Global river slope: A new geospatial dataset and global-scale analysis

Sagy Cohen⁎, Tong Wan⁎, Md Tazmul Islam⁎, J.P.M. Syvitski⁎

⁎Department of Geography, The University of Alabama, Tuscaloosa, AL, USA
⁎⁎Community Surface Dynamics Modeling System, INSTAAR, University of Colorado, Boulder, CO 80309, USA

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ABSTRACT

A rivers’ longitudinal gradient (i.e. slope) is a key parameter in fluvial hydrology, hydraulics, and geomorphology. It affects a multitude of fluvial variables such as flow velocity and sediment transport. Limitations in river slope data, both its availability and accuracy, constrain the fidelity of fluvial modeling, particularly at larger or global scales. Traditional slope calculation algorithms cannot accurately predict river slopes as these are based on cell-by-cell calculation, which is only suitable for hillslopes and small mountainous streams. This paper presents a methodology for calculating global river slope and a procedure to upscale it for relatively coarse resolution, suitable for global scale modeling. The methodology is based on a simple principle of calculating slope from elevation depression over the length of a river segment, which is automated to allow global scale calculations. Version 1.0 of the Global River-Slope (GloRS) geospatial dataset is introduced and shown to be a step improvement over a previous product (NHDplus for the contiguous United States) and compares favorably to observed slope data collected from the literature. Statistical analysis of Earth’s continents and large basins highlights interesting spatial trends. A semi-empirical regression analysis between basin-average river slope and other basin-scale parameters show that terrain slope accounts for 67% of the variability in basin-average river slope, with average discharge, sediment load and basin temperature contributing additional improvements to global predictions of 3%, 4%, and 3%, respectively.

1. Introduction

River slope gradient is a key parameter in hydrological and geomorphic modeling. Slope controls the gravitational related factors of water flow and sediment movement in fluvial systems (Du Boys, 1879; Meyer-Peter and Müller, 1948; Bagnold, 1966). In hydrologic and hydraulic applications, river slope is a key parameter controlling flow velocity (Manning, 1891). River slope, through its control on flow velocity, affects the shear stress exerted on sediment particles and thus their transport rates and mechanism (Meyer-Peter and Müller, 1948; Bagnold, 1966). Slope also controls the gravitational potential exerted on sediment and rock and thus their susceptibility to movement. As a result, the dominant sediment transport mechanism in steep mountainous streams is typically bedload transport while most sediment transported in lowland rivers is typically in suspension (about 90%; Meade et al., 1990; Bartram and Ballance, 1996). It is important to note that these differences in sediment transport mechanisms between headwater and lowland rivers are also driven by sediment size characteristics and local hydraulic and geomorphic processes (e.g. river evolution, floodplain erodibility; Mueller and Pitlick, 2013).

Slope calculation for a river reach is simple: dividing the elevation difference between the up and downslope points by the length of the reach. These parameters can be measured in the field for individual reaches or extracted from a Digital Elevation Model (DEM) and aerial imagery in a GIS system for long reaches and even entire river systems. Traditional automated slope calculation algorithms, on the other hand, are based on measuring the elevation difference between each grid cell in a DEM and one of its neighboring cells. In most slope algorithms, the adjacent grid-cell selection is based on steepest elevation descent (D8 algorithm; O’Callaghan and Mark, 1984). More directionally flexible algorithms have been developed over the years (e.g. Dinf; Tarboton, 1997). Several river slope calculation approaches were developed over the years based on calculating the distance between a river location and a downstream point or the basin outlet (e.g. Moore et al., 1991; Thieken et al., 1999; Walker and Willgoose, 1999; Olivera, 2001; Fekete et al., 2001; Reed, 2003; Mayorga et al., 2005; Lin et al., 2006). These approaches can be highly inaccurate when based on relatively coarse resolution DEMs, used in regional and global scale modeling, as grid-cells may represent both the river and surrounding landscape and may not capture small scale meandering.

Slope calculations are scale-dependent and are thus sensitive to the spatial resolution of the DEM (Gregory and Schumm, 1987; Snow and...
river slope using standard slope calculation algorithms. High-resolution DEMs (e.g. LiDAR-based) may provide sufficient resolution but are challenging to use for medium and large rivers as the channel width will be represented by a large number of grid cells, and thus different slope values, which will complicate large-scale modeling and analysis.

Here we present an automated method for calculating river slope based on river segment length and elevation depression. The methodology is used to calculate the first Global River Slope layer (referred to herein as GloRS). The accuracy of GloRS is evaluated by comparing the calculated slope against reported slope values and an independent hydrography dataset. Employing GloRS offers a first set of river slope statistics at global and continental scales and within large river basins.

In this paper, basin-averaged river slope values are used for an exploratory exercise, looking at potential causality or predictability of other basin-scale parameters (e.g. water and sediment discharge, lithology, temperature).

2. Methodology

2.1. River slope calculation

Our river slope methodology is following Hannon (2011), where slope for a given river segment length was calculated using the difference between its highest and the lowest elevation (derived from an underlying DEM), corresponding to its most upstream and downstream locations respectively. We apply this method to a global-scale stream-network and DEM to compile GloRS through an automated procedure (using a Python script).

The interval length of the stream-network’s river segments influences the accuracy of river slope calculation and the resulting dataset spatial resolution. Longer segments yield coarser resolution while shorter segments are limited by the DEM vertical and horizontal resolution. Stream-network layers are typically split into feature segments at river confluences. Quite often many of these segments will be very long, primarily along the main stem of large rivers. The GloRS calculation script includes a feature-splitting procedure which splits river-network segments longer than a user-defined value (e.g. 50 km). It works by generating points at the user-defined distances along the stream-network (Fig. 1) which are then used to add new joints to the original stream-network line features. The user-defined splitting interval controls the maximum reach length. The stream-network will include many shorter features that originally existed between confluence points. The splitting procedure will therefore only affect segments longer than the user-defined length while retaining the ‘natural’ stream network segments which are shorter than the user-defined value.

Following the stream-network splitting, the minimum and maximum elevation of each segment are extracted from an underlying DEM. The segment lengths are calculated using a GIS tool. These values are added to the stream-network layer attribute table as new fields (columns). Elevation depression is calculated as the difference between the maximum and minimum elevations, for each river segment. River slope is then calculated by dividing the elevation depression attribute value by the river segment’s length attribute value. The stream-network vector layer can then be converted to raster layer based on the slope attribute value, ensuring that the raster extent and spatial resolution are similar to the DEM used.

2.2. Upscaling

Using as high as possible resolution of the stream-network and DEM is advisable for the aforementioned river slope calculation, as these will better capture river sinuosity and in-stream elevation. We will discuss the importance of these factors later. Upscaling a river slope layer to coarser spatial resolution is warranted for different applications, such as large-scale river modeling frameworks (e.g. WBMsed; Cohen et al., 2013, 2014). Standard GIS resolution-conversion tools average the cell values of the high-resolution grid-cells underlying a coarse-resolution grid-cell (Fig. 2) which will lead to overestimation of river slope. This is because a grid-cell in the upscaled raster layer is meant to represent the highest-order river reach within its spatial domain. Think, for example, of a 6 arc-min (∼11 × 11 km) river layer. A grid-cell with such a resolution will cover, with the exception of few very large river reaches, not just the largest river in that domain but also many of its smaller tributaries. Averaging the values of all the fine-resolution grid-cells will, therefore, skew the resulting river slope in the upscaled layer as it will also capture (and give equal weight to) smaller river reaches which typically have higher slopes. To alleviate this problem, we develop an upsampling procedure that extracts the minimum value of the underlying high-resolution grid-cells and uses this value for the upscaled raster layer (Fig. 2). This approach assumes that the lowest slope value in the high-resolution layer represents the largest river reach within the coarse-resolution grid-cell domain. While this is a reasonable approximation, it may not be accurate in areas where the river network is complex or where there are significant topographic variations.

Fig. 1. Illustration of the stream-network splitting procedure. Points are generated on top of the stream network line features at user-defined distances (e.g. 50 km), the point layer is used to split each feature.

Fig. 2. Illustration of the upsampling ‘neighborhood’. In a standard GIS conversion tools, the value of a coarse-resolution cell (red outline; Cell 1, 2, 3 and 4) will be calculated based on the average of all its underlying cells (gray outline). Our procedure extracts the minimum value of the underlying high-resolution cells and uses it as the value for the coarse-resolution cells. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
assumption, its simplicity means that cells at the upscaled GloRS dataset may not align with the stream network for a specific DEM product in some locations. Users should therefore use caution when using GloRS as an input dataset for a model. Stream network based upscaling approaches (e.g. Wu et al. (2011) Dominant River Tracing (DRT) approach) and the use of e.g. contributing area or stream order to identify the largest reach within an upscaled domain will be used in future versions of GloRS.

2.3. Input datasets

For version 1.0 of GloRS, the the 15arc-sec resolution (∼460 × 460 m) SHuttle Elevation Derivatives at multiple Scales (HydroSHEDS) DEM and stream-network were used (downloaded from http://hydrosheds.cr.usgs.gov/index.php). The 15 arc-sec HydroSHEDS product (Lehner et al., 2008) is available as a post-processed continental-scale GIS file and includes flow direction, accumulated area and stream network layers, an advantage over higher resolution global DEM products (e.g. 3 arc-sec HydroSHEDS, 1 arc-sec ASTER). As the HydroSHEDS product is limited to below latitude 60°N, we also use the 1 arc-min etopo DEM (Amante and Eakins, 2009) for higher latitudes. Unlike HydroSHEDS, river network layers are not available for etopo and need to be calculated using the standard stream delineation methodology. The file size of these products is suitable for continental-scale calculations, which considerably simplifies the calculation algorithm but considerably reduce the confidence in the resulting river slope layer for small rivers and streams. We will discuss this later.

A 50 km interval was used to split the stream-network features. River-slope layers using 10 and 100 km splitting intervals were also calculated and found to have weaker correlation to the validation datasets (results not shown here).

2.4. Validation

Two datasets were used to evaluate the accuracy of GloRS: observed slope values obtained from literature sources, and the National Hydrography Dataset Plus Version 2 (NHDPlusV2) layer. Only observation locations with a drainage area greater than 1000 km² were used in this study given the resolution of the upscaled GloRS (∼11 × 11 km). A total of 34 river slope observations (slope measurement of riverbed or water surface) were collected (Fig. 3; Table A1) from Hinton et al. (2016), Williams and Rosgen (1989), Graf (1984), Knott and Lipscomb (1985), and Jones and Seitz (1979). Observation sites are concentrated in North America (29 out of 34) due to the greater availability of data from the U.S. While not ideal for global-scale analysis, the U.S. sites represent diverse river reaches, ranging from the Rocky Mountains to the Great Plains and the tectonically-active Alaska through California. The dataset also include three sites along the Nile River and one location in Loire River in France. The observational range of river-slope values was approximately two orders of magnitudes across the 34 sites.

NHDplus v2 is a geospatial, geospatial and hydrologic framework dataset produced by the U.S Environmental Protection Agency (Mckay et al., 2012). It is a geospatial dataset for the continental U.S. that integrates features of the National Hydrography Dataset (NHD), the National Elevation Dataset (NED) and the Watershed Boundary Dataset (WBD) based on the medium resolution NHD (1:100,000 scale). NHDplus slope estimates are calculated using a similar concept as our methodology (extraction of elevation depression and length of each stream-network segment) but based on higher resolution DEM and more detailed and better-curated stream-network. We compare NHDplus river slope values to GloRS and the observational dataset. The comparison between NHDplus and GloRS is based on 500 random points were generated along rivers with a total drainage area larger than 1000 km². The use of random point for comparison is done because spatial mismatch between the two stream networks complicate feature-to-feature comparison. With a reasonable-sized point dataset, biases in the comparison due to differences in the location of the river feature can be identified by calculating differences in drainage area. Here points with a difference of ±15% were removed from the analysis. The NHDplus dataset also includes stream features with a calculated slope of zero or a set minimum value of 0.00001 m/m. Points that fell on these reaches were also removed from the analysis. The total number of point remaining after these removals was 173.

3. Results and discussion

The upscaled (6 arc-minute) GloRS layer is shown in Fig. 3. Half the river segments have a slope value smaller than 0.0006 m/m (dark blue color in Figs. 3 and 4) and the world-average river-reach slope is 0.0026 m/m. High river slope values are observed at the headwaters of major river basins. These high slope values are expected and demonstrate that the slope dataset is highly sensitive to intra-basin spatial dynamics, even at this resolution. It also shows that the slope values can range by over four orders of magnitudes within large river basins (Table A2). It is important to remember that while Fig. 3 may look like a
standard terrain slope layer, their values and utility are considerably different. For comparison, we calculated a global-scale terrain slope map (not shown here) based on 15 arc-sec HydroSHEDS and 1 arc-min etopo DEMs, using standard D8 slope calculation. Global-average terrain

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**Table 1**

Comparison between river slope databases in discrete number (N) of points.

<table>
<thead>
<tr>
<th>Comparison</th>
<th>N</th>
<th>R²</th>
<th>RMSE</th>
<th>Difference in Averages</th>
</tr>
</thead>
<tbody>
<tr>
<td>GloRS 6-min vs. Observations</td>
<td>34</td>
<td>0.64</td>
<td>0.0016</td>
<td>(0.0019 − 0.001) = 0.0008</td>
</tr>
<tr>
<td>GloRS 15-sec vs. Observations</td>
<td>34</td>
<td>0.63</td>
<td>0.0034</td>
<td>(0.0031 − 0.001) = 0.002</td>
</tr>
<tr>
<td>Adjusted GloRS vs. Observations</td>
<td>34</td>
<td>0.63</td>
<td>0.0016</td>
<td>(0.0015 − 0.001) = 0.0004</td>
</tr>
<tr>
<td>NHDPlus vs. Observations</td>
<td>25</td>
<td>0.48</td>
<td>0.0078</td>
<td>(0.0003 − 0.00012) = 0.0017</td>
</tr>
<tr>
<td>GloRS 6-min vs. Observations</td>
<td>25</td>
<td>0.5</td>
<td>0.0019</td>
<td>(0.0024 − 0.00002) = 0.0011</td>
</tr>
<tr>
<td>GloRS 6-min vs. NHDPlus</td>
<td>173</td>
<td>0.5</td>
<td>0.0025</td>
<td>(0.0023 − 0.0003) = −0.00076</td>
</tr>
</tbody>
</table>

* Observations.
** Subset of the observation dataset (excluding non-contiguous U.S. sites).
^ Random points.

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Fig. 4. Histogram of GloRS values for all grid-cell values for the adjusted 6 arc-min products. Both x and y axis are logarithmically transformed.

Fig. 5. Comparison between observed river slope (n = 34 for all) and the 15 arc-sec and 6 arc-min GloRS products for (a) initial GloRS estimation and (b) bias relative to observed values for the 6 arc-min product; (c) initial and adjusted 6 arc-min GloRS and (d) bias relative to observed values for adjusted 6 arc-min GloRS.
slope was found to be 6.12 m/m, compared to GloRS’s 0.003 m/m.

3.1. Validation

Analysis of GloRS accuracy is based on Root Mean Square Error (RMSE), difference in mean values, and log-log linear regression (equivalent to power-law regression on the original variables). A log-log analysis is used given the high positive skewness of the data (Fig. 5) which means that a linear analysis will reduce the influence of low slope values on the regression results. As low slope reaches are often associated with large rivers, these low values are particularly important given the scale and potential application of GloRS (input to global riverine modeling). The results show that the 6 arc-min GloRS corresponds relatively well to observed slope data (Fig. 5a; Table 1).

The correlation between GloRS and observed data is similar for the 6 arc-min and 15 arc-sec products (0.64 and 0.63 respectively). RMSE and difference in average slope are high for the 15 arc-sec product, by a factor of over 2. These results show that the 6 arc-min upscaling not only does not reduce the accuracy of the river slope layer, it actually improves it. This can be explained by the fact that the upscaling procedure mitigate overestimation in individual river reaches in the 15 arc-sec product by assigning the lowest river slope value within each 6 arc-min grid-cell.

Both products overpredict river slope, by an average factor of nearly 2 for the 6 arc-min comparison and a factor of 3 for the 15 arc-sec layers (Table 1). Overestimations are likely due to under-representation of river sinuosity and spatial mismatch in the stream-network layer. Sinuosity can considerably effect reach-scale slope calculation due to its

Fig. 6. Comparison between (a) observed river slope and GloRS (adjusted, 6 arc-min) and NHDplus products (n = 20) and (b) GloRS (adjusted, 6 arc-min) and NHDplus (n = 173 random locations).

Table 2
Continental-scale river slope statistics calculated from the 6 arc-min GloRS and mean terrain slope calculated from a global-slope layer (described above).

<table>
<thead>
<tr>
<th>Continent</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Range</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>CV</th>
<th>Mean Terrain Slope</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>6.45E-07</td>
<td>0.0305</td>
<td>0.0305</td>
<td>0.00061</td>
<td>0.0013</td>
<td>2.086</td>
<td>2.89</td>
</tr>
<tr>
<td>Africa</td>
<td>4.29E-07</td>
<td>0.1423</td>
<td>0.1423</td>
<td>0.00180</td>
<td>0.0033</td>
<td>1.803</td>
<td>4.59</td>
</tr>
<tr>
<td>Europe</td>
<td>9.02E-07</td>
<td>0.1014</td>
<td>0.1014</td>
<td>0.00186</td>
<td>0.0038</td>
<td>2.061</td>
<td>5.27</td>
</tr>
<tr>
<td>N. America</td>
<td>3.19E-07</td>
<td>0.1064</td>
<td>0.1064</td>
<td>0.00239</td>
<td>0.0043</td>
<td>1.793</td>
<td>6.11</td>
</tr>
<tr>
<td>S. America</td>
<td>2.31E-06</td>
<td>0.2515</td>
<td>0.2515</td>
<td>0.00324</td>
<td>0.0078</td>
<td>2.402</td>
<td>8.66</td>
</tr>
<tr>
<td>Oceania</td>
<td>2.43E-06</td>
<td>0.2842</td>
<td>0.2842</td>
<td>0.00348</td>
<td>0.0062</td>
<td>1.780</td>
<td>9.37</td>
</tr>
<tr>
<td>Asia</td>
<td>3.72E-07</td>
<td>0.2842</td>
<td>0.2842</td>
<td>0.00348</td>
<td>0.0062</td>
<td>1.780</td>
<td>9.37</td>
</tr>
</tbody>
</table>

Fig. 7. Average, standard deviation and coefficient of variation in river slope based on the adjusted 6 arc-min GloRS.
effect on reach-length. Using higher resolution stream-network and DEM will likely reduce this source of bias. A DEM resolution coarser than the river floodplain can lead to overestimation of river slope as the maximum elevation used to calculate it is not that of the upstream river node but of the surrounding terrain. As shown later, this issue is expected to be particularly problematic in river reaches confined within steep valleys. This source of bias could be alleviated by using a higher resolution DEM and, as done here, a stream-network layer which was derived directly from it.

An adjustment equation was developed to better fit GloRS predictions to observed values. The bias in GloRS values decreases with slope values (Fig. 5b), meaning that high slope reaches require little adjustment while low slope values require a greater one. The adjustment equation was developed by fitting a linear regression between the highest and lowest data points. An adjustment value of 1 (no change) was set to the high slope point (0.0041) and an adjustment value of 0.15 was set to the lowest slope data point (0.00018). The resulting equation was applied to the 6 arc-min GloRS layer:

\[ S_{\text{adj}} = S_{\text{obs}}(216.84S_{\text{adj}} + 0.111) \]  

where \( S_{\text{adj}} \) is adjusted and \( S_{\text{obs}} \) is original river slope values.

The adjusted 6 arc-min GloRS resulted in similar \( R^2 \) and RMSE as the pre-adjusted 6 arc-min (Table 1) but the bias in the low slope values is greatly reduced (Fig. 5c and d) and the adjusted GloRS log-log-linear trend line now much better matches a 1:1 trend line (Fig. 5c). The RMSE did not seem to improve because the differences between the two layers in the low-slope values, which, while improved considerably percent wise, exert little influence on the RMSE calculation. The improvement in low-slope values (reduction of biases from a factor of 4–8 to less than 2; Fig. 5b and d) is a considerable improvement given the intended usage of GloRS for global scale modeling of large rivers.

Three observation points (mid-range observed slope values) remains with a considerable bias (Fig. 5d). These sites (Clearwater River (drainage area \( \sim 24,000 \text{ km}^2 \)) and North Fork Clearwater River (drainage area \( \sim 3,300 \text{ km}^2 \)) in Idaho and Yampa River (drainage area \( \sim 20,000 \text{ km}^2 \)) in Colorado; Table A1) are all within narrow mountainous valleys. Excluding these three sites from the validation analysis considerably improves the correlation between GloRS and the observation (\( R^2 = 0.79 \) for the adjusted 6 arc-min product).

Overall, no correlation was found between drainage area and bias in river slope calculations for any GloRS product (results not shown here). The range of drainage area in the validation dataset, used here, is between \( \sim 1000 \) and \( \sim 3,000,000 \text{ km}^2 \). This indicates that river slope predictions within the GloRS dataset are quite robust for mid- and large-size rivers but, as discussed earlier, are much less so for rivers with narrow floodplains. GloRS V.1.0 (presented here) is based on a 15 arc-sec resolution (\( \sim 460 \times 460 \text{ m} \)) DEM. We can, therefore, conclude that the confidence in GloRS values decrease for river reaches with a drainage area less than \( 1000 \text{ km}^2 \) and floodplains narrower than at least 500 m. While drainage area is easy to calculate, floodplain width is very challenging to estimate at a global scale. Using higher resolution DEMs for future GloRS versions is expected to improve its accuracy and considerably expend its range of applicability, particularly for medium-resolution global modeling.

The correlation between GloRS (pre-adjustment) and NHDplus is mild (\( R^2 = 0.5; n = 173; \) Table 1) but show a fairly close 1:1 trend (Fig. 6b). When both GloRS and NHDplus are compared to the 25 observation points (excluding 9 non-contiguous U.S. sites from the 34 observation locations), NHDplus resulted in a weaker correlation, higher RMSE and greater difference in mean from observed slope compared to GloRS (Table 1 and Fig. 6a). Six (6) of the points have an NHDplus value of 0.00001, the constant minimum value within NHDplus. This minimum value is common for large river segments at the NHDplus dataset, with nearly half the river segments in the greater than 1000 km\(^2\) subset, with either NoData (\( \sim 9998 \)) or 0.00001 values. This is a major disadvantage of NHDplus. Excluding these 6 points from the analysis (not shown) does not improve the regression between NHDplus and observed slope. The weaker correspondence of NHDplus to observed slope values compared to GloRS, is likely due to its much shorter stream segments. Even though NHDplus river slope was calculated based on a higher resolution DEM and better curated stream-network, its high-resolution network lead to much shorter stream-network segments. This means that slope calculations for each segment is more sensitive to the DEM vertical resolution and biases. This is consistent with our sensitivity analysis (not presented here) that showed that a 50 km splitting value yielded better results than 10 km.

In addition to the DEM resolution, its accuracy is also likely play an important role in the accuracy of river slope derived from it. Accuracy issues in global DEMs are well documented, particularly for SRTM (e.g. Rodriguez et al., 2006). A number of new high resolution global DEMs have recently been or are expected to be released (e.g. Advanced Land Observing Satellite (ALOS), World 3D-DEM (Tadono et al., 2015); TanDEM-X DEM (Krieger et al., 2007)). Yamazaki et al. (2017) generated the MERIT DEM (at 3 arc-sec (\( \sim 90 \text{ m} \)) resolution) which is based...
on automatic error correction procedure of two existing DEMs (SRTM3 v2.1 and AW3D-30 m v1). These new and upcoming DEM products could considerably improve GloRIS but, due to their much higher resolution, will require considerable enhancement of its calculation procedure. This will be the focus of future work.

3.2. Distribution analysis

Average continental river slope (Table 2 and Fig. 7) range by a factor of nearly 6 between the continents, with Australia having the lowest average (0.0006) and Asia the highest (0.0035). Low river slope averages in Australia are expected given the absence of a significant continental mountain ranges, attributable to its generally older basement geology. South America is particularly interesting as it includes both very high river slope values, concentrated along the narrow Andes, and extensive areas of relatively low sloping rivers (primarily within the Amazon Basin) (Fig. 3). This contrast results in South America having the greatest variability in river slope (Fig. 7 and Table 2). The continents show relatively similar coefficient of variance, except for Oceania whose river-slope values are dominated by small mountainous Islands (primarily Papua and New Zealand); while average river-slope is high, variability within the islands is small.

Basin-scale analysis reveals a heterogenetic mosaic of average river slopes (Fig. 8, Table A2). High river-slope basins include Himalayan-fed and Rocky Mountain-fed basins. Low river-slope basins include northeast Europe and central Africa rivers. Of the world’s 30 largest river basins, three Asian rivers (Indus, Ganges-Brahmaputra, and Yangtze) have the highest average slope (Fig. 9a). These rivers are among the world’s most tectonically active basins. Fig. 9b demonstrates that there is no direct link between basin size and its average river slope. High within-basin variability in river slope is associated with rivers draining continental mountain ranges (Fig. 10). Central Asian basins
yielded the highest variability followed by South American basins. The most homogeneous basins are clustered in northeast Europe (e.g. Volga and Don Basins). Basins with high CV (Fig. 11) include large rivers draining mountain chains and developing extensive floodplains. Typically, these rivers are those draining into the passive margin side of large continental plates.

3.3. Factors affecting river slope

An exploratory exercise was conducted to investigate the potential influence of different factors on river slope by testing the correlation between basin-averaged river slope as the dependent variable (n = 234) and basin-statistics (mean, max, STD, and range) of lithology, discharge, sediment flux, precipitation and terrain slope (Table 3). The goal of this analysis is to identify potential linkages that may lead to broader understanding of the factors controlling river slope distribution at large (e.g. basin) scales. Log-converted values were used for both the dependent and independent parameters. A step-wise multiregression analysis was first used that included all the listed parameters. Following this initial analysis, a semi-empirical model (not purely based on regression algorithm but also on user knowledge) was developed.

Basin-averaged terrain slope explains 67% of the variability in basin-average river slope (Table 4). This is an expected outcome given that rivers draining steep terrain have high slopes. This suggests that 37% of the variability in basin-averaged river slope is explained by other factors. The strongest multi-regression result with the parameters listed in Table 3 (adj. R² = 0.8) found the following parameters as having significant contribution (ordered in strength of contribution; arrows represent positive (↑) or negative (↓) correlation): TSlopeMEAN↑, QsMEAN↑, TMEAN↓, QsSTD↓, QSTD↓, QsMAX↑, and PMEAN↓. The positive relationship with sediment load (QsMEAN, QsMAX) may be explained by the fact that basins with high topographic relief have relatively higher sediment fluxes (Syvitski and Milliman, 2007). Basin-averaged sediment flux, in this context, can also be thought of as a proxy or indicator of the impact of tectonic (uplift) rates on river slope.

The inverse relationship found between river slope and basin-
Intra-basin variability in water and sediment fluxes (QSTD and QsSTD) are inversely correlated to river slope. High spatial variability in river fluxes is indicative of larger basins, which tend to have overall lower average river slopes. The inverse relationship between river slope and precipitation was the weakest among all the parameters. Given the difficulty in demonstrating causality between some parameters and river slope at this scale we propose the following, semi-empirical, regression model based on the above analysis and our general assertions about the underlying drivers and mechanisms that may control river slope:

$$R\text{slope}_{\text{MEAN}} = 10.1182 \cdot T\text{slope}_{\text{MEAN}}^{0.86} \cdot Q\text{MEAN}^{0.17} \cdot Q\text{sMEAN}^{0.19} \cdot T\text{MEAN}^{6.18}$$

(2)

The adjusted $R^2$ of this model is 0.76 (Fig. 12), a decrease in parameter estimation. As before, terrain slope accounts for 67% of the variability in basin-averaged river-reach slope (Table 4). $Q\text{MEAN}$ contributed an additional 3%, $Q\text{sMEAN}$ adds 4% and $T\text{MEAN}$ 3%. While the model can estimate basin-averaged river slope quite well (Fig. 12), its main utility is as an initial framework for exploring the factors influencing river slope. Beyond terrain slope, the contribution of water discharge, sediment flux, and temperature to the model are quite similar and are marginal. Causality between these parameters and river slope is difficult to assess at this scale. It is reasonable however to speculate that discharge ($Q\text{MEAN}$) represent the sediment transport capability of a basin which will be inversely correlated to river slope as higher capacity will enable greater rates of topographic degradation. The potential relationships between sediment and temperature were discussed earlier.

### 4. Conclusions

We introduce a version 1.0 of the Global River Slope (GloRS) geospatial database. GloRS is calculated based on a simple principle of obtaining the maximum (upstream) and minimum (downstream) elevation of each river segment from an underlying DEM and calculating the reach average slope by dividing the elevation range by the segment’s length. To reduce biases due to the size of the DEM cells, the use of high-resolution DEM and relatively long river reach segments are warranted. Here we used the 15 arc-sec HydroSHEDS DEM and stream network for ± 60° latitude and the 1 arc-min etopo DEM for greater than 60° latitude. The use of higher resolution and quality DEM (e.g. Yamazaki et al., 2017) is expected to improve the calculation results, particularly for smaller rivers, but introduce computational challenges for global- or even continental-scale calculations given the file size of these datasets. This will be the focus of future development.

The 15 arc-sec GloRS product was upscaled to 6 arc-min resolution to align it with typical global-scale riverine modeling applications. An upscaling procedure was developed in which the value of the coarse resolution output (6 arc-min in this case) is based on the grid-cell in the

<table>
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<th>Step</th>
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<th>P value</th>
<th>$R^2$</th>
</tr>
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<tr>
<td>1</td>
<td>$\log(T\text{slope}_{\text{MEAN}})$</td>
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<tr>
<td>2</td>
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<td>3</td>
<td>$\log(Q\text{sMEAN})$</td>
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<tr>
<td>4</td>
<td>$\log(T\text{MEAN})$</td>
<td>0.0000</td>
<td>0.77</td>
</tr>
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</table>
underlying high-resolution input (15 arc-sec in this case) with the lowest (minimum) value. This is meant to capture the slope value of the largest river (typically will have the lowest slope) within each of the upscaled raster grid-cell domain. While the results of this upsampling procedure seemed to produce a very favorable output (better correlate to observations), more sophisticated approaches could further improve GloRS. This will also be a focus of future development efforts.

GloRS river slope values were compared to 34 point observations and to the U.S. National Hydrography Dataset, NHDPplus (in 173 random locations). The 6 arc-min GloRS product was found to have the strongest correlation to observed river slope, compared to both the 15 arc-sec GloRS product and NHDPplus. It was however found to consistently overpredict slope for mid and low values, likely due to underrepresentation of river meandering in the input stream-network layer. An adjustment equation was developed which resolved this bias.

The adjusted 6 arc-min GloRS was used to explore globe-, continent- and basin-scale river slope statistics, providing a first of its kind insights into global distribution of river slope. River slope values ranged by 5 orders of magnitude from flat coastal reaches of large rivers to steep reaches along continental mountain ranges. Differences in average slopes between continents were found to be large (a factor of 6) and the inter-continental variability was found to be associated with the topographic configuration of the continent. Variability between and within global basins was found to be very high. These results demonstrate the importance of a spatially explicit estimation of river slope.

The factors controlling basin-averaged river slope were investigated. Basin-averaged terrain slope was found to be the strongest explanatory variable, explaining 67% of the variability. This means that river slope, at least at the basin-averaged scale, is not solely a function of the terrain, but that other factors affect its distribution. Our initial analysis found that basin-averaged suspended sediment flux, mean air temperature, and precipitation, and intra-basin variability in sediment and water discharge, explain an additional 13% of the variability in basin-averaged river slope (adj. R² = 0.8). Based on the regression results, a simpler semi-empirical, model was developed in which terrain slope, mean sediment and water discharge, and air temperature are the independent variables. The resulting model (Eq. (2)) explains 77% of global-scale variability in basin-averaged river slope.

Causality between the dependent and independent variables is difficult to assess at this scale. This exercise was, however, useful for proposing hypotheses that may explain the relationships identified. The inverse relationship between river slope and mean air temperature supported our initial assertion that higher temperature will lead to higher rates of rock weathering which will contribute to lower slopes. The positive relationship between average sediment flux and river slope was proposed to be co-linked to basins’ terrain but also as an indicator of tectonic uplift rates. Inverse relationship to average water discharge was proposed to be associated with basins’ material transport capacity, where higher capacity will promote lowering of terrain and river slopes.

Acknowledgment

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Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version, at https://doi.org/10.1016/j.jhydrol.2018.06.066.

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