Comparing Empirical Sediment Transport Modeling Approaches in Michigan Rivers

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Abstract

Excess or limited fluvial sediment transport can contribute to and exacerbate many environmental issues including nutrient loading, aquatic habitat degradation, flooding, channel navigation dredging, dam operation, and stream degradation or aggradation. However, fluvial sediment transport is difficult and expensive to comprehensively characterize because it can vary substantially both temporally and spatially. Having better estimates of fluvial sediment transport is important for understanding and solving these environmental issues when it is not possible to collect fluvial sediment samples. Different modeling approaches can be used to help estimate suspended sediment when sampling data are limited or unavailable. This study compared dimensionless sediment rating curves (DSRCs) developed in Pagosa Springs Colorado, Minnesota, and Michigan to determine if these DSRCs were suitable to make predictions of suspended sediment for Michigan rivers.

Approximately 3,000 suspended sediment samples collected in or near Michigan from the mid-1960s through August 2022 were used to develop two DSRC models. The DSRCs developed in Michigan include a pooled DSRC model which uses nonlinear least squares regression, and a mixed-effects DSRC model which uses a mixed-effects modeling approach. In general, there was not a noticeable improvement in the performance of the Michigan mixed-effects DSRC model over the Michigan pooled DSRC model. The two Michigan DSRCs were evaluated against DSRCs developed for Pagosa Springs and Minnesota. The results showed DSRC models developed from Minnesota and Michigan were similar to each other. In contrast, the Pagosa Springs DSRC predicts higher suspended-sediment concentration (SSC) at low flows and increases at a higher rate due to having a greater exponent. The Pagosa Springs DSRC produces higher SSC predictions that do not approximate the observed data well at most of the Michigan sites in the study. The results suggest that the Pagosa Springs DSRC was not suitable to make predictions of suspended sediment for Michigan rivers. The similarity of the DSRC equations developed for Minnesota and Michigan compared to the Pagosa Springs DSRC equation suggest that there may be regional patterns of SSC in the upper Midwest rivers that differ from those in other areas of the country like Pagosa Springs. A regionally applicable model could be developed and strengthened by combining data from additional midwestern states. Since the Michigan DSRCs goodness-of-fit metrics were comparable to the site-specific simple linear regressions (SLRs) and outperformed them in the aggregate goodness-of-fit metrics, the Michigan DSRCs are suitable to make predictions of suspended sediment in Michigan rivers with limited data. However, the availability of the DSRCs from this study should not diminish

the value of collecting physical samples and exploring alternative modeling approaches because of the uncertainty associated with using DSRCs.

Introduction

An understanding of sediment transport is necessary for river studies, bridge designs, flood-level computations, aquatic habitat assessments, cumulative watershed analyses, river restoration plans, and addressing Federal and State concerns relating to excessive sediment in streams. However, the training, time, and equipment needed to collect accurate sediment samples makes sediment studies expensive to conduct. Physical sediment samples collected in strategic locations can be used to develop empirical models that can maximize the utility of limited data collection efforts to provide estimates of sediment transport in rivers and provide the data needed to address sediment-related resource management issues (Barry et al. 2008; Rosgen 2006, 2010; Troendle et al. 2001). One example of an empirical model is a dimensionless sediment rating curve (DSRC).

Developing and applying DSRCs requires a strong relation between streamflow and sediment data (suspended-sediment concentration [SSC] or bedload) and involves developing dimensionless relations between streamflow and SSC or bedload. Bankfull streamflow is used as a normalization parameter to develop the DSRC models. One study developed four DSRCs from a small group of streams located in the San Juan River Basin near Pagosa Springs, Colorado and showed these equations could be used to estimate sediment transport for geographically far-removed streams with different flow regimes, geology, and climate and provided improved predictions over theoretical equations (Rosgen 2010). The four Pagosa Springs DSRC model equations (Pagosa DSRCs) were delineated by Pfankuch (1975) stream stability categories. Ellison et al. (2016) tested to see if these Pagosa DSRCs could provide reasonable estimates in Minnesota where the geographic, flow regimes, geology, and climate are much different than Pagosa Springs, Colorado. The study also developed DSRCs with data collected in Minnesota and found the Minnesota DSRCs performed better than the Pagosa DSRCs.

However, this method cannot be used everywhere because it is limited to sites that have a strong and positive relation between streamflow and SSC which is not the case for every site. It is common for streamflow and sediment transport to be uncorrelated which can be caused by many sediment supply and transport processes (Gellis 2013) that will not be elaborated in this paper. Also, the methods used in this study can only be used at sites that have bankfull streamflow estimates and have samples collected near bankfull streamflow. Even though the method requires data collection (3 samples), it is less than what is required when conducting a full sampling campaign (approximately 30 samples or greater). Rosgen (2010) suggested estimates of bankfull sediment data could be developed from an equation fitted through drainage area versus bankfull sediment to obtain inputs for the DSRCs when it is not possible to collect sediment data; however, that introduces additional uncertainty to the predictions that could be substantial. Alternatively, if enough data are available, another empirical model such as machine learning model could be developed to make predictions without the need for bankfull sediment data as was done in Lund et al. (2022).

This study was a collaborative effort between the U.S. Geological Survey (USGS) Upper Midwest Water Science Center and the Michigan Department of the Environment, Great Lakes, and Energy (EGLE) Water Resources Division to explore whether DSRCs developed from data collected in Pagosa Springs (Rosgen 2010), Minnesota (Ellison et al. 2016), and Michigan were suitable to make predictions for other Michigan rivers. Existing SSC and streamflow data collected in Michigan were used to develop site-specific regression equations and two Michigan DSRCs. Site-specific regression equations and the Michigan DSRCs were compared to DSRCs developed in Minnesota (Ellison et al. 2016) and Pagosa Springs, Colorado (Rosgen 2010) to compare how well each model fit the collected data. There were some potential issues with how DSRC models were evaluated in Ellison et al. (2016) which this study tried to improve. One of the Michigan DSRC models was developed using a mixed-effects approach to address the lack of independence in the observational data due to repeated samples at each site.

Description of the Study Area

Michigan encompasses 58,110 square miles in the upper Midwestern United States (Library of Michigan 2022). Michigan contains two peninsulas, both of which are nearly surrounded by four of the Great Lakes: Huron, Michigan, Erie, and Superior (Library of Michigan 2022). The Great Lakes play an important role in moderating the state's climate, causing it to be more temperate and moist than other north-central states (Frankson et al. 2022). Precipitation is common in the state but varies regionally. Statewide annual precipitation has ranged from a low of 22.7 inches in 1930 to a high of 41.8 inches in 2019 (NOAA NCEI 2022). Parts of the Upper Peninsula receive more than 180 inches of snow annually (Frankson et al. 2022). Michigan contains nine hydrologic unit code (HUC) HUC–level four basins (Western Lake Superior, Southern Lake Superior, Northwestern Lake Michigan, Southwestern Lake Michigan, Southeastern Lake Michigan, Northeastern Lake Michigan, Northwestern Lake Michigan, Northwestern Lake Huron, Southwestern Lake Huron, and St. Clair – Detroit (U.S. Geological Survey 2019). The fifteen sampling locations selected for this study represent a cross section of varying sized drainage areas within the major basins present in Michigan (Figure 1; Table 1).

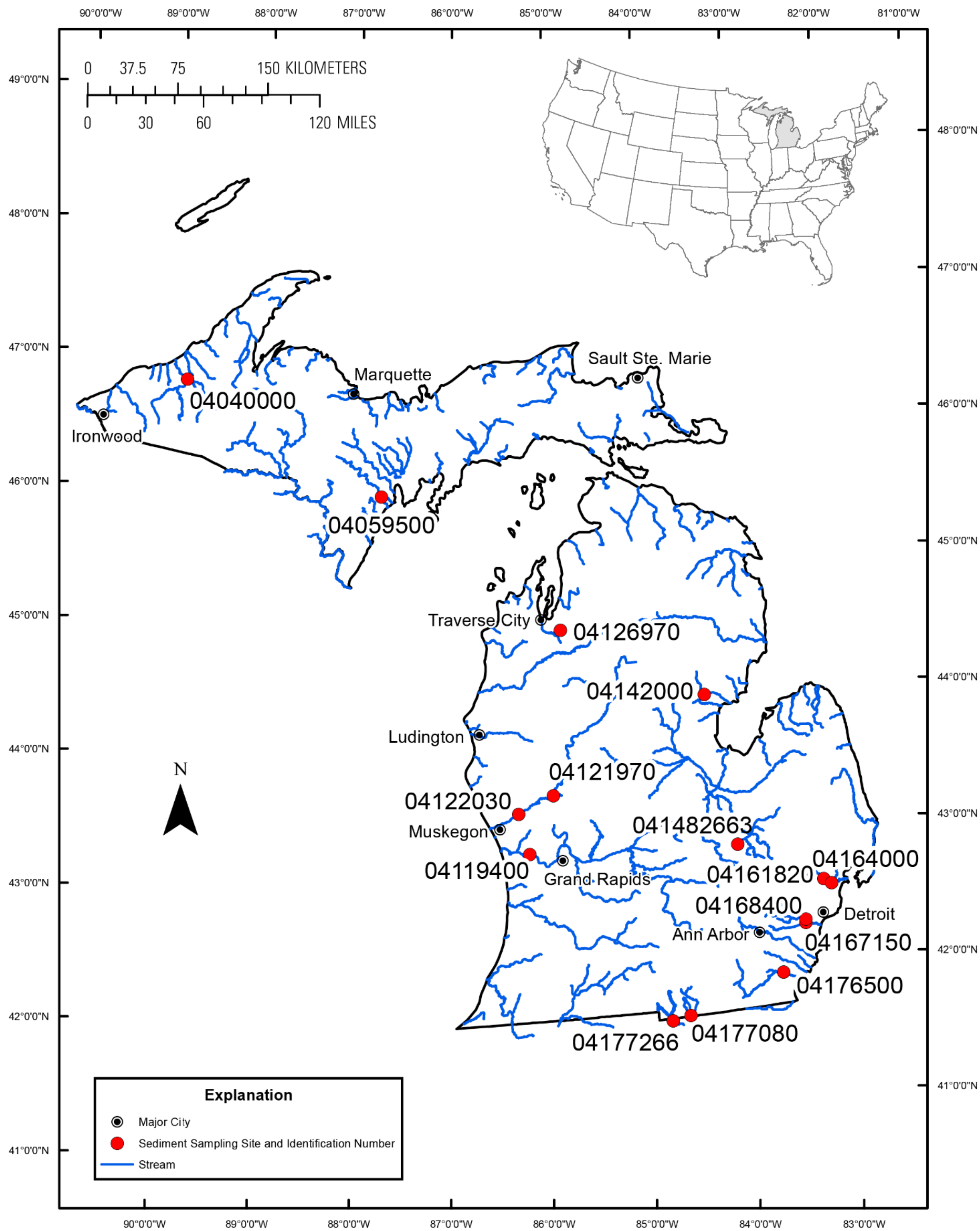

Figure 1. Map of Michigan and 15 U.S. Geological Survey streamflow-gaging stations where suspended-sediment concentration samples were collected. Base modified from U.S. Geological Survey and U.S. Census Bureau, various dated and various scales, and in Universal Transverse Mercator, zone 15, North American Datum of 1983.

Table 1. Station information for 15 selected sites in Michigan.
[mi², square miles; UP, upper peninsula; W, west; E, east; SW, southwest; NW, northwest; NE, northeast; SE, southeast; S, south]

Station Number	Start Date	End Date	Drainage Area (mi²)	Region	Latitude	Longitude	Pfankuch Stability Rating
04040000	1974	2022	1,340	UP-W	46.72080	-89.20690	Good/Fair
04059500	1974	2022	450	UP-E	45.75500	-87.20200	Good
04119400	2011	2022	5,290	SW	43.01470	-85.95580	Good
04121970	2011	2013	2,313	NW	43.43470	-85.66530	Good/Fair
04122030	1974	1990	2,480	NW	43.31810	-86.03640	Good
04126970	1984	2008	141	NW	44.65670	-85.43670	Excellent
04142000	1966	2022	320	NE	44.07250	-84.02000	Fair
04161820	1996	2022	309	SE	42.61450	-83.02670	Good/Fair
04164000	1966	2006	444	SE	42.57780	-82.95170	Good/Fair
04167150	2014	2016	110	SE	42.33060	-83.24810	Fair
04168400	2014	2022	91	SE	42.30830	-83.25280	Fair
04176500	1967	2022	1,042	SE	41.96060	-83.53110	Good
04177080	2018	2022	70.8	S	41.70940	-84.49080	Poor
04177266	2018	2022	102	S	41.68330	-84.67000	Fair
041482663	2012	2022	19	SE	42.94190	-83.84610	Poor

Methods

Data Compilation and Site Selection

The USGS compiled and reviewed existing SSC, bedload, and streamflow data from the National Water Information System ([NWIS] U.S. Geological Survey 2022) collected in the State of Michigan from the mid-1960s through August 2022 (Table 1). Since bedload data were limited, bedload was not included as part of the study. Instantaneous streamflow was used when available, and daily streamflow was used when instantaneous was unavailable. The data compilation resulted in a list of potential sites that could be used for the study.

Determining Bankfull and Pfankuch Stability Ratings

The list of potential sites compiled by USGS was shared with EGLE, and they selected sites and performed site evaluations that would include bankfull streamflow determinations and Pfankuch stability ratings (Rosgen 2001; Pfankuch 1975). The evaluations also included documentation of the sites with photos. EGLE compiled station descriptions and stage/streamflow rating information. The bankfull elevations were determined by a combination of methods involving surveys and identifying bankfull indicators such top of point bars, stain lines, bank undercuts, changes in slope, bank material, and vegetation (Leopold et al. 1964; Rosgen, 1994, 1996). For streamgages, bankfull elevations were referenced to the stage/streamflow rating curve to obtain the bankfull streamflow (bnkfulQ).

Determining Suspended Sediment at Bankfull Streamflow

Samples used to determine SSC at bankfull streamflow (SSCbank) were limited to samples collected within the range of one-half to two times bnkfulQ. At least three samples were required within this range to estimate mean SSCbank at a site. An initial estimate of SSCbank was computed by multiplying bankfull streamflow and the ratio of mean SSC to mean streamflow for samples within the range of one-half to 2 times bankfull streamflow (Ellison et al. 2016). The initial estimate of SSCbank was recalculated using a jackknife resampling procedure described in Ellison et al. (2016) to reduce potential bias in this estimate due to small sample sizes.

Data Analysis

Because there were only two sites (USGS station numbers 041482663 and 04177080) that had a poor Pfankuch stability rating (Table 1), there were not enough data to develop a separate DSRC from these data like what was done in Rosgen (2010) and Ellison et al. (2016). Since the data collected at the poor stability sites did not deviate from the data collected at good/fair stability sites, data from all 15 sites in Michigan were combined to develop the DSRC models. Dimensionless values of streamflow (dimQ) and SSC (dimSSC) were computed by dividing each sample SSC and streamflow measurement by their SSCbank and bnkfulQ value, respectively (Table 2). Kendall's tau (Kendall, 1938, 1975) was computed at each site to determine if there was a significant monotonic relation between dimQ and dimSSC (Table 2). Data from sites without significant relations (p-values of 0.05 or greater) were not used to develop models. The final dataset consisted of 2,988 SSC samples from 15 sites (Table 2).

Table 2. Summary statistics and bankfull values for 15 selected sites in Michigan. [tau, Kendall's tau; n, number of samples; bnkfulQ, bankfull streamflow; Q, streamflow; sd, standard deviation; SSC, suspended-sediment concentration; --, not available]

Station Number	tau*	n	bnkfulQ	minQ	maxQ	meanQ	sdQ	minSSC	maxSSC	meanSSC	sdSSC
04040000	0.53	248	9,421	236	23,700	1,664	2,426	9	1,540	94	200
04059500	0.4	290	2,383	19	4,250	438	558	--	100	7	11
04119400	0.3	135	16,500	1,020	34,900	6,414	4,602	2	899	34	108
04121970	0.27	57	6,046	921	10,800	3,807	2,350	1	34	6	6
04122030	0.57	108	5,571	810	20,200	2,443	2,160	3	312	25	36
04126970	0.71	26	247	99	338	172	70	3	65	18	17
04142000	0.46	351	1,930	80	2,685	439	433	1	358	45	62
04161820	0.38	334	946	51	2,140	298	229	1	913	43	73
04164000	0.4	32	1,301	109	2,380	584	648	2	412	127	136
04167150	0.51	38	588	22	1,015	191	193	8	240	69	69
04168400	0.47	45	735	34	965	212	241	4	341	80	94
04176500	0.49	266	3,327	53	13,500	1,412	1,848	1	807	76	114
04177080	0.48	274	145	9	1,520	154	171	4	2,117	127	200
04177266	0.49	281	376	3	1,710	202	213	1	672	90	108
041482663	0.51	503	127	0	552	49	72	3	22,130	278	1,383

*All tau p-values are less than 0.001 from Z-test

The relation between dimQ and dimSSC was quantified using a nonlinear least squares (nls)regression model and a nonlinear mixed-effects model. The resulting DSRC equations can be used to estimate dimSSC at streamflows with limited SSC measurements. Dimensionless SSC estimates can then be converted into dimensional units by multiplying dimensionless value by

SSCbank. Weighted nonlinear least squares regression was used to quantify the relation between dimQ and dimSSC using the following equation form:

$$y = B + (1 - B)X^{B_2} \qquad (1)$$

where

y	is a dimensionless ratio value of SSC,
B	is a coefficient determined from the data,
X	is a dimensionless ratio value of streamflow, and
B_2	is a coefficient determined from the data.

This equation form was developed in Ellison et al. (2016) such that the fitted model would pass through the calculated SSCbank at bnkfulQ. However, the equation developed in this study was weighted differently than the equation in Ellison et al. (2016), which was weighted by the inverse of dimQ because the residuals increased as dimQ increased. The residuals from the DSRC equation developed from the Michigan data did not follow this pattern. Instead, the Michigan DSRC was weighted with the inverse of the number of samples at the site. This approach equalizes the influence of the different sites and reduces the potential bias that can occur because some sites had many samples, and other sites had fewer samples. Equations were fit using the nls function in R (R Development Core Team, 2022).

The data used to develop the Michigan DSRC equation contain a different number of samples from each of the 15 sites ("n" in Table 2). The DSRC was fit by pooling all samples together and fitting a regression line. However, these pooled data violate the regression assumption of independence because observations from a particular site may have a different relation than samples from other sites or the general population. This can result in heteroskedastic errors if observations from different sample sites exhibit dissimilar residual patterns. It can also skew the fitted equation towards one or more sites with larger sample sizes at the expense of less-sampled sites. To address this lack of independence, a nonlinear mixed-effects DSRC model was also fit to the same data.

A mixed-effects model quantifies fixed effects (relations between dimQ and dimSSC that are the same across all sites) and random effects (differences in the relation between dimQ and dimSSC from one site to another site). The mixed effects model produces site-specific model coefficients for each site in the dataset as well as a population-level model coefficients which can be used to predict dimSSC at new locations. The nonlinear mixed effect model was fit using the nlme package in R (Pinheiro and Bates 2022).

Site specific log-simple linear regression (SLR) equations were independently developed for each site. These equations relate the logarithm of measured SSC to the logarithm of streamflow. Site specific equations were developed as benchmarks for the performance of the DSRC models.

Evaluating Model Performance

Model performance was first assessed by comparing observed SSC values to cross-validated model predictions as well as visual methods. Cross-validation model predictions of SSC were obtained at each site by first removing the data collected at that site and refitting a model with the remaining data. Then, the refit model was used to predict SSC at the site which was removed from the dataset. This process was done at each site of the 15 sites. Cross-validation predictions are more representative of model performance for new predictions because the data for the site being predicted are not in the model development data set. This method of validation was an improvement compared to how the models were evaluated in Ellison et al. (2016) which used the same data to develop and validate the models.

Cross-validation model predictions were evaluated by using several goodness-of-fit metrics including a modified Nash-Sutcliffe efficiency (mNSE) and the Kling-Gupta efficiency (KGE). The Nash-Sutcliffe efficiency ([NSE] Nash and Sutcliffe 1970) is commonly used to assess hydrologic model performance. An NSE of zero represents the same performance as could be obtained by using the mean of the data. Positive NSE values represent an improvement on this baseline and negative values indicate performance worse than the mean. Because the NSE incorporates the squared difference between model predictions and observed values in the numerator, it is oversensitive to and can be biased by large outliers in the data. The mNSE lessens this bias by using the absolute value of the difference between predictions and observations rather than the squared difference (Legates and McCabe 1999).

The KGE is increasingly used as an alternative to the NSE in assessing hydrologic model performance. The KGE addresses several shortcomings of the NSE by combining the correlation, bias, and variance of model predictions in a more balanced way (Gupta et al. 2009). Interpretation of the KGE is similar to NSE, with positive values up to 1 indicating 'good' performance and low or negative values indicating 'poor' performance.

Results

The pooled DSRC and mixed-effects DSRC models developed from the Michigan data as well as the Pagosa and Minnesota DSRC models are presented below (Figure 2):

Michigan Pooled DSRC (good/fair/poor stability): $SSC = 0.023 + 0.977Q_d^{0.913}$ (2)

Michigan Mixed-Effects DSRC (good/fair/poor stability): $SSC = 0.11 + 0.89Q_d^{1.09}$ (3)

Pagosa DSRC (good/fair stability): $SSC = 0.0636 + 0.9326Q_d^{2.4085}$ (4)

Minnesota DSRC (good/fair stability): $SSC = 0.026 + 0.974Q_d^{0.951}$ (5)

SSC is a dimensionless ratio value of suspended-sediment concentration,

and

Q_d is a dimensionless ratio value of streamflow.

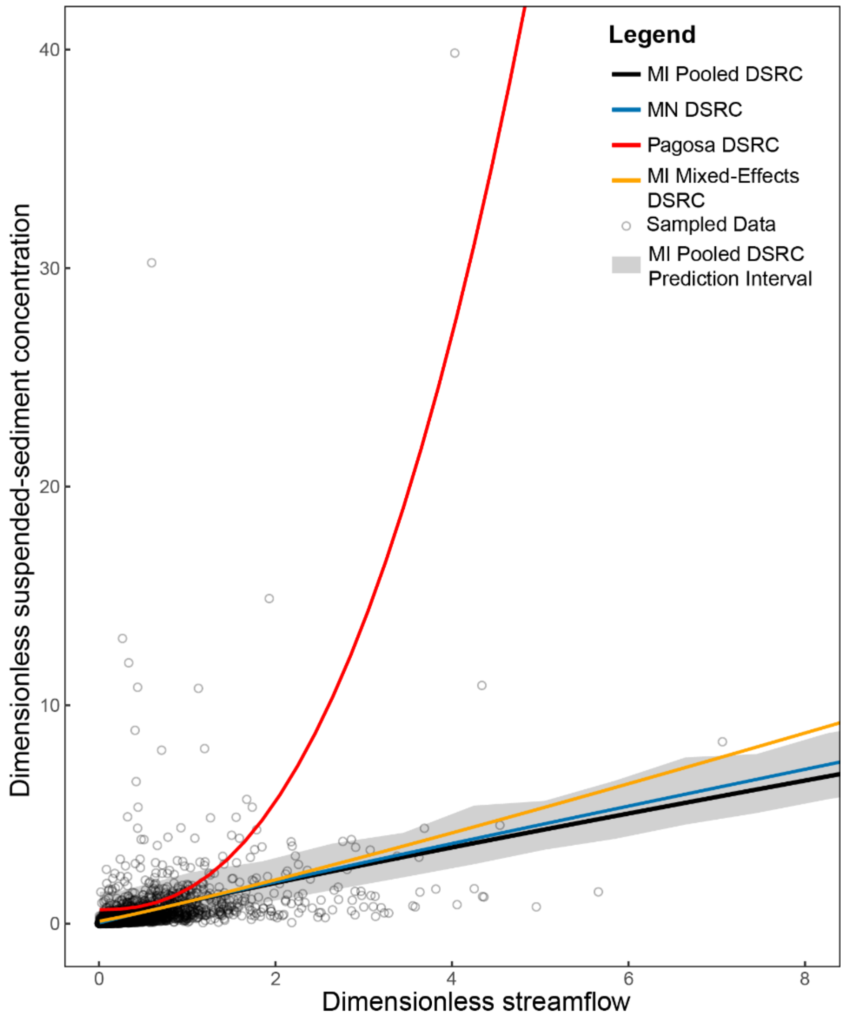

Figure 2. Four dimensionless sediment rating curve (DSRC) equations applied to select Michigan (MI) rivers.

The uncertainty in regression coefficients was due to variability and uncertainty in the underlying sample dataset. When quantifying the uncertainty in regression predictions, bootstrap prediction intervals were computed for the Michigan DSRC equation (gray shade in Figure 2) using the nlstools package (Baty et al. 2015). These intervals represent the range of values that contain the true value in a specified prediction 95-percent of the time. It is important to consider that there is additional uncertainty in these equations because dimensionless values were computed using SSCbank estimates which also has uncertainty. This additional uncertainty is not included in the bootstrap prediction intervals. Additionally, prediction intervals are representative of the uncertainty in the dimSSC only and do not include the additional uncertainty in SSC predictions, which are multiplied by the SSCbank.

Regression trend lines are shown for each site in Figure 3. Site specific SLR models are also included for comparison as they are assumed to provide the most accurate predictions of suspended sediment at a given location. DSRCs developed for Michigan (Equation 2) and Minnesota (Equation 3) are nearly linear, with exponents near 1 and a y- intercept near zero. In contrast, the Pagosa DSRC predicts higher SSC at low flows and increases at a higher rate due to having a greater exponent. The Pagosa DSRC (Equation 4) produces higher SSC predictions that do not approximate the observed data well (Figure 4) and at most sites (Figure 3). The similarity of DSRC equations developed in Minnesota and Michigan in contrast to the Pagosa DSRC equation suggest that there may be regional patterns of SSC in upper Midwest streams that differ from those in other areas of the country. A regionally applicable equation could be developed and strengthened by combining data from additional midwestern states.

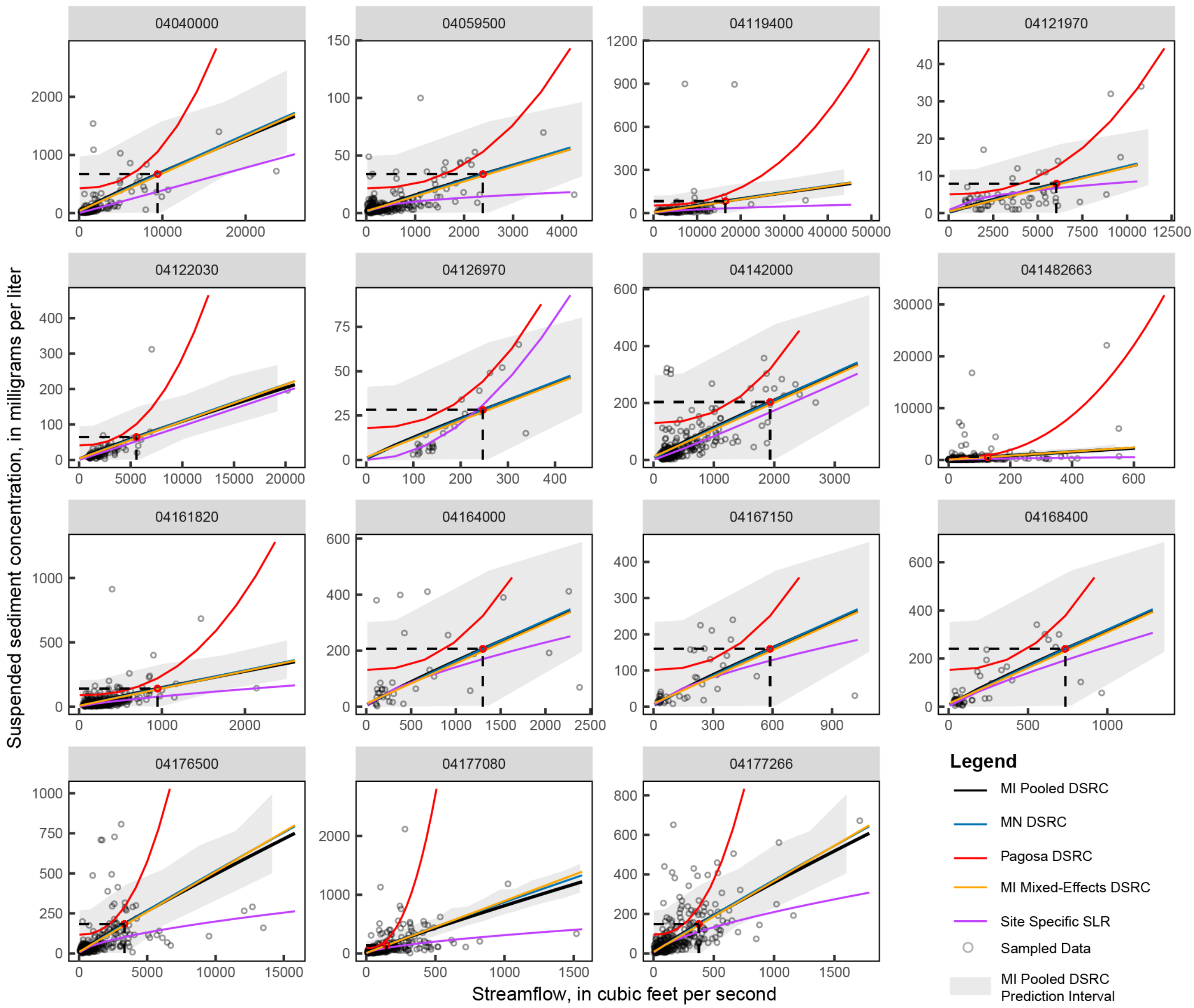

Figure 3. Four dimensionless sediment rating curves (DSRCs) and site specific simple linear regression (SLR) models with trendlines and prediction intervals for 15 selected rivers in Michigan (MI). The number above each panel is the site's station number.

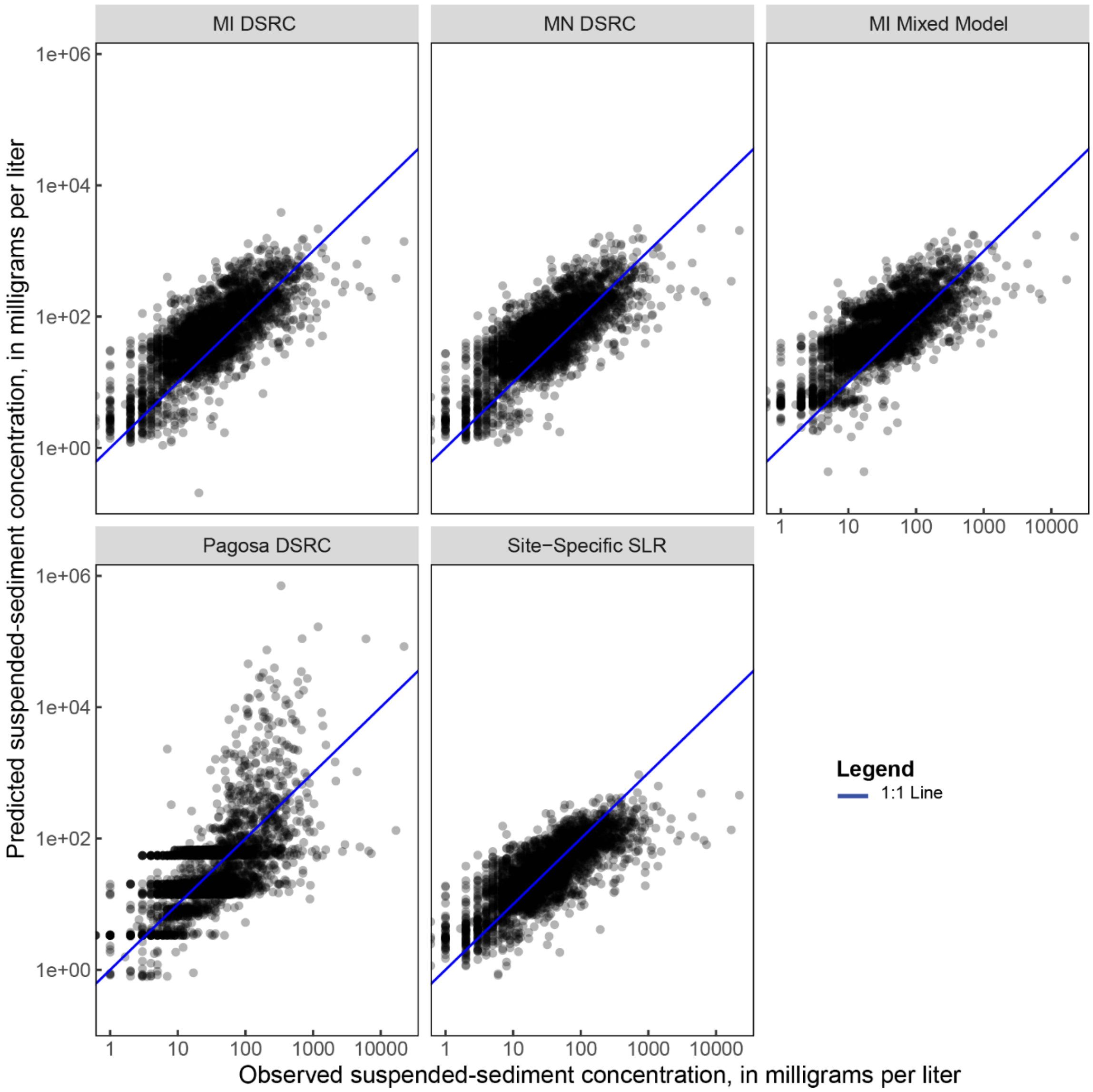

Figure 4. Observed versus predicted values of suspended-sediment concentrations from five models.

The mNSE and KGE were computed for cross-validated predictions at each site using the pooled DSRC and mixed-effects DSRC models developed from Michigan data as well as predictions using the site-specific SLRs, and the Pagosa and Minnesota DSRC models. Median values of mNSE and KGE are shown in Table 3 while site specific KGEs are shown in Figure 5. Regionally developed upper Midwestern DSRC equations (Minnesota and Michigan) outperformed the Pagosa DSRC equation at most sites (Figure 5). Model performance was comparable across site specific models and the DSRC equations developed in Minnesota and Michigan. The Pagosa DSRC had the worst model performance with a median mNSE and a median KGE of -0.33 and -0.89, respectively (Table 3). Median mNSE values across sites were 0.24 and 0.16 for the Michigan pooled DSRC and the Michigan mixed-effects DSRC respectively, and median KGE values were 0.37 and 0.34 (Table 3). The Michigan pooled DSRC model had higher KGE values than the site-specific models (Figure 5). Due to the poor goodness-of-fit metrics of the Pagosa

DSRC, it is not suitable to make predictions of SSC for Michigan rivers compared to the other DSRC equations.

Table 3. Goodness-of-fit metrics for simple linear regression (SLR) models, Michigan (MI), Pagosa, and Minnesota (MN) dimensionless sediment rating curves (DSRCs), and the MI mixed model. [med, median; rmse, root mean squared error; pbias, percent bias; nse, Nash-Sutcliffe efficiency; mnse, modified Nash-Sutcliffe efficiency; kge, Kling-Gupta efficiency]

Equation	med.rmse	med.pbias	med.nse	med.mnse	med.kge
Site-specific SLR	73.01	-30.5	0.15	0.31	0.15
MI DSRC	65.88	5.6	0.31	0.24	0.37
Pagosa DSRC	190.42	1.3	-6.82	-0.33	-0.89
MN DSCRC	66.53	3	0.32	0.26	0.37
MI Mixed Model	68.06	14.1	0.2	0.16	0.34

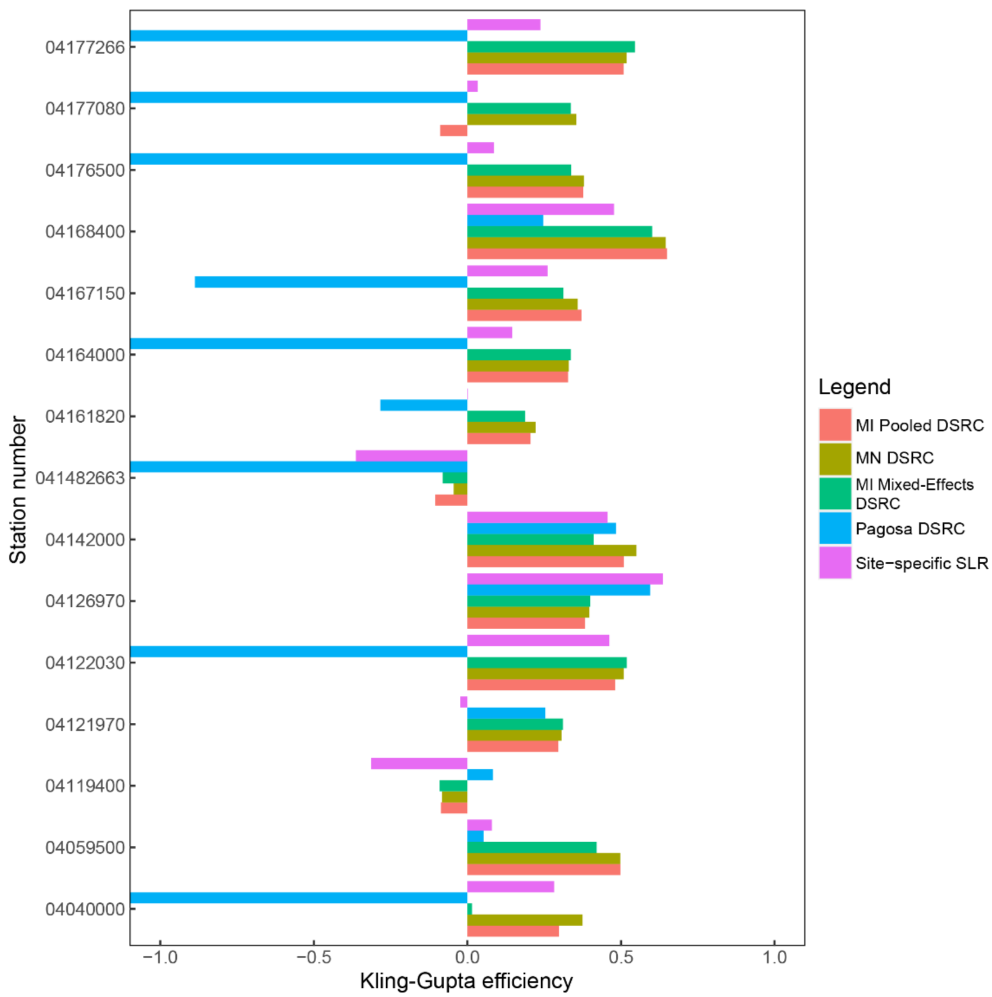

Figure 5. Kling-Gupta efficiency values for Pagosa, Minnesota (MN), Michigan (MI) dimensionless sediment rating curves (DSRCs), MI mixed model, and site-specific simple linear (SLR) regression models for selected rivers in Michigan.

Some site-specific SLR did not perform as well as expected. Lack of fit in these SLRs was due to a combination of small sample size and outlier influence. Additionally, site-specific SLRs assumed a linear relation between the log of SSC and log of streamflow; however, at some locations, the assumption of linearity was not true at very low streamflows, causing bias and poor fit which is not obvious in Figure 3. At some sites, the site-specific SLRs performed well, and their KGEs were comparable or better than the Michigan pooled DSRC model (Figure 5). The Michigan pooled DSRC model benefits from being less affected by outliers because there are more data points. Goodness-of-fit metrics are subject to bias due to sampling uncertainty such as sampling sizes, high variability, or outliers. The goodness-of-fit metrics used here try to overcome this bias but are still prone to uncertainty. Therefore, we used a suite of goodness-of-fit metrics, not just a single metric, to compare between models (Althoff and Rodrigues 2021; Clark et al. 2021). In general, there was no improvement in the performance of the Michigan mixed-effects DSRC model over the Michigan pooled DSRC model. Since the Michigan DSRCs goodness-of-fit metrics were comparable to the site-specific SLRs (Figure 5) and outperformed them in the aggregate goodness-of-fit metrics (Table 3), the Michigan DSRCs are suitable to make predictions in Michigan rivers with limited data.

Although regional Midwestern DSRCs (Minnesota and Michigan) provide more accurate predictions in Michigan than the Pagosa DSRC equation, the variability of the data may not be well explained by either equation. There are several types of variability which may be degrading the performance of Minnesota and Michigan DSRC equations. Some sites have very high outlier values of SSC at lower streamflows which do not follow the relation of other samples at that site. In some cases, SSC values seem to have two diverging relations with streamflow. For example, at one site (USGS station number 04176500), there are apparently two relations – one in which SSC increases rapidly around bankfull streamflow and one in which SSC remains moderate at high streamflows (Figure 3). These high SSC values could be due to upstream and or local sediment and streamflow related factors that could explain these differences. If these factors could be identified, they could be incorporated into a new equation or a machine learning model to provide better estimates.

Summary

A thorough understanding of sediment transport is necessary for river studies because excess or limited fluvial sediment transport can contribute to and increase many environmental issues including: nutrient loading, aquatic habitat degradation, flooding, channel navigation dredging, dam operation, and stream degradation or aggradation. However, fluvial sediment transport is difficult and expensive to comprehensively characterize because it can vary substantially both temporarily and spatially. Having better estimates of fluvial sediment transport is important for understanding and solving these environmental issues. Different modeling approaches can be used to help provide estimates of suspended sediment when sampling data are not available. This study compared DSRCs developed in Pagosa Springs, Minnesota, and Michigan to determine if these DSRCs were suitable to make predictions of suspended sediment for Michigan rivers.

Approximately 3,000 suspended sediment samples were collected in or near Michigan from the mid-1960s through August 2022. These samples were used to develop two DSRC models for Michigan. Site-specific regression equations were compared to DSRCs developed in Michigan, Minnesota, and Pagosa Springs to compare how well each model fit the collected data. The results showed that the DSRC equations developed from Minnesota and Michigan were more similar than the DSRC equation developed from data collected in Pagosa Springs. In contrast, the Pagosa DSRC predicts higher SSC at low flows and increases at a higher rate due to having a greater exponent. The Pagosa DSRC produces higher SSC predictions that do not approximate the observed data well at most of the sites in the study. The results suggest that the Pagosa Springs DSRC was not suitable to make predictions of suspended sediment for Michigan rivers. In general, there was not a noticeable improvement in the performance of the Michigan mixed-effects DSRC over the Michigan pooled DSRC. The similarity of the DSRC equations developed in Minnesota and Michigan compared to the Pagosa DSRC equation suggests there may be regional patterns of SSC in the upper Midwest rivers that differ from those in other areas of the country. A regionally applicable model could be developed and strengthened by combining data from additional midwestern states. Since the Michigan DSRCs goodness-of-fit metrics were comparable to the site-specific SLRs (Figure 5) and outperformed them in the aggregate goodness-of-fit metrics (Table 3), the Michigan DSRCs are suitable to make predictions in Michigan rivers with limited data available. However, the availability of the DSRCs from this study should not diminish the value of collecting physical samples and exploring alternative modeling approaches because of the uncertainty associated with using DSRCs.

Disclaimer

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References

Althoff, D. and Rodrigues, L.N. 2021. "Goodness-of-fit criteria for hydrological models: Model calibration and performance assessment," Journal of Hydrology, Volume 600, 26674, ISSN 0022-1694. [Also available at, https://doi.org/10.1016/j.jhydrol.2021.126674.]

Baty, F., Ritz, C., Charles, S., Brutsche, M., Flandrois, J., and Delignette-Muller, M. 2015. A Toolbox for Nonlinear Regression in R: The Package nlstools. Journal of Statistical Software, 66(5):1-21. https://www.jstatsoft.org/article/view/v066i05. doi 10.18637/jss.v066.i05.

Clark, M.P., Vogel, R.M., Lamontagne, J.R., Mizukami, N., Knoben, W.J.M., Tang, G., Gharari, S., Freer, J.E., Whitfield, P.H., Shook, K.R., Papalexiou, S.M. 2021. "The abuse of popular

performance metrics in hydrologic modeling" Water Resources Research, Volume 57, 9, SN 0043-1397. [Also available at, https://doi.org/10.1029/2020WR029001.]
Ellison, C.A., Groten, J.T., Lorenz, D.L., and Koller, K.S. 2016. “Application of dimensionless sediment rating curves to predict suspended-sediment concentrations, bedload, and annual sediment loads for rivers in Minnesota,” U.S. Geological Survey Scientific Investigations Report 2016, 5146: 68 p. http://dx.doi.org/10.3133/sir20165146.
Frankson, R., Kunkel, K.E., Champion, S.M., and Runkle, J. 2022. Michigan State Climate Summary 2022, NOAA Technical Report NESDIS 150-MI, NOAA/NESDIS, Silver Spring, MD, 4 p.
Gellis, A.C. 2013. “Factors influencing storm-generated suspended-sediment concentrations and loads in four basins of contrasting land use, humid-tropical Puerto Rico,” Catena, 104:39–57, https://doi.org/10.1016/j.catena.2012.10.018.
Gupta, H.V., Kling, H., Yilmaz, KK.K., and Martinez, G.F. 2009. “Decomposition of the mean squared error and NSE performance criterial: Implications for improving hydrological modelling,” J. Hydrol., 377(1-2):80-91, doi:10.1016/j.jhydrol.2009.08.003.
Kendall, M.G. 1938. “A new measure of rank correlation,” Biometrika, 30:81–93. [Also available at http://dx.doi.org/10.2307/2332226.]
Kendall, M.G. 1975. Rank Correlation Methods (4th ed.). London, Charles Griffin, 202 p.
Legates, D. R., and McCabe, G. J. Jr. 1999. “Evaluating the Use of ‘Goodness-of-Fit’ Measures in Hydrologic and Hydroclimatic Model Validation,” Water Resour. Res., 35(1):233-241.
Leopold, L.B., Wolman, M.G., and Miller, J.P. 1964. Fluvial Processes In Geomorphology. San Francisco, California, Freeman, 522 p.
Library of Michigan. 2022. Land: accessed December 9, 2022, at https://www.michigan.gov/libraryofmichigan/public/michigan/home-intro/the-library-of-michigan-presents-michigan-in-brief
Nash, J.E., and Sutcliffe, J.V. 1970. “River flow forecasting through conceptual models part 1–A discussion of principles," Journal of Hydrology, 10:3282–3290. [Also available at http://dx.doi.org/10.1016/0022-1694(70)90255-6.]
NOAA NCEI. n.d. “Climate at a Glance: Statewide Time Series, Michigan,” National Oceanic and Atmospheric Administration, National Centers for Environmental Information, Asheville, NC, accessed December 9, 2022. https://www.ncdc.noaa.gov/cag/statewide/time-series/20/
Pfankuch, D.J. 1975. “Stream reach inventory and channel stability evaluation: Missoula, Montana, U.S. department of Agriculture Forest Service,” no. R1-75-002, GPO no. 696-260/200, 26 p.
Pinheiro J., and Bates D., R Core Team 2022. _nlme: Linear and Nonlinear Mixed Effects Models_. R package version 3.1-160, https://CRAN.R-project.org/package=nlme.
R Core Team 2022. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.
Rosgen, D.L. 1994. “A classification of natural rivers,” Catena, v. 22, p. 169–199. [Also available at http://dx.doi.org/10.1016/0341-8162(94)90001-9.]
Rosgen, D.L. 1996. Applied River Morphology. Pagosa Springs, Colorado, Wildland Hydrology, 388 p.
Rosgen, D.L. 2006. “Flowsed/Powersed––Prediction models for suspended and bedload transport,” Proc. of the 8th Federal Interagency Sedimentation Conference (8th FISC), April 2–6, 2006, Reno, Nevada, pp 761–769.
Rosgen, D.L. 2010. “The application and validation of dimensionless sediment rating curves,” Proc. 2nd Joint Federal Interagency Conference, Las Vegas, Nevada, June 27–July 1, 2010, 11 p.

Troendle, C.A., Rosgen, D.L., Ryan, S., Porth, L., and Nankervis, J. 2001. “Developing a ‘reference’ sediment transport relationship,” Proc. 7th Federal Interagency Sedimentation Conference, Reno, Nevada, March 25–29, pp 73–80

U.S. Geological Survey 2019. National Hydrography Dataset (ver. USGS National Hydrography Dataset Best Resolution (NHD) for Hydrologic Unit (HU) 4 - 2001 (published 20191002)), accessed December 9, 2022 at https://www.usgs.gov/national-hydrography/access-national-hydrography-products

U.S. Geological Survey 2022. USGS water data for the nation, U.S. Geological Survey National Water Information System Database, https://doi.org/10.5066/F7P55KJN.