Regional regression models of watershed suspended-sediment discharge for the eastern United States

David C. Roman [a,1], Richard M. Vogel [a,*], Gregory E. Schwarz [b]

[a] Department of Civil and Environmental Engineering, Tufts University, Medford, MA 02155, United States
[b] US Geological Survey, Reston, VA 20192, United States

ARTICLE INFO

SUMMARY

Estimates of mean annual watershed sediment discharge, derived from long-term measurements of suspended-sediment concentration and streamflow, often are not available at locations of interest. The goal of this study was to develop multivariate regression models to enable prediction of mean annual suspended-sediment discharge from available basin characteristics useful for most ungaged river locations in the eastern United States. The models are based on long-term mean sediment discharge estimates and explanatory variables obtained from a combined dataset of 1201 US Geological Survey (USGS) stations derived from a SPAtially Referenced Regression on Watershed attributes (SPARROW) study and the Geospatial Attributes of Gages for Evaluating Streamflow (GAGES) database. The resulting regional regression models summarized for major US water resources regions 1–8, exhibited prediction R^2 values ranging from 76.9% to 92.7% and corresponding average model prediction errors ranging from 56.5% to 124.3%. Results from cross-validation experiments suggest that a majority of the models will perform similarly to calibration runs. The 36-parameter regional regression models also outperformed a 16-parameter national SPARROW model of suspended-sediment discharge and indicate that mean annual sediment loads in the eastern United States generally correlates with a combination of basin area, land use patterns, seasonal precipitation, soil composition, hydrologic modification, and to a lesser extent, topography.

1. Introduction

Suspended-sediment, nutrients, detritus, and other organic matter delivered at appropriate concentrations are critical to the health of river and stream ecosystems. In excess, suspended-sediment discharge can inhibit respiration and feeding of stream biota, diminish the transmission of light needed for plant photosynthesis, and reduce reservoir storage capacity (USEPA, 1986; Vorosmarty et al., 2003). Conversely, low suspended-sediment discharges, which often occur downstream of river modifications such as dams, can result in the loss of native fish species and riparian ecosystems, subsidence and loss of wetlands, and decreased nutrient delivery to coastal estuaries (USEPA, 2003; Syvitski et al., 2005). In addition, many contaminants including pesticides, metals, and polycyclic aromatic hydrocarbons (PAHs) readily sorb to sediments and are able to resist degradation (USEPA, 2000). Contaminated sediments can cause detrimental effects to the surrounding ecosystem including conversion from sensitive to pollution-tolerant species (e.g., phytoplankton to cyanobacteria) and by providing a source of contaminants to the aquatic food chain (USEPA, 2004). According to US Environmental Protection Agency (USEPA) National Water Quality Inventory Reports to Congress, sediment/siltation was listed among the top five leading causes of impairment to assessed rivers and streams in 1998, 2000, and 2002.

In order to manage suspended-sediment related water quality issues in fluvial systems, it is important to accurately quantify sediment transport at desired river locations. However, the vast majority of rivers in the US have either no or sparse suspended-sediment data. Larsen et al. (2010) report that the number of daily-record sediment-monitoring stations operated by the USGS declined from 364 to less than 100 between 1981 and 2005 due in part to increases in sediment-monitoring costs. If a local watershed manager, agency, or researcher has interest in reliable records of long-term mean sediment discharge for a given site, they must implement a rigorous and costly multi-year sediment and river discharge monitoring program. Another solution to this problem is to develop regional regression models that predict long-term mean annual suspended-sediment discharge from readily obtained basin characteristics. Though not a substitute for data

* Corresponding author. Tel.: +1 617 627 4260; fax: +1 617 627 3994.
E-mail addresses: droman@geosyntec.com (D.C. Roman), richard.vogel@tufts.edu (R.M. Vogel), gschwarz@usgs.gov (G.E. Schwarz).
[1] Present address: Geosyntec Consultants, 1330 Beacon Street, Suite 317, Brookline, MA 02446, United States.

collection, such models would enable estimation of suspended-sediment discharge at most ungaged river locations. For example, models of this form could be used to predict the loading of a reservoir to arrive at an estimate of fill time or to develop an approximate dredging schedule.

Regional regression models for predicting hydrologic statistics at ungaged sites are not new, and are widely used for estimating flood, average, and low river discharges (USGS, 2010). For example, Vogel et al. (1999) developed regional multivariate regression models for estimation of the mean and variance of annual stream-flow at ungaged sites in the United States as a function of basin area, mean basin precipitation and mean basin temperature. Those relations developed for the mean annual streamflow for each of 18 US water resource regions resulted in adjusted R^2 values ranging from 90.2% to 99.8% and an average value of 96.2% across the continent. Analogous regional hydrologic models for predicting low-flow and flood-flow statistics have been developed for all regions of the US for most states by the USGS and have been in common usage for the last decade (e.g., StreamStats; Reis et al., 2008). It is hoped that the types of regional suspended-sediment models introduced here will find similar use for broad regions of the US and that in the not too distant future, all offices of the USGS will routinely develop and update regional models of suspended-sediment discharge, in much the same way they now perform similar analyses for flood and low-flow statistics. It should be noted that this paper is focused on the estimation of suspended-sediment discharge and does not consider bed load.

1.1. Review of previous regional regression models of suspended-sediment discharge

In comparison to regional hydrologic models of flow statistics described earlier, there are surprisingly few studies that have sought to model mean annual river suspended-sediment discharge on a regional scale. We were unable to find any previous regional regression models of sediment transport developed strictly for basins in the eastern US; however, Hindall (1975) did develop regional regression models of average suspended-sediment yield for Wisconsin using an array of independent variables including topography, soils, land use, stream hydraulics, and climate conditions. The resulting average model prediction error of estimate for the models ranged from 28% to 38%.

Several global regression models of sediment discharge are summarized below as well as the more complex SPAtially Referenced Regression On Watershed attributes (SPARROW) model developed for the conterminous United States.

1.1.1. Global regression models

Holeman (1968), Curtis et al. (1973), Milliman and Meade (1983), and others have reported that a positive relation exists between average annual sediment discharge and drainage area. Milliman and Syvitski (1992) developed simple global models of sediment discharge for watersheds in each of five different relief classes of the form:

$$Q_s = cA^d \tag{1}$$

where Q_s is mean annual suspended-sediment discharge in kilograms per second (kg/s), A is drainage area in square kilometers (km^2), and c and d are model coefficients. For these models, Milliman and Syvitski (1992) reported coefficients of determination ranging from $R^2 = 70\%$ to $R^2 = 81\%$. Mulder and Syvitski (1996) condensed the five relief classes into a single maximum relief variable R, expressed in kilometers (km), resulting in:

$$Q_s = aA^{1.41}R^{1.3} \tag{2}$$

where a is a constant of proportionality. They reported an $R^2 = 67\%$ for the model in (2) based on a global database of measured suspended-sediment discharge for 292 rivers.

To account for climatic variations in sediment discharge, Syvitski et al. (2003) developed a mean basin temperature variable computed from basin location (latitude, longitude) and the adiabatic lapse rate. Multivariate regression models were then developed using an updated global dataset of 340 river basins for each of the major hemispheric climate regions (polar, temperate, and tropic) of the form:

$$Q_s = \alpha_3 A^{\alpha_4} R^{\alpha_5} e^{kT} \tag{3}$$

where the α and k values represent regression coefficients and T is average basin temperature in °C. They reported coefficients of determination ranging from $R^2 = 54\%$ to $R^2 = 76\%$ for the area/relief/temperature (ART) model (3).

The most recent and successful global model was developed by Syvitski and Milliman (2007) using a database of 488 rivers. Their model accounted for 63% of the land surface draining to the global ocean and 66% of the predicted sediment discharge. That model takes the form:

$$Q_s = \omega B Q^{.31} A^{.5} RT \quad \text{for } T \geq 2\,°C \tag{4a}$$

$$Q_s = 2\omega B Q^{.31} A^{.5} R \quad \text{for } T \leq 2\,°C \tag{4b}$$

where $\omega = 0.02$, Q is discharge (streamflow) in cubic kilometers per year (km^3/year). They report a coefficient of determination of $R^2 = 95\%$ for the model in (4) when applied to the global database of 488 rivers. Much of the improvement in (4) over the previously cited global models results from the B term, defined as:

$$B = IL(1 - T_E)E_h \tag{4c}$$

where I is a glacier erosion factor, L is an average lithology factor ranging from soft to hard, T_E is the trapping efficiency of lakes and human-made reservoirs, and E_h is a human-influenced soil erosion factor. Without the B term in (4) the variables Q, A, R, and T only accounted for 65% of the overall variance of the sediment discharge observations. Syvitski and Milliman (2007) provide a detailed explanation and derivation of B.

1.1.2. SPARROW national model of suspended-sediment

SPARROW is a watershed modeling tool developed by the US Geological Survey intended for regional interpretation of water-quality monitoring data. It uses a hybrid statistical/process based approach to estimate pollutant sources and contaminant transport in watersheds and surface waters (Smith et al., 1997) and has been spatially represented by the Enhanced River Reach File 2.0 (E2RF1) reach network; a database of 62,776 interconnected stream reach segments comprising the surface water drainage system for the United States (Nolan et al., 2003). For detailed information on SPARROW modeling techniques see Schwarz et al. (2006) and USGS (2009).

Schwarz (2008) utilized the SPARROW model to predict long-term mean annual suspended-sediment discharge for watersheds in the conterminous United States. The analysis was based on sediment flux estimates compiled from 1828 long-term monitoring stations operated by the USGS during the period 1975–2007, each with at least 15 concentration measurements and standard errors (associated with resulting mean annual discharge estimates) that did not exceed 80% of the flux estimate. The SPARROW model inputs include source coefficients (land-use classes and reach length), land-to-water delivery factors (reach slope, soil permeability, soil erodibility, precipitation, and streamflow), and stream attenuation factors (reach travel time and reservoir settling

velocity). The results indicate that agricultural land sources and the stream channel are major sources of watershed sediment discharge delivery, whereas reservoirs are major sites for sediment attenuation. The SPARROW model achieved an overall R^2 of 71.1% and a root mean square error (RMSE) of 1.4 (e.g., the predicted sediment flux in any given reach has an error of approximately 140%) using data from the 1828 gaged sites located throughout the conterminous United States.

1.2. Study purpose

A review of the literature revealed only one previous regional regression model that predicts long-term suspended-sediment yield and three previous global multivariate regression models reported in (2), (3), and (4) that predict long-term suspended-sediment discharge using watershed characteristics. This is notable given the large amount of readily accessible sediment and watershed data currently available, especially in the US. The global models are shown later (Section 3.1) to be unsuitable for regional prediction of sediment discharge within the US. One goal of this preliminary study was to evaluate the potential for developing regional models of suspended-sediment discharge using basin characteristics similar to those identified by Syvitski et al. (2003) and Syvitski and Milliman (2007). An alternative approach is to develop a regional SPARROW model; however, such basin-wide characteristics are not easily identified in the context of a spatially referenced model (although it may be possible to develop spatially referenced analogs of these metrics). Also, the methodology adopted in this study is amenable to the study of suspended-sediment frequency of occurrence statistics; an analysis that is not easily implemented in the mass balance method used by SPARROW. Finally, regionalization of a SPARROW model has the potential problem that any individual region may lack the number of sampling sites or sufficient spatial variation of the explanatory variables to obtain statistically significant estimates for all model coefficients. This concern is specifically addressed in recent work by Schwarz et al. (2011).

The primary purpose of this study was to develop readily applied regional regression models of long-term river suspended-sediment discharge for water resource regions 1–8, located within the eastern United States. The resulting regional models may be used to predict the long-term mean annual sediment discharge of rivers as a function of readily available basin characteristics, including morphology, topography, climate, hydrology, anthropogenic influences, soils, and land use at any river location with available upstream basin characteristics data. A secondary purpose of this study was to provide guidance for future studies that seek to improve upon the types of regional statistical models developed here for other regions of the US. This was accomplished by exploring (1) the homogeneity of suspended-sediment discharge and (2) the primary drivers of watershed-based suspended-sediment discharge in the eastern United States.

2. Methods and database

The development of regional regression models requires extensive datasets gathered from multiple sources as described below.

2.1. Suspended-sediment discharge estimation

Estimates of long-term mean annual suspended-sediment discharge for this study were computed from observations of suspended-sediment (USGS water quality parameter 80154; Edwards and Glysson, 1988; Guy, 1969) and discharge (streamflow) by Schwarz (2008) using a standardized approach coded into the

Fluxmaster computer program (Schwarz et al., 2006), which implements the maximum likelihood regression approach developed by Cohn (2005). The Fluxmaster program computes unbiased estimates of detrended, long-term mean annual sediment discharge at individual monitoring stations. The detrended estimates use 1992 as the common base year for all stations, this year falling in the middle of the time period water-year[2] (WY) 1975–2007 when the suspended-sediment data used in the study were collected. Complete details of the approach are outside the scope of this paper. See Schwarz et al. (2006), Schwarz (2008), and Cohn (2005) for further information on sediment discharge estimation methods and detrending techniques.

2.2. Suspended-sediment concentration and water discharge data

Following Schwarz (2008), of the 2242 monitoring sites on the E2RF1 stream network for which USGS suspended-sediment concentration and daily streamflow data are available, 1828 were selected with at least 15 suspended-sediment concentration values during the period WY 1975–2007 and a standard error of the estimated long-term mean annual suspended-sediment discharge (see Cohn, 2005, and Schwarz et al., 2006) was less than 80%.

2.3. Basin characteristics data

The primary source of basin characteristics, including morphology, topography, climate, hydrology, anthropogenic influence, and soils characteristics were obtained from the Geospatial Attributes of Gages for Evaluating Streamflow (GAGES) database developed by Falcone et al. (2010). GAGES includes data compiled from USGS streamgages and their upstream watersheds within the conterminous United States with at least 20 complete years of uninterrupted streamflow records over the period 1950–2007. Several hundred watershed and site characteristics were derived from national data sources for each of the 6785 streamgages included in GAGES. Land use variables from 1992 were gathered from the Schwarz (2008) SPARROW study by accumulating upstream attributes of each E2RF1 reach segment in accordance with the reach network.

2.4. Combined dataset

The 1828 stations containing SPARROW long-term mean annual suspended discharge estimates and land use data were merged with the 6785 stations containing basin characteristics obtained from GAGES to form a combined dataset of 1201 matched stations sorted by the major water resources regions shown in Fig. 1. See Table 2 for a count of stations used in each of the eight major eastern US water resources regions.

2.5. Multivariate regional regression analysis

Ordinary Least Squares (OLSs) regression procedures were used to obtain regional equations for mean annual suspended-sediment discharge Q_s (kg/s):

$$Q_s = e^{\beta_0} X_1^{\beta_1} X_2^{\beta_2} \cdots X_n^{\beta_n} v \tag{5}$$

where X_1 through X_n are basin characteristics, β_0 through β_n are model coefficients, and v represents lognormally distributed model errors. Taking natural logarithms yields:

$$\ln(Q_s) = \beta_o + \beta_1 \ln(X_1) + \beta_2 \ln(X_2) + \cdots + \beta_n \ln(X_n) + \varepsilon \tag{6}$$

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[2] A USGS Water Year is defined as the 12-month period October 1, for any given year through September 30, of the following year.
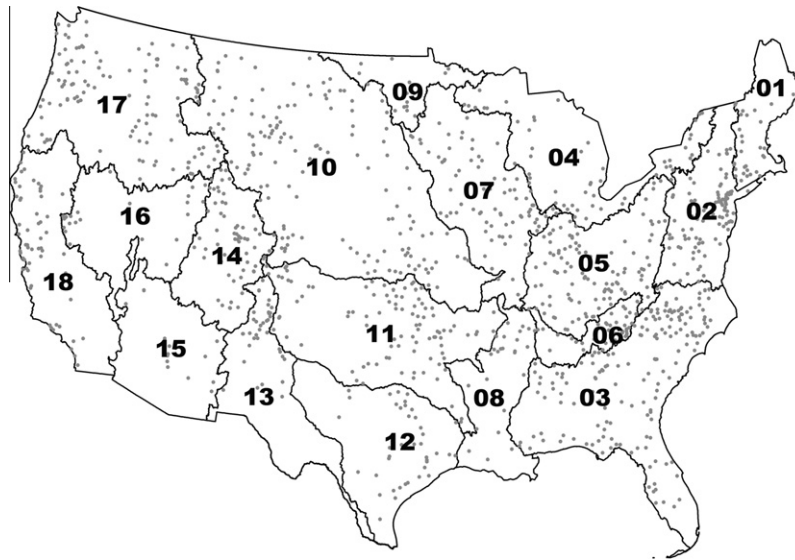
Fig. 1. Location of the 1201 matched GAGES/SPARROW stations in relation to major water resources regions in the conterminous United States.

where the residuals, $\varepsilon = \ln(v)$ are normally distributed with zero mean and constant variance σ_ε^2.

MINITAB[3] Release 15 statistical software package (Minitab, 2007) was used to perform a combination of backward elimination and forward selection stepwise regression procedures and best subsets regression to initially identify basin characteristics (predictors) that best describe Q_s. In order to avoid over parameterization, the number of variables in each model was limited to a maximum of 6. Both stepwise and best subsets regression are screening methods and may not identify the optimal model. Accordingly, after identifying potential models from the screening procedures, the variables and coefficients making up the models were carefully examined to ensure that they physically made sense (e.g., a model was not accepted if it predicted a decrease in sediment load due to increasing drainage area). Regional models were selected that maximized the prediction R^2 and Nash Sutcliffe Efficiency (NSE) and minimized average model prediction error (SE), while keeping the number of basin characteristics used in each model to a minimum.

The prediction R^2 is computed through use of the prediction sum of squares (PRESS) metric, a validation type estimator of error which, rather than splitting the dataset in half, iteratively develops the regression equation with $n - 1$ observations and estimates the value of the left out observation (Helsel and Hirsch, 2002). The prediction R^2, unlike R^2, will generally not increase when adding additional explanatory variables to a multivariate regression model. The NSE, commonly used in hydrology, provides a measure of both the variance and root mean square error of the model. The value of NSE may vary between negative infinity and 1 (Nash and Sutcliffe 1970). Variance inflation factors were used to ensure that none of the models exhibited multicollinearity (Marquardt, 1970) and Cook's D was employed to identify influential observations (Belsley et al., 1980). It is not advisable to remove influential sites without a compelling reason, so sites identified as influential using the value of Cook's D were only removed if the standard error of their annual suspended-sediment discharge exceeded 70%, following the reasoning that this was close to the standard error removal cutoff specified earlier. Normal probability plots were created to ensure that model residuals (ε) were approximately normally distributed. Finally, cross-validation was performed on the regression models

to evaluate their ability to adequately predict suspended-sediment discharge in practice. Refer to Section 3.4 for additional details. Helsel and Hirsch (2002) provide in-depth discussion of goodness-of-fit diagnostics and validation methods for multiple linear regression methods.

The regression models were estimated in log space as shown in (6); yet to implement the models, retransformation to real space is needed, resulting in (5). Resulting discharge estimates exhibit retransformation bias, which can be corrected by multiplying the regression by the bias correction factor (BCF):

$$\text{BCF} = \exp\left(\frac{\sigma_\varepsilon^2}{2}\right) \tag{7}$$

introduced by Ferguson (1986) where σ_ε^2 is the variance of the residuals in (6). The BCF in (7) was used in this study, though other more complex approaches are often advocated (see Cohn, 2005, for further discussion).

3. Results and discussion

3.1. Spatial extent of models

Initially, the combined SPARROW/GAGES dataset was used to develop a single multivariate regression model to estimate long-term mean annual suspended-sediment discharge for the entire conterminous United States, but the model performed poorly with an R^2 of only 64%. This poor national result contrasts with previous global suspended-sediment modeling efforts by Syvitski and Milliman (2007) that reported much higher values of R^2. The national model was compared with the models developed by Syvitski and Milliman (2007) by employing the combined SPARROW / GAGES dataset, which covers the conterminous United States, to fit a model of the form given by Syvitski and Milliman (2007) in (4). The resulting model exhibited an R^2 of just 28%. The poor performance of the Syvitski and Milliman model on the US dataset is likely due to the fact that their model was based on many large basins such as the Amazon, Congo, and Mississippi. The mean drainage area and sediment discharge reported in the global database are 25 and 45 times larger than those reported in the combined GAGES/SPARROW dataset, respectively. Additionally, the model developed by Syvitski and Milliman (2007) was developed with the intent of predicting suspended-sediment discharge in coastal zones rather

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[3] Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the US Government.

than at any ungaged river location within a watershed, as is the case here. These initial comparisons led us to develop regression models of suspended-sediment discharge for the eastern US at finer regional (spatial) scales.

3.2. Sediment discharge models for the eastern US

Table 1 summarizes the variables found to correlate with suspended-sediment discharge in the study regions. The B term, defined previously in (4c) and given in Syvitski and Milliman (2007), was approximated using variables from the GAGES and Schwarz (2008) SPARROW data sources.

Regression models for mean annual suspended-sediment discharge of the form given in (5) were estimated for water resources regions 1–8 and are summarized in Table 2. For example, sediment discharge in kg/s is predicted in region 1 by:

$$Q_s = e^{-9.14} DA^{1.07} \%Ag^{.265} \qquad (8)$$

Note that model coefficients reported in Table 2 can be interpreted as elasticities; meaning that a 1% change in magnitude of any of the independent explanatory variables results in a percent change in sediment discharge given by its model coefficient, on average, holding all other variables constant. For example, the coefficient on drainage area, DA, in (8) is interpreted as follows: A 1% increase in drainage area leads to a 1.07% increase in mean annual sediment discharge, on average, holding the impacts of agricultural land use, %Ag, constant. Elasticities have been used in other areas of hydrology to interpret model coefficients (e.g., Sankarasubramanian et al., 2001).

3.2.1. Model goodness of fit

Across the eight regions considered Table 2 reports prediction R^2 values that range from 75.9% to 92.7%, while NSE values range from 78.1% to 93.9%. The average prediction error (SE) of the models ranges from 56.5% to 124.3%, confirming the inherent inaccuracies

associated with modeling suspended-sediment discharge identified in previous studies (Schwarz, 2008; Syvitski and Milliman, 2007). Regional regression models developed for estimating other hydrologic statistics, such as mean annual streamflow generally perform better. For example, the prediction error of 10 streamflow statistics including flood, daily discharge, and low-flow were estimated using regional regression techniques in the Potomac River Basin by Thomas and Benson (1970). The resulting models exhibited prediction errors ranging from less than 10% for average annual flow to greater than 100% for 20-year 7-day low-flow, with an average prediction error of roughly 35%. Thus estimation of mean annual suspended-sediment discharge using regional regression methods appears to result in models with average prediction errors that are similar to those developed for low-flow statistics.

Fig. 2 illustrates model goodness of fit by comparing the performance of (A) the eight individual regional models plotted on a single graph to (B) the semi-national model (labeled as "1–8" in Table 2) containing all 8 regions. Results indicate that the individual regional suspended-sediment discharge models are more meaningful and accurate than the single, semi-national model based on overall reported NSE values of 86.7% and 80.7%, corresponding to the regional and single semi-national plots, respectively, in Fig. 2. The disparity in the model results depicted in Fig. 2 is due in part to the wide range of variables that comprise the regional models. For example, sediment discharge in region 1 is adequately explained using only drainage area and agricultural land use area, whereas sediment discharge in region 3 requires a different set of explanatory variables including drainage area, average May precipitation, and average soil permeability.

3.2.2. Guidance on application of resulting models

All models developed in this study are multivariate statistical models and extrapolation outside the bounds of the explanatory variables used to develop the models is not recommended. For example, caution should be exercised when using the regional

Table 1
List of explanatory basin characteristics included in regression models to predict suspended-sediment discharge. Unit abbreviations are as follows: square kilometers (km^2), meters (m), centimeters (cm), inches per hour (in./h), millimeters (mm), and people (ppl). GAGES data are from Falcone et al. (2010); SPARROW data are from Schwarz (2008).

Variable name	Description	Units	Data source
Geomorphic/topographic/hydrologic variables			
DA	Drainage area	km^2	GAGES
ElevMean	Mean watershed elevation	m	GAGES
StrahlerMax	Maximum Strahler stream order in watershed	Unitless	GAGES
Land use variables (1992)			
%Wet	Wetland, includes woody and emergent herbaceous wetlands	Percent	SPARROW
%Ag	Agricultural land, includes cultivated crops, pasture, and hay	Percent	SPARROW
%Urb	Urban land, includes low/high intenstiy residential land and commercial/industrial/transportation land	Percent	SPARROW
Climatic variables (period of record 1971–2000)			
P-Feb, P-May, P-Jun	Mean monthly precipitation for February, May, and June	cm	GAGES
P-Seas	Precipitation seasonality index, ranges from even monthly precipitation (0) to all precipitation falls in a single month (1)	Unitless	GAGES
Soils variables			
%No200	Average value of percent by weight of soil material less than 3 in. in size and passing a No. 200 sieve (.074 mm)	Percent	GAGES
%No10	Average value of percent by weight of soil material less than 3 in. in size and passing a No. 10 sieve (2 mm)	Percent	GAGES
%Sand	Average value of sand content	Percent	GAGES
Perm	Average permeability	cm/hr	GAGES
B Term			
B	$IL(1 - T_E)E_h$, see Syvitski and Milliman (2007) and Roman (2010) for additional calculation details	Unitless	GAGES/ SPARROW
I	Glacial erosion factor (1 + .09A$_g$), where A$_g$ is the percentage of the drainage basin covered with pernnial ice/snow	Unitless	GAGES
L	Dominant lithology factor, ranges from hard (.5) to weak (3)	Unitless	GAGES
T$_E$	Upstream reservoir trapping efficiency, ranges from no sediment trapping (1) to majority of sediment is trapped (1), calculated by the Brune Equation following Syvitski et al., 2003 such that $T_E = 1 - (.05/\Delta\tau_r^{0.5})$; where $\Delta\tau_r = V/Q$, V = total upstream reservoir storage volume before 1990 (km^3) (Note: reservoirs with storage volumes of less than .5 km^3 were not evaluated), and Q = average long-term mean annual discharge (km^3/year)	Unitless	GAGES/ SPARROW
E$_h$	Anthropogenic erosion factor, ranges from population density > 200 ppl/km^2 (.3) to <200 ppl/km^2 (1)	Unitless	GAGES

Note: Many other explanatory variables were considered than those included in this table (i.e., temperature, dam density, and others). This list represents variables found to correlate with suspended-sediment discharge in the 8 study regions. Land use variables were computed as a percentage of total basin drainage area.

Table 2
Regression models for estimation of mean annual suspended-sediment discharge (expressed in kilograms per second) by region.

Variable	Region								
	1	2	3	4	5	6	7	8	1–8
Intercept	−9.14 (−22.96)	−16.44 (−13.26)	−12.95 (−9.03)	−39.25 (−5.98)	−1.94 (−1.63)	−14.00 (−15.08)	−25.26 (−13.62)	−16.17 (−6.06)	−20.10 (−30.71)
DA	1.07 (20.33)	1.07 (22.21)	.832 (18.81)		.988 (17.75)	1.25 (18.69)	1.17 (14.64)	1.10 (7.91)	1.06 (36.61)
MeanElev					−1.21 (−4.64)				
%Wet				−.614 (−5.51)				−1.68 (−6.11)	
%Ag	.265 (3.78)	.344 (4.01)						.680 (4.85)	
%Urb						.820 (6.70)			.321 (6.48)
P-Feb								4.67 (4.18)	
P-May			3.38 (6.04)				3.60 (4.52)		2.44 (9.18)
P-Jun				6.67 (4.70)					
P-Seas									.341 (4.96)
%No200		2.01 (5.69)					2.19 (6.14)		1.77 (16.01)
%No10				3.60 (3.51)					
%Sand					.893 (2.77)	1.13 (4.93)			
Perm			−0.48 (−9.28)						
B						.538 (5.38)	.346 (3.53)	.419 (2.70)	.199 (4.62)
StrahlerMax				5.81 (11.28)					
n	30	96	161	54	101	41	78	23	590
Adj-R^2	93.4%	88.2%	79.1%	80.3%	77.4%	93.0%	80.8%	87.0%	80.5%
Pred-R^2	92.7%	87.4%	78.5%	78.0%	75.9%	91.1%	79.3%	80.3%	80.2%
NSE	93.9%	88.6%	79.5%	81.8%	78.1%	93.7%	81.8%	90.0%	80.7%
RMSE	0.526	0.830	0.928	0.839	0.876	0.528	0.774	0.533	0.966
SE	56.5%	99.7%	116.8%	101.0%	107.4%	56.7%	90.5%	57.3%	124.3%
BCF	1.134	1.393	1.522	1.380	1.446	1.132	1.325	1.119	1.587

Note: The table reports model coefficients (β's in Eqs. (5) and (6)) along with their *t*-ratios (in parentheses), the number of stations used to develop the regression models in each region (n), adjusted and prediction R^2 (adj-R^2 and pred-R^2), Nash–Sutcliffe Efficiency (NSE), root mean square error (RMSE), Bias Correction Factor (BCF) and the average prediction error, expressed as a percent of the prediction, (SE) for each model. A *t*-ratio is the ratio of the estimated model coefficient (β) to its standard error. All goodness of fit statistics were computed and reported in logarithmic space except for the SE which was retransformed and computed in real space. All coefficients were significant at the 1% level. See Table 1 for variable definitions.

regression models to predict suspended-sediment discharge at stations with upstream drainage areas smaller or larger than those listed in Table 3 because the models were not estimated for watersheds outside the reported ranges. In such instances, the use of process-based simulation methodologies such as GeoWEPP (LESAM, 2010) is recommended. In addition, the regional regression approach used in this study relies on average basin values upstream of each station. As a result, limitations inherent in this approach include (1) spatial variation of variables within basins (e.g., soil properties) and (2) the spatial arrangement of sediment sources and sinks in each basin. Spatially-distributed models such as SPARROW are able to directly address the effect of spatial variability directly by calculating suspended-sediment discharge on a reach-by-reach basis.

3.3. Discussion of model results

The model explanatory variables quantified in Table 2 indicate that suspended-sediment discharge in the eastern United States generally correlates with a combination of drainage area, land use, seasonal precipitation, soil composition, hydrologic modification, and to a lesser extent, topography (e.g., mean elevation). Of all explanatory variables considered, a unit change in monthly

average precipitation results in the greatest change in magnitude of long-term suspended-sediment discharge. Significant in five of the nine models, model coefficients associated with monthly average precipitation variables range from 2.4 to 6.7, indicating a highly positive and non-linear response of sediment discharge to monthly average precipitation. The highly non-linear sensitivity to rainfall indicates that even a small increase in seasonal rainfall can dramatically increase long-term suspended-sediment discharge in many regions. Such a result may be quite important in future studies that seek to evaluate the impact of climate change on sediment delivery rates.

3.4. Model cross validation experiments

Cross-validation was performed on the regression models to evaluate their ability to adequately predict suspended-sediment discharge in practice. A repeated random sub-sampling validation method was performed on each model by splitting each regional dataset randomly into training (75%) and validation (25%) datasets. A regression was performed on each training data set using the independent variables comprising each regression model reported in Table 2. This training regional regression model was then used to estimate sediment discharge at all watersheds in the validation
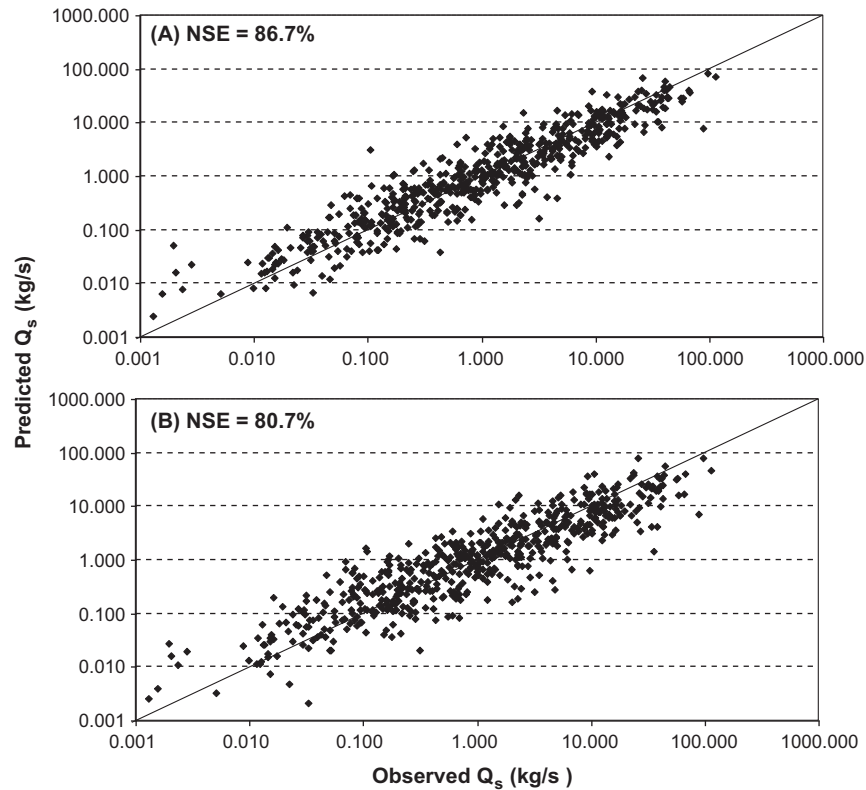
Fig. 2. Comparison of mean annual suspended-sediment discharge regression models using (A) 8 individual regions and (B) All 8 regions combined into a semi-national model. Q_s is mean annual suspended-sediment discharge, expressed in kilograms per second (kg/s), and NSE is the Nash–Sutcliffe Efficiency statistic. Observed Q_s refers to the values computed by Fluxmaster as discussed in Section 2.1, while Predicted Q_s refers to values computed using the multivariate regression models presented in Table 2.

Table 3
Upstream drainage area statistics expressed in square kilometers (km^2), by region (see Fig. 1 for the definition of each region).

Region	Min.	Max.	Median
1	25	25,050	574
2	19	47,364	641
3	20	49,802	1384
4	107	16,409	984
5	33	45,577	811
6	14	13,215	355
7	106	42,041	2811
8	131	13,843	2073
1–8	14	49,802	1126

dataset. An issue inherent in random sub-sampling is that some observations may never be selected in the validation sub-sample, while other observations may be selected many times. The random sub-sampling procedures were repeated 1000 times to ensure that any such disparities were kept to a minimum. Fig. 3 displays the results from the 75% training, 25% validation split through comparison of average Nash Sutcliffe Efficiency values obtained from the 1000 dataset splits. Fig. 3 demonstrates that in most cases, only small reductions in model efficiency result when the validation dataset is used, leading to the overall conclusion that the models will be effective in predicting sediment discharge in practice, at ungaged sites where an average error of model prediction over 100% is acceptable.

There is a large difference between the calibration and validation average NSE in region 8, which is likely due to the small number of sites in that region (23 sites). There were only six sites in each 25% validation sub-sample in that region, making validation results suspect. Region 8 only achieved a prediction R^2 of 53.3% after three independent variables had been added to the regression. It
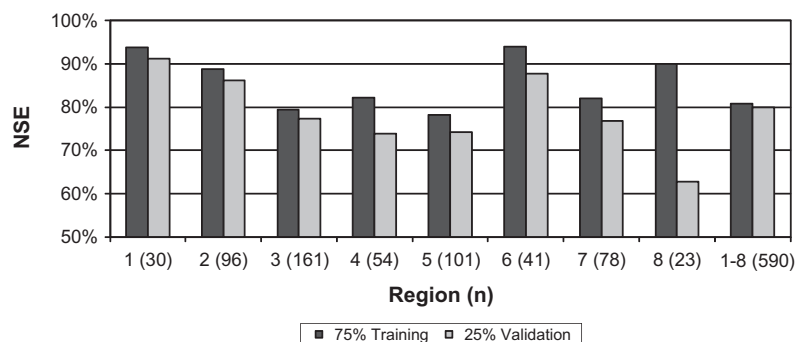

Fig. 3. Cross-validation showing average Nash Sutcliffe Efficiency (NSE) of 1000 random sub-sampling runs using a 75% training, 25% validation dataset split for each model. The number of stations used to model each region is denoted as (n). For example, 72 sites were used for training and 24 were used for validation in region 2.
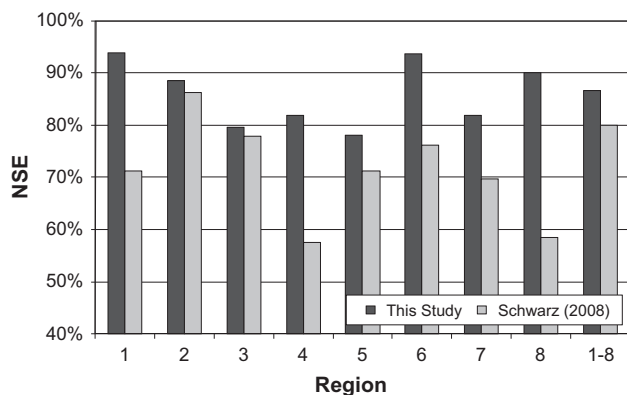
Fig. 4. Comparisons of the Nash–Sutcliffe Efficiency (NSE) statistic between regional regression models and predictions from the national SPARROW model for suspended-sediment. Note that the 1–8 value plotted as "This Study" was computed using all eight of the regional regression models rather than the semi-national "1–8" model reported in Table 2.

took five independent variables to achieve a prediction R^2 of 80.3%, which is a rather excessive number of variables to include in a model based on only 23 sites. It is recommended that any results obtained from the region 8 model be treated with caution.

3.5. Regional regression model comparisons with SPARROW

The multivariate regression models developed as a part of this study (see Table 2) employ sediment discharge estimates from Schwarz (2008), which were computed using Fluxmaster for a national SPARROW sediment-discharge model. Thus, direct comparisons could be made between the two modeling approaches. Fig. 4 displays the computed NSE of the two competing models by region in log space.

The uniformly larger NSE values shown in Fig. 4 indicate that the multivariate regression models reported here generally predict mean annual suspended-sediment discharge with greater accuracy than the SPARROW model. It is likely that models developed here performed better than the SPARROW model because the regional models employ a combined 36 parameters to estimate suspended-sediment discharge specifically for the eight eastern regions of the US, whereas the SPARROW model uses only 16 parameters and was estimated for the entire conterminous United States. For example, the R^2 of the initial national regression model discussed previously was 64% compared to an R^2 of 71.1% for the national SPARROW model. Future work will investigate regionalization of the national SPARROW model for suspended-sediment discharge predictions using recently developed methods for the national nutrient SPARROW models (Schwarz et al., 2011); the present analysis demonstrates the potential improvement in
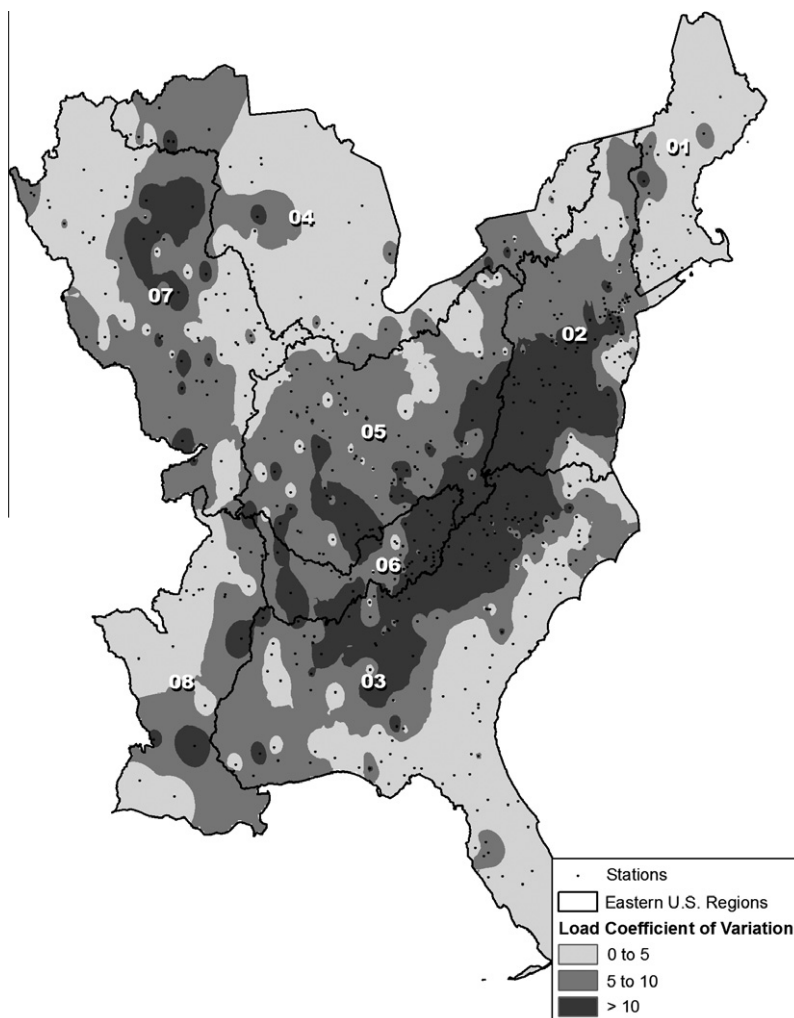

Fig. 5. Contour map of the coefficient of variation of estimated daily suspended-sediment discharge.

Table 4
Regression Goodness of Fit Based on Coefficient of Variation (CV) Classes, Goodness of Fit statistics include prediction R^2 (Pred-R^2), adjusted R^2 (Adj-R^2), Nash–Sutcliffe Efficiency (NSE), and average prediction error expressed as a percent of the prediction (SE); n is the number of monitoring stations in each CV class. All coefficients reported by these models are significant at the 1% level.

Model	CV	n	Pred-R^2	Adj-R^2	NSE	SE
1	0–5	269	87.7%	88.1%	88.4%	98.9%
2	5–10	160	84.9%	85.8%	86.3%	99.8%
3	>10	161	74.4%	75.3%	76.0%	110.8%

model accuracy that may be realized through such a regional-scale analysis. In fact, a recent SPARROW model of suspended-sediment flux in the Chesapeake Bay watershed, which encompasses much of region 2, reported a RMSE of 0.96 (Brakebill et al., 2010). This is comparable to the average model prediction error reported for the region 2 regional regression model seen in Table 2.

3.6. Influence of sediment discharge variability on regression precision

The definition of regions in this study is somewhat arbitrary because they were simply based on the major water resource regions. Vogel et al. (1998) report that the persistence and year-to-year variability of annual streamflow are relatively homogeneous within each of the 2-digit US hydrologic regions. However, no studies have evaluated the homogeneity of suspended-sediment discharge at a regional or national scale. Variability was estimated using the coefficient of variation, CV, of the daily discharge defined as the standard deviation divided by its mean. Fig. 5 illustrates a contour map of values of CV for three different classes of CV: 0–5, 5–10, and greater than 10.

The gross variations in CV of daily suspended-sediment discharge illustrated in Fig. 5 indicate that unlike annual streamflow, daily sediment discharge is not homogenous throughout regions 1–8. To test the impact that variations in sediment discharge have on model precision, regression models were developed for the regions associated with each of the three classes of CV. The results (Table 4) indicate that improved regressions were obtained for low CV stations (CV < 10) over regressions for all regions reported as the "1–8" model in Table 2 (prediction R^2 of 80.2%). Clearly, the largest challenge to improving regional regressions in the future will be discerning a better way to predict suspended-sediment discharge for regions with highly variable suspended-sediment discharge.

4. Conclusions

This is the first study we are aware of that has developed regional regression models for predicting mean annual sediment discharge at ungaged river locations in the eastern US through use of easily obtainable watershed characteristics. The resulting relations exhibit prediction R^2 values ranging from 76.9% to 92.7%, with an average value of 82.9% across the eastern US. The average prediction error (SE) of the models ranges from 56.5% to 124.3%, which is analogous to the errors associated with regional regression models for estimating low-flow statistics. These results demonstrate the feasibility of predicting suspended-sediment discharge from relatively simple regression equations of the type used in other hydrologic regionalization studies for estimating flood and low-flow statistics. The results of this study represent an improvement in prediction accuracy over previous modeling efforts, which sought to predict sediment discharge using worldwide regression models and a national SPARROW model.

The models indicate that sediment discharge in the eastern US is generally correlated with basin area, land use patterns, seasonal precipitation, soil composition, hydrologic modification, and to a lesser extent, topography. Among all basin characteristics considered, suspended-sediment discharge delivery across the eastern US is most sensitive to changes in seasonal rainfall and soil composition.

The regional regression models for estimating suspended-sediment discharge developed here are easy to apply once upstream basin characteristics have been obtained, and have the potential to be useful for a variety of applications by a variety of constituencies including policy makers, environmental scientists, water resource engineers and managers, the agriculture industry, and state and federal agencies. Cross validation of resulting models confirmed that the models are expected to perform similarly to calibration runs. The exception to this is the region 8 model, which performed poorly in cross-validation experiments, likely due to poor spatial coverage of suspended-sediment and flow data within southern portions of the region.

To advance this research further, the following steps are suggested: (1) Determine the cause(s) of the high variations in sediment discharge depicted in some regions shown in Fig. 5. (2) Develop indicators of homogeneous suspended-sediment behavior and use those indicators to identify regions in the United States in which the variability of sediment discharge is homogenous. (3) Expand the combined GAGES/SPARROW database with a richer class of explanatory variables identified in this study that are expected to be correlated with sediment discharge. (4) Develop a suite of models that predict the mean and variance of annual suspended-sediment discharge as a function of basin characteristics for the entire nation based on identified homogeneous regions of suspended-sediment discharge behavior, while constraining models to each include a single variable from each identified watershed characteristics class (e.g., drainage area, land use, soils, precipitation, and topography). Estimates of both the mean and variance of suspended-sediment discharge will enable one to develop a more complete description of the stochastic properties of sediment discharge at ungaged sites.

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