellite data allow DEMs with a spatial resolution of approximately 3 m to be generated, although obtaining optimal results requires careful pre- and post-processing. While these steps can benefit from ground-truth measurements, ground-control points should be selected with great care and spread out evenly throughout the study area to avoid bias.

Using a 3 m tri-stereo DEM, we developed a new technique to divide individual channels into segments of similar slope using connected-component analysis. We are able to show that different transport processes form connected components that are unique with regard to their mean slope and component length. Debris-flow channels in particular are characterized by relatively linear and steep channel profiles that form single, long (200–1,000 m) and steep connected components.

Within our study area, the Quebrada del Toro in the northwestern Argentine Andes, we constrain debris-flow activity by assessing the similarity between mapped debris-flow segments and unclassified components. We find that debris-flow activity dominates in the eastern side of our study area and is found in close proximity to the hanging-wall sectors of two major fault systems that bound the Quebrada del Toro basin. Here, pervasively fractured bedrock, sparse vegetation cover, and steep topography combine to form ideal conditions to generate debris flows.

Identifying channels shaped by debris flows based on topographic signature has the potential to constrain hazardous sectors within a landscape based on a single, meter-scale DEM. Through the segmentation of channel profiles into connected components related to different transport processes, debris-flow-prone channel segments can be identified and constrained to much greater detail. Compared to traditional drainage-area-based approaches, our method does not average signatures over entire catchments. The inherent bias of the slope-area framework is thus avoided as topographic signatures are investigated along individual channels only. This has the great potential to reveal more details of intra-catchment variability of dominating transport processes.

Our work has demonstrated that the abilities of high-resolution topographic data are not fully realized by conventional methods for analyzing topography. New approaches such as connected-component analysis to detect different topographic signatures offer several new opportunities to better understand landscape forming processes and improve local hazard assessment.

Data Availability Statement

All data sets used in this study are publicly available. The 3 m DEM generated from SPOT-7 tri-stereo satellite and the code used to constrain and classify connected components can be accessed via https://doi.org/10.5281/zenodo.5653779. Ongoing updates to the code will be available at https://github.com/UP-RS-ESP/DEM_ConnectedComponents. The authors thank Mikael Attal, Adam M. Booth, Stuart Grieve, and two anonymous reviewers for their feedback and comments that improved the manuscript.

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