Geophysical Research Letters

Supporting Information for

Patterns of river width and surface area revealed by the satellite-derived North American River Width (NARWidth) dataset

George H. Allen, Tamlin M. Pavelsky

Department of Geological Sciences, University of North Carolina, Chapel Hill, NC

Contents of this file

Text S1 to S3
Figures S1 to S4

Additional Supporting Information

Captions for Table S1

Introduction

This document contains detailed descriptions of the methodologies used to develop the Landsat-derived NARWidth dataset and to calculate the total surface area of North American rivers and streams.
Text S1. Methods for Developing the NARWidth dataset

Text S1.1 Determining time of year when rivers are at mean discharge

NARWidth is composed of planform morphometric measurements of rivers at approximately mean discharge. While bankfull discharge usually represents the channel-forming flow [Wolman and Miller, 1960], mean discharge occurs much more often and is thus more consistently observable from limited remotely sensed imagery. Studies of river form suggest that geomorphic relationships relating width to discharge or drainage area are similar regardless of the discharge frequency used [Leopold and Maddock, 1953; Stewardson, 2005]. Temporal fluctuations in discharge are a combined result of unpredictable events (e.g. storms and droughts) and more predictable seasonal variability in runoff. Unfortunately, no high-density, global-scale, daily discharge datasets exist to track the specific days that rivers are at their mean discharge. Instead, we approached the problem by determining the time of year that rivers in different parts of the globe are most likely to be at mean discharge.

To determine the optimal time of year to measure rivers, we used an international archive of long-term (>10 years) mean monthly discharge measurements [GRDC, 2011] composed of 1920 gauges in North America. For each station with a complete record (i.e. no missing data values), we constructed a mean monthly hydrograph and calculated the mean and standard deviation (1σ) for all monthly measurements (Figure 2). All months with discharges that fall within one standard deviation of the mean were scored according the following equation,

\[\text{score}(m) = Q_m - \frac{1}{2}Q_m - \frac{1}{4}(Q_{m-1} + Q_{m+1}),\]  

(S1)

where \(m\) is a given month being scored, \(Q_m\) is the mean of all monthly discharges, \(Q_m\) is the mean monthly discharge of the given month, \(Q_{m-1}\) is the mean monthly discharge one month before month \(m\), and \(Q_{m+1}\) is the mean monthly discharge of the month after month \(m\). River discharge is more likely to be at or near the overall mean value during months with lower scores. Thus at each gauge station we produced a list of months that were ranked by the probability that the river was at mean discharge. To assign the monthly rankings from the gauge stations to each Landsat tile (landsat.usgs.gov), we considered both the proximity to gauge location and the monthly ranking. For example, the highest ranked month from the nearest gauge station has the greatest weight in setting the monthly preference order at a given Landsat tile. Each Landsat footprint is assigned at least one monthly preference and up to five ordered preferences (Figure S1b).

To evaluate the validity of this method, we used in situ records to determine the variability of river width within each of the top ranked months. We restricted the analysis to United States Geological Survey (USGS) and the Water Survey of Canada (WSC) stream gauge records that were used to validate the NARWidth dataset and that contained river width measurements during the top ranked month (\(N = 1,026\)). For each stream gauge, we calculated the standard deviation of (a) all recorded width measurements and (b) widths collected only during the top-ranked month. The median standard deviation of all width measurements was 30.0% of the mean annual river width while the standard deviation of width from the top ranked month was 17.3%. Thus, this method reduces the degree of variability associated with measuring rivers from satellite imagery by 42.3% relative to random sampling of rivers year round.
Text S1.2 Landsat imagery acquisition

Landsat TM and Landsat ETM+ (SLC-on) scenes were acquired from two data sources. We automatically downloaded the majority of scenes (1071 out of a total of 1756 scenes) from the Global Land Cover Facility (GLCF) (glcf.umd.edu). The highest ranking scene was downloaded first. Upon download, each scene was visually inspected for flaws (e.g. clouds, river ice, shadows, flooding, no rivers) and either kept for use or discarded. If discarded, the next highest ranking scene was automatically downloaded. Once all available imagery was downloaded from the GLCF site, we manually downloaded Landsat scenes from the USGS (earthexplorer.usgs.gov) in order of monthly preference. Thirty-four Landsat tiles in North America, located primarily in the tropics, had no cloud-free scenes available. To address this problem, we developed a program in IDL (version 8.0) that identified clouds based on their spectral signature and splices two or more complementary scenes together to eliminate clouds [Martinuzzi et al., 2007]. Fourteen tiles located high in the Canadian Archipelago had no scenes free of cloud and ice available during any of the monthly preferences listed. These scenes most likely have few if any wide rivers because they are located on relatively small and gladdly dominated islands. Apart from these fourteen tiles, we successfully acquired imagery for all observable rivers in North America.

Text S1.3 Image processing and GIS

We visually inspected several water classification methods including: the normalized difference water index [McFeeters, 1996], the modified normalized difference water index [Xu, 2006], the normalized difference vegetation index [Rouse, 1973], Monitoring the vernal advancement and retrogradation of natural vegetation), and the tasseled cap wetness index [Crist and Cicone, 1984]. We found that the best performing classification method was the modified normalized difference water index,

\[
MNDWI = \frac{(\text{green}-\text{MIR})}{(\text{green}+\text{MIR})},
\]

where MIR is the middle infrared band (e.g. TM Band 5) and green is the green band (i.e. TM Band 2) [Xu, 2006]. We applied the MNDWI formula to all Landsat scenes, mosaicked, and clipped images to 4° Latitude by 6° Longitude tiles. We then created a binary water mask by applying a dynamic threshold [Li and Sheng, 2012] which was visually inspected and corrected for any gaps in continuity and classification errors. These errors stem from sources including river view obstruction by topographic shadows, bridges, or dams, or the erroneous inclusion of swamps, large lakes, or deltas in the river network. RivWidth (version 0.4) calculated a channel centerline for all river reaches longer than 10 km (Figure S2). After RivWidth runs on a mosaic image, we visually inspected the RivWidth output for errors.

Reservoirs and lakes connected to the fluvial network were labeled using GIS methods and several water body datasets: 1) the Global Lakes and Wet Lands Database [Lehner and Döll, 2004]; 2) the Global Reservoir and Dam Database [Lehner et al., 2011]; 3) the U.S. and Canada Water Polygons dataset [TomTom North America, 2012]; and 4) the Mexico Water Bodies dataset [Sistemas de Información Geográfica, 2008]. The locations of lakes and reservoirs were then visually inspected and corrected in ArcGIS.
**Text S2. NARWidth validation methods**

We validated Landsat-derived river width measurements using 1,049 stream flow and river width records from the USGS (http://nwis.waterdata.usgs.gov/nwis) and the WSC (http://www.ec.gc.ca/rhc-wsc/) (See supplemental validation table document). At each gauge location, we estimated the river width at mean annual discharge and compared this value to the average of the five spatially closest RivWidth measurements (Figure S3). We excluded river width measurements that: 1) were taken more than 200 m upstream or downstream from the gauge station; 2) were taken when river ice was observed; or 3) were labelled as “Poor” measurements. We then took the mean of all width measurements that were taken when river discharge was within 5% of the mean annual discharge (red dots, Figure S3) and compared mean in situ width with the mean width of the five nearest NARWidth river width measurements. The residuals between in situ and remotely sensed width measurements show the effect of Landsat’s 30 m resolution on the validation analysis (Figure S4). The residuals show heteroscedasticity, are uncorrelated, and are unbiased with changing in situ width.

**Text S3. Surface area calculation**

River surface area was computed at each centerline pixel by multiplying river width and length. River width was calculated by the RivWidth software, and river length was calculated using the Euclidean distance between each centerline pixel and the next adjacent centerline pixel. Thus at each centerline pixel, width, length, and surface area metrics were estimated. To characterize the relationship between river surface area and width, we binned surface area by width using 100 m width intervals (Figure 4). We then multiplied the binned surface area data by the bin interval (100 m) and performed a least squares linear regression of the data in log space. We calculated the total surface area of rivers and streams with widths narrower than 100 m by taking the definite integral of this curve from $1.6 \pm 1.1$ m (estimated by Downing et al. [2012]) to 100 m. Finally, we summed this extrapolated surface area and all measured surface areas in rivers wider than 100 m to estimate the total surface area of all rivers and streams in North America.
**Figure S1.** Method for determining the time of year to analyze rivers. a) Example mean monthly hydrograph (George River, CN). Months with discharges within one standard deviation (gray box) of the mean discharge (dashed horizontal line) are ranked (blue numbers) based on their discharge and that of their two neighboring months (equation S1). The best month to measure river width is September. b) Month that rivers are most likely to be at mean discharge for each Landsat tile.
Figure S2. The RivWidth program calculates a river centerline (blue) from a binary river mask (black) derived from Landsat imagery [modified from Miller et al., 2014]. At each centerline pixel, RivWidth computes the river width and braiding index. A river length was computed at each width measurement by calculating the Euclidean distance between each centerline pixel and the next adjacent centerline pixel.
Figure S3. Example in situ river discharge-width rating curve used to validate NARWidth. Mean annual discharge was calculated using daily discharge over at least a 10 year period (black line). The corresponding river width (red line) was then compared to the mean of the five nearest Landsat-derived NARWidth measurements at that location (blue line).
Figure S4. In situ and remotely sensed river width residuals. Landsat’s spatial resolution of 30 m excludes any residuals below the dashed blue line, demonstrating the influence of Landsat’s resolution on the regression analysis of the full range of width data (blue line in Figure 2).
Table S1. Validation table containing the stream gauge agency name (USGS, United State Geological Survey; WSC, Water Survey of Canada), site number, decimal degree Latitude and Longitude, upstream drainage area, mean annual discharge, river width at mean annual discharge, Landsat-derived NARWidth river width.
References


GRDC (2011), Long-Term Mean Monthly Discharges and Annual Characteristics of GRDC Station, edited by G. R. D. Centre, Federal Institute of Hydrology (IfG), Koblenz, Germany.


Rouse, J. W., Jr. (1973), Monitoring the vernal advancement and retrogradation (green wave effect) of natural vegetation, edited by NASA, United States, College Station, TX.

Sistemas de Información Geográfica, S. A. (2008), Mexico Water Bodies [electronic resource], edited, Esri, Redlands, California, USA.

