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Rating Curve Development for the Upper James Fork, Lower James Fork and Hinkle Jones Creek in the Upper Poteau River Watershed in Arkansas

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Rating Curve Development for the Upper James Fork, Lower James Fork and Hinkle Jones Creek in the Upper Poteau River Watershed in Arkansas

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Biological Engineering Program

Biological and Agricultural Engineering Department

College of Engineering

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Undergraduate Honors Thesis

ADVISORY AND COMMITTEE SIGNATURE PAGE

This thesis has been approved by the Biological and Agricultural Engineering Department for submittal to the College of Engineering and Honors College at the University of Arkansas

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Acknowledgments:

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Abstract:

Stream discharge is necessary to estimate loads and calibrate and validate watershed models. Access to long-term water quality data and discharge measurements allows for modeling of water quality changes across a watershed over time. However, discharge monitoring stations are often expensive to install and maintain, particularly in small rivers. A more cost-effective method for monitoring streamflow has been implemented in the Upper Poteau River Watershed (UPRW) in Arkansas. This method consists of an SonTek acoustic doppler instrument for measuring storm stream flow, with is combined with manual baseflow discharge measurements. The combined stormflow and baseflow measurements are combined with a continuous stage record from a HOBO water level logger, in order to develop a rating curve. The goal of this honors project was to evaluate the optimal regression technique or combination of techniques for predicting the relationship between stage and discharge at three sites in the UPRW, and create a rating curve for each site.

Introduction

Despite the passage of the Clean Water Act of 1972, nutrient pollution in streams and rivers is still widespread (Manuel, 2014). Excess nutrients in waterways can result in accelerated eutrophication, which threatens natural ecosystem and human health. The main source of these excess nutrients is nonpoint source pollution, which generally takes form as runoff from agricultural or urban land (US EPA, 2015). Point sources, such as wastewater treatment plants, are also major contributors to nutrient pollution. Improvement strategies such as best management practices (BMPs) and total maximum daily load (TMDL) developments have been implemented in order to mitigate nutrient pollution and improve water quality (Manuel, 2014).

Evaluating and modeling transport of nutrients and sediments within a watershed is important in order to establish watershed management practices and pollution prevention strategies (Chaubey et al., 2007). Along with constituent concentration, discharge is required to estimate loads, conduct trend analyses, and calibrate watershed models. Long-term water-quality data and discharge measurements are used to trace and identify water quality changes across a watershed. The effectiveness of management practices in reducing nutrient and sediment loads can then be evaluated, and additional decisions can be made to address water quality concerns.

Discharge monitoring stations are often costly and at times difficult to install, especially in small streams, which complicates load estimates and flow-adjusting of concentrations for trends. A common method for estimating discharge is the velocity-area method, where discharge is calculated as the product of stream cross sectional area and velocity through the cross section. Discharge in small streams is often measured using hydrologic control structures, such as a weir or flume. In these cases, the discharge can be calculated based on changes in flow depth. However, these methods are still impractical for monitoring numerous natural channels of streams across a watershed.

Due to the difficulty in collecting continuous discharge measurements, rating curves are often developed. A rating curve is a relation of discharge versus stage (water depth) for cross sections or particular points in a stream or river. Creating rating curves requires empirical measurements of stage and corresponding discharge, and a continuous stage record is often cheaper and easier to obtain. By measuring discharge over a variety of stages (e.g. using the velocity-area method), rating curves can then be used to establish a relationship between the stage and discharge for a particular site. Once a rating curve has been established, a continuous discharge record can be estimated and used in load estimation, model calibration and even water quality trends.

The purpose of this study is to develop rating curves for three streams in the Upper Poteau River Watershed (UPRW) in Arkansas. A novel method has been used to collect stage and discharge data across small watersheds in this area. However, rating curves still must be developed to provide a daily record of discharge. The objectives of this study were to evaluate the use of regression, a nonparametric regression, and combination of the two at predicting discharge. The rating curves developed in this study will aid in load estimation at smaller watersheds within the UPRW.

Methods:

Study Site description:

The UPRW is a designated priority watershed under the Arkansas Nonpoint Source Pollution Management Plan (ANRC, 2018). The Poteau River, which originates near Waldron, Arkansas, flows west into Lake Wister in Oklahoma, which serves as a drinking water source for several rural counties in eastern Oklahoma. Land use in the watershed is 5% developed, 59% forested, 9% grassland, 24% agriculture, 1% open water, and 1% wetlands (*Model My Watershed*, 2017).

In the UPRW, a more cost-effective method for monitoring streamflow has been implemented at select streams. A HOBO U20 water level logger (model number U20-001-04) was used to continuously measure stage (Figure 1), and a SonTek-IQ Series acoustic doppler instrument was used to monitor discharge during high flow events (Figure 2).

Figure 1: HOBO U20 water level logger (Onset, 2019)

Figure 2: SonTek-IQ Series acoustic Doppler instrument (SonTek, Inc., 2015)

Each SonTek is calibrated to the specific geometry of the stream channel in which it resides and uses the Doppler shift to measure the channel water velocity. Below depths of 1.5 ft, the SonTek measurements may not be accurate (SonTek, Inc., 2015). Therefore, SonTeks are most commonly used for storm or high flow data. Due to this SonTek depth limitation, base flow measurements are typically made manually. Base flow discharge measurements are collected each month using velocity area methods and are combined with select SonTek data to develop rating curves. This combination of base flow and select SonTek data is used instead of continuous data, in order to have consistency between the three sites.

Stage and discharge data were available for three sites in the UPRW: The Upper James Fork, Lower James Fork, and Jones Creek (Figure 3). The available stage and discharge data was from October 2017-January 2019. Before I acquired the data, the base flow values and select SonTek discharge values had already been combined for each site. The Upper James Fork watershed covers an area of 39 km^2, and the land use is 1% urban, 84% forested, 2% open water, 2% grassland, and 9% agriculture. The Lower James fork watershed covers an area of 95 km^2, and the land use is 4% urban, 70% forested, 1%

open water, 7% grassland, and 18% agriculture. The Jones Creek watershed covers an area of 72 km^2 , and the land use is 3% urban, 85% forested, 5% open water, 4% grassland, and 2% agriculture (Table 1; *Model My Watershed*, 2017).

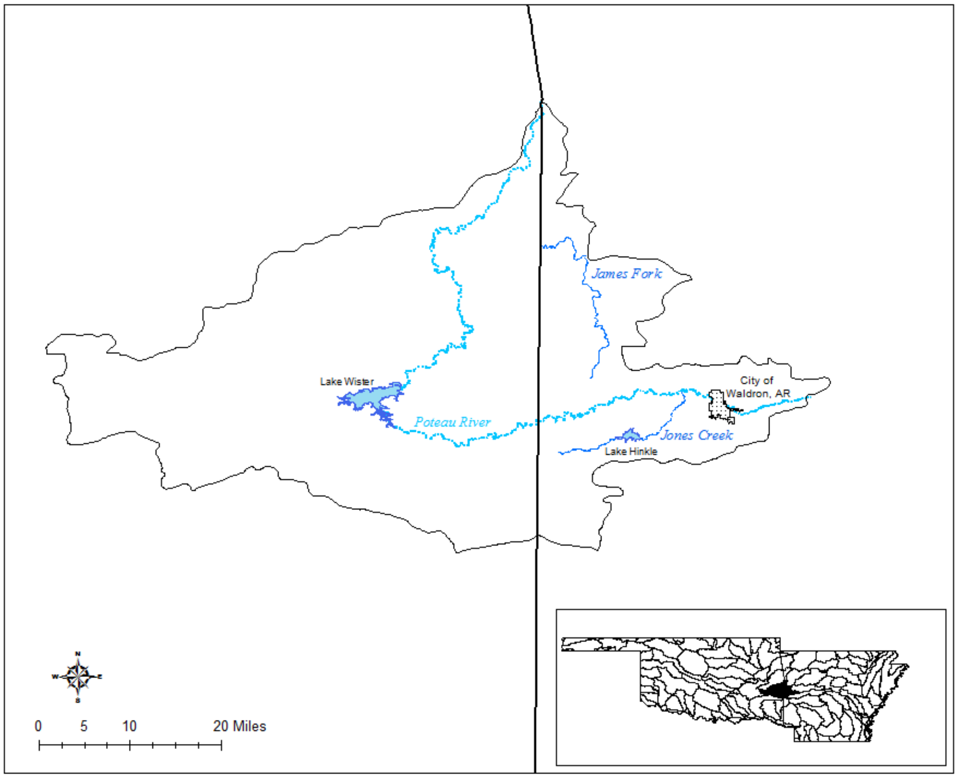

Figure 3: Site Map of the Poteau River Watershed

Table 1: Land Use distribution for the Upper James Fork, Lower James Fork, and Hinkle Jones watersheds

		% of Land Use in Watershed				
Site	**Total area (km^2)**	**Urban**	**Forested**	**Open Water**	**Grassland**	**Agriculture**
Upper James Fork Watershed	39	1%	84%	2%	2%	9%
Lower James Fork Watershed	95	4%	70%	1%	7%	18%
Hinkle Jones Creek Watershed	72	3%	85%	5%	4%	2%

Rating Curve Development:

Prior to any data transformation, the raw stage and discharge data was analyzed for each site. If discharge values of “0 cfs” were present in the raw data, these values were removed. After zeroes were removed, the data for each site was log transformed. A log transformation was chosen because the most common transformation in water quality and hydrology is typically a log transformation (Grabow et al., 1998). The entire range of the data was plotted to manually inspect the relationships of the log transformed data. The two regression techniques used in developing the rating curves were a simple linear regression, and a locally weighted regression (LOESS). LOESS is a nonparametric regression technique that smooths the dependent variable in a moving fashion, and requires no linearity assumptions that are typical for conventional regression methods (Cleveland and Devlin, 1988).

Before separating the rating curve data into different sections, a simple linear regression was applied to the entire data range. Similarly, a LOESS fit was performed on the entire data range. At each site, the LOESS smoothing parameter (*f*) was manually inspected to find the value which minimized error but did not over fit the data. The LOESS smoothing parameter or span *(f)* allows for avoiding over-smoothing or overfitting of the data, where the smoothing of the curve increases as the span increases (Simpson and Haggard, 2018). Root Mean Square Error (RMSE) and residuals were calculated for the LOESS and linear regression fits across the entire data range for each site. After initial regressions and LOESS fits were ran, manual inspection of the plots was used to divide the data into separate groups using the following general method.

- Separate the data into different ranges, based on the visual shifts in the discharge and stage relationships.
- Perform a LOESS analysis using the best smoothing parameter through manual inspection for each separate group of data.
- Perform a linear regression on each group.
- Combine and plot these separate groups onto one rating curve to evaluate if this further reduced the RMSE.

The resulting graphs were evaluated visually to see how the separate curves fit together. The end goal was to minimize the RMSE with the selected rating curve. The physical fit and plot generated also had to visually fit the data, across the range in stage. This process was applied to all three sites. The final decision regarding which regression technique should be applied to each section should be made with consideration given to the total RMSE of the combination and also to the physical fit and plot generated from the overall combination. This general process was followed for all three sites. A number of iterations were completed, in order to pinpoint the best fit for the overall rating curve data. The final plot chosen for each site was selected by considering the total RMSE, the continuity of the curve, and the visual appeal of the combined LOESS and linear regression curves.

Results

Lower James Fork

A total of nine iterations were performed for the Lower James Fork. The first iteration used three different data ranges, and all other iterations used two different data ranges. I walk through two iterations, in which the first uses three separate data ranges, and the second uses two data ranges. As subsequent iterations were performed, the total RMSE for the rating curve decreased to a final RMSE of 0.2219 (Figure 4).

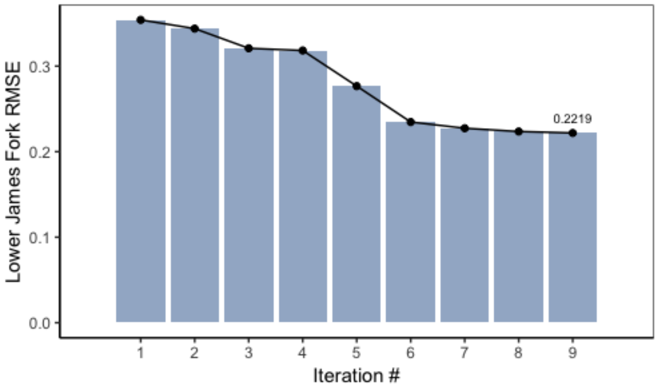

Figure 4: RMSE vs. Iteration Number for Lower James Fork

At the Lower James Fork, peak discharge values ranged from 323-768 cfs, at stage values of 4.0-6.8 ft, respectively. Discharge increased exponentially until a stage value of 4.8 ft. Once the stage exceeded 4.8 ft, discharge gradually increased until the maximum stage value of 9.0 ft (Figure 5). The raw discharge-stage data at the Lower James Fork was log transformed and was manually inspected to determine a break point to separate the data into groups.

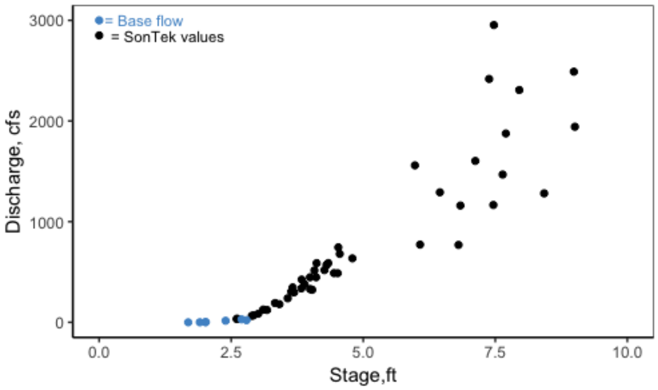

Figure 5: Discharge as a function of stage for the Lower James Fork from October 2017-January 2019, with manual base flow and SonTek flow values indicated

In the first iteration at the Lower James Fork, the data was separated into three groups (Figure 6). The first, second, and third groups occurred at log-transformed stage ranges of 0.28-0.60 log-ft, 0.61-0.78 log-ft, and 0.80-0.95 log-ft, respectively. These breaks were chosen based on the natural separation of the data points after log-transforming the data.

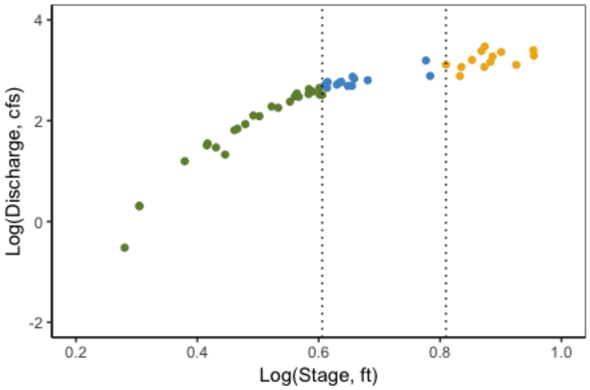

Figure 6: Lower James Fork first iteration for manual inspection and sorting into groups, indicated by vertical lines.

In order to have a base method of comparison between different iterations, a LOESS fit and a simple linear regression were both ran through the entire data range, and the RMSE for each regression type was calculated (Figure 7). The RMSE for the LOESS and linear regression over the entire data range are used as base comparisons against the RMSE calculated from applying different regression techniques to different data groups.

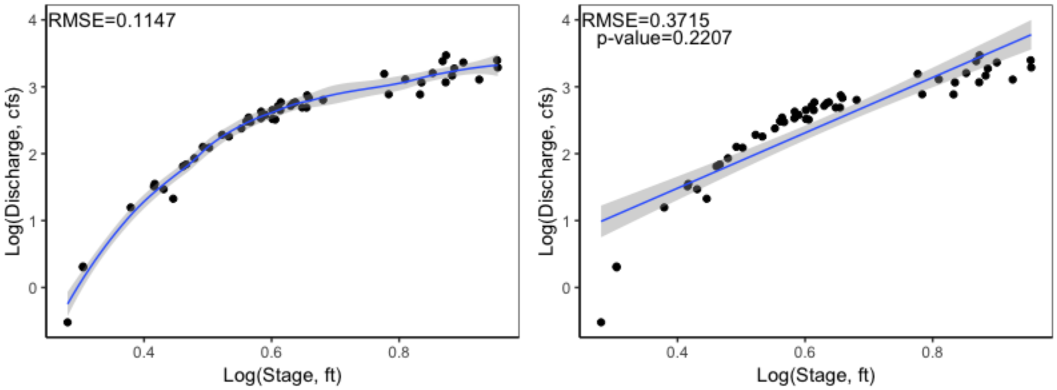

Figure 7: Comparison of LOESS fit and linear regression applied to the entire Lower James Fork data range, with resulting RMSE included.

Next, a LOESS fit and linear regression were applied to each individual data group, and the respective RMSEs were calculated. Following the calculation of the RMSEs for each regression technique applied to all three groups, the total RMSE for all possible combinations of regression techniques was calculated. This process was used in conjunction with a visual examination of the resulting combinations. Including the visual examination helped to account for any discontinuities in graphs that would otherwise be missed if the sole consideration was the total RMSE (Figure 8). The importance of the visual examination is also shown by the comparison of the RMSE for combination 1 and 2; Combination 2 has the lower total RMSE, but Combination 1 is visually the better option (Figure 8, Table 2).

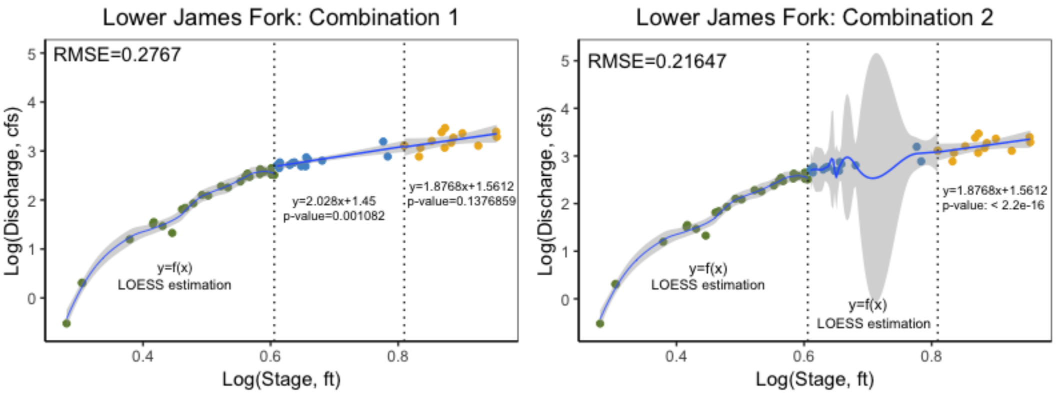

Figure 8: Examples of two combinations of different regression techniques applied to the three different groups, split at stages 0.60 ft and 0.80 ft for the first Lower James Fork iteration

Table 2: Example of total RMSE comparison for two different combinations of regression techniques for each group for the Lower James Fork, for the first iteration

Group	**LOESS RMSE (*f=0.4*)**	**Linear RMSE**
1	0.0787	0.2062
2	1.12E-15	0.0602
3	0.0876	0.1377
Combination 1		
Group	**Regression**	**RMSE**
1	LOESS (*f =0.4)*	0.0787
2	LINEAR	0.0602
3	LINEAR	0.1377
	Total RMSE	**0.2767**
Combination 2		
Group	**Regression**	**RMSE**
1	LOESS (*f =0.4)*	0.0787
2	LOESS (*f =0.4)*	1.12E-15
3	LINEAR	0.1377
	Total RMSE	**0.21647**

Based on this first iteration, the Lower James Fork data was separated into two groups as opposed to three. The first group included the values in the stage range from 0.28-0.681 ft, and the second group included the values in the stage range of 0.681-0.95 ft (Figure 9). Similar to the first iteration, a LOESS fit and linear regression were applied to both groups of data, and the RMSE for both regressions for each group was calculated (Table 3).

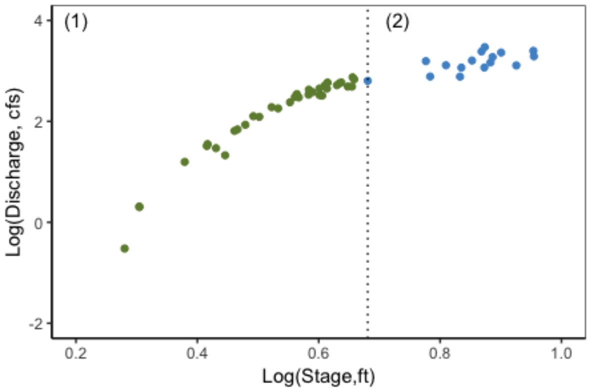

Figure 9: Lower James Fork second iteration for manual inspection and sorting into groups, indicated by vertical dotted line at stage of 0.681 ft.

Table 3: Total RMSE comparison for possible combinations of regression techniques for both groups at the Lower James Fork, for the second iteration

Group	**Loess RMSE (*f=0.4*)**	**Linear RMSE**
1	0.0897	0.2219
2	0.0989	0.1378
Combination 1		
Group	**Regression**	**RMSE**
1	LOESS (*f =0.4)*	0.0897
2	LINEAR	0.1378
	Total RMSE:	**0.2275**
Combination 2		
Group	**Regression**	**RMSE**
1	LINEAR	0.2219
2	LOESS (*f =0.4)*	0.0989
	Total RMSE:	**0.3209**

Based on the visual inspection and the total RMSE, Combination 1 was the better option (Figure 10). Combination 1 had a LOESS regression applied to the first data group, and a linear regression applied to the second data group (Figure 10, Table 3).

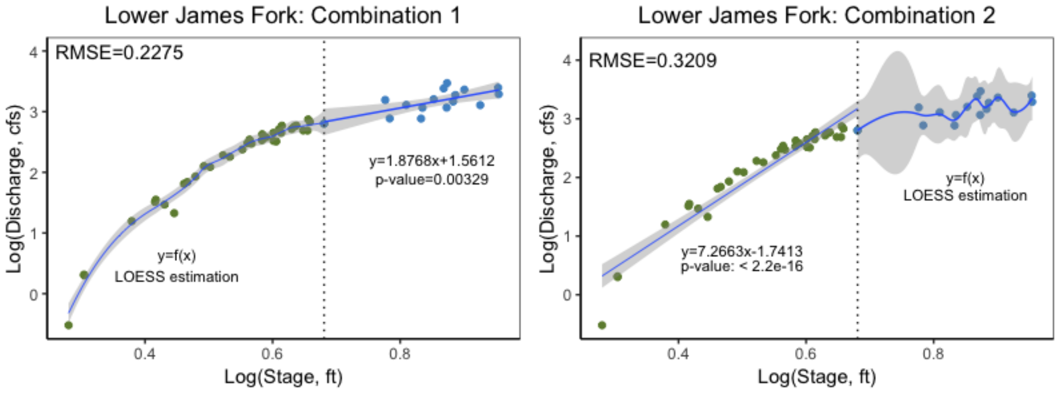

Figure 10: The two possible combinations of regression techniques applied to the two groups split at a stage of 0.681 ft for the second Lower James Fork iteration

This second iteration was used as the basis for the final rating curve developed for the Lower James Fork. The threshold between the first and second group moved from 0.681 ft to 0.6558 ft. In order to create a smoother transition between the two regression techniques, the second group overlapped with the first group at the point (0.6484 ft, 2.8322 cfs). The RMSEs for both possible combinations of regressions and groups were calculated, and considered along with a visual inspection of the combinations (Table 4, Figure 11).

Table 4: Total RMSE comparison for possible combinations of regression techniques for both groups at the Lower James Fork, for the final rating curve

Group	LOESS RMSE	Linear RMSE
1	0.0910	0.2154
2	0.0989	0.1309
Combination 1		
Group	Regression	RMSE
1	LOESS *(f =0.4)*	0.0910
2	Linear	0.1309
	Total RMSE	**0.2219**
Combination 2		
Group	Regression	RMSE
1	Linear	0.2154
2	LOESS *(f =0.4)*	0.0989
	Total RMSE	**0.3143**

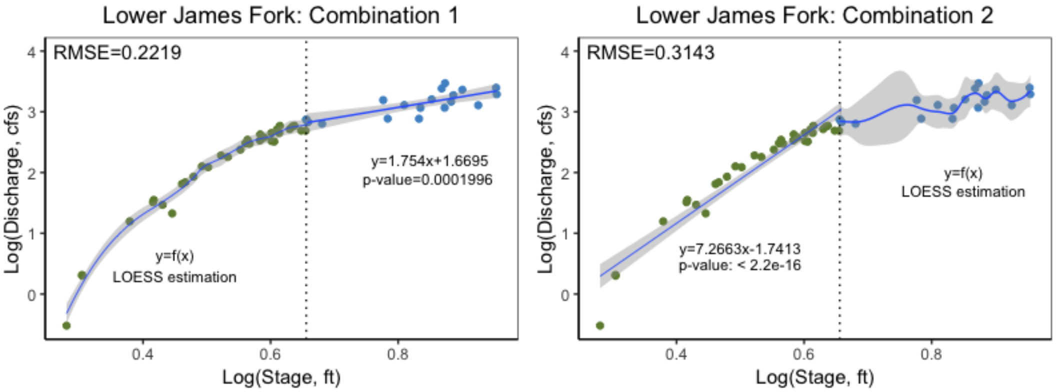

Figure 11: Combinations used for developing the final Lower James Fork rating curve where the break point is 0.6558 ft.

Combination 1 was chosen for the final rating curve (Figure 12). In the first group, for stages of 0.28-0.658 ft, a LOESS regression with a span of *f*=0.4 was applied. A linear regression was applied to the second group, for stage values of 0.6558-0.95 ft, giving the equation $y = 1.754x + 1.6695$.

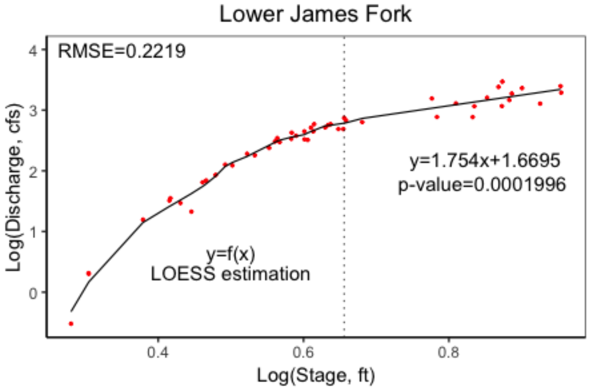

Figure 12: Final Lower James Fork rating curve

The RMSE for the final rating curve was 0.2219, which is greater than the RMSE for the initial LOESS fit applied across the entire data range, equaling 0.1147 (Figure 7). Although the RMSE of the final rating curve is larger than this initial LOESS fit, the combination of regression techniques was still chosen for the final rating curve. The inclusion of a linear regression in the second group allows for better extrapolation for stage values exceeding the maximum observed stage value of 9.007 ft, or the log transformed value of 0.95 ft. Using the equation for the linear portion of the final rating curve (y=1.754x+1.6695), the discharge corresponding to a log transformed stage value of 1.1 ft (i.e., a true stage value of 12.6 ft) was estimated (Figure 13).

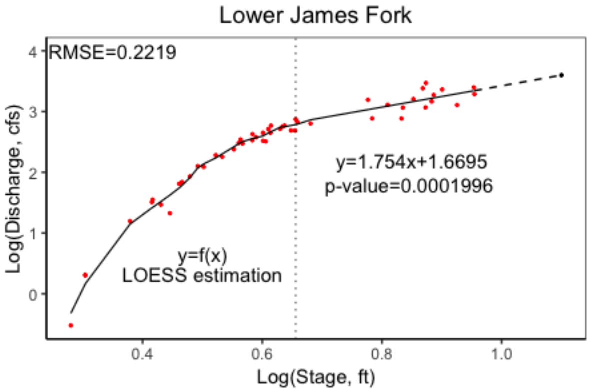

Figure 13: Final Lower James Fork rating curve with extrapolation of a stage value of 12.6 ft, or a log stage value of 1.1 ft

Upper James Fork:

A total of 11 iterations were performed in developing the final Upper James Fork rating curve, with a final total RMSE of 0.2514 (Figure 14).

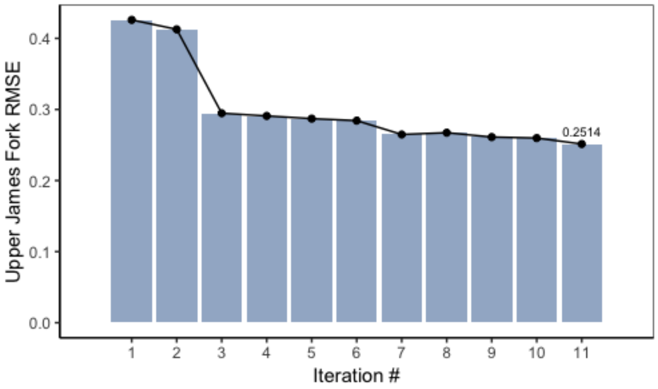

Figure 14: RMSE vs. Iteration Number for Upper James Fork

At the Upper James Fork, peak discharge values ranged from 86.0 to 1026 cfs, with corresponding stage values ranging from 1.78 to 3.95 ft. Discharge during base flow conditions linearly increased with stage up to a stage value of 2.5 ft. Once the stage exceeded 2.5 ft, discharge steeply increased until the maximum stage value of 3.95 ft (Figure 15).

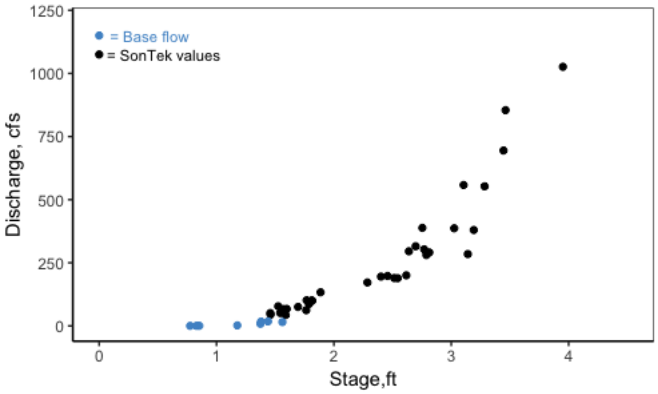

Figure 15: Raw discharge and stage data at the Upper James Fork from October 2017-January 2019

The raw discharge-stage data at the Upper James Fork was log transformed prior to being separated into data groups. The final rating curve for the Upper James Fork consisted of two separate data groups, with the first group ranging from true stage values of 0.775-2.812 ft (corresponding log-transformed stage values of -0.11-0.449 log-ft) and the second group containing true stage values of 2.753-3.95ft (corresponding log-transformed stage values of 0.439-0.59 log-ft) (Figure 16).

Similar to the final rating curve for the Lower James Fork, the final groups for the Upper James Fork overlapped at four data points, from stage ranges of 2.763-2.813 ft. However, the LOESS span of *f=0*.8 was used for the first Upper James Fork group, as opposed to the span of *f=0.4* used for the first Lower James Fork group. The span was increased to *f=0.8* to avoid overfitting the data points in the first group. A linear regression was used for the second data group, giving a final equation of $y = 3.5519x + 0.8982$ (Figure 16).

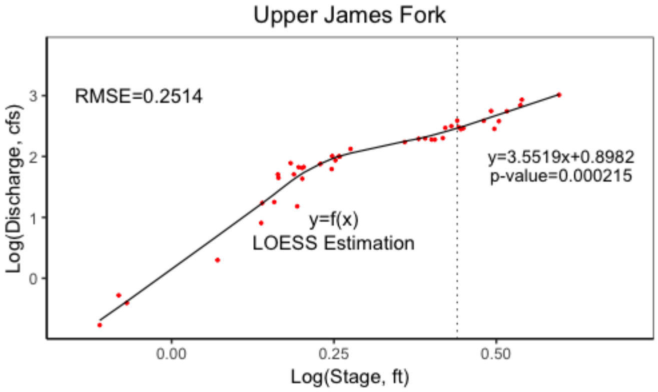

Figure 16: Final Upper James Fork Rating Curve

Similar to the rating curve developed for the Lower James Fork, the use of a linear regression in the second data group allows for extrapolation of stage values exceeding the maximum observed stage. To demonstrate this, the discharge corresponding to a log transformed stage value of 0.65 ft (i.e., a true stage value of 4.47 ft) was estimated, using the linear equation for the second half of data (Figure 17).

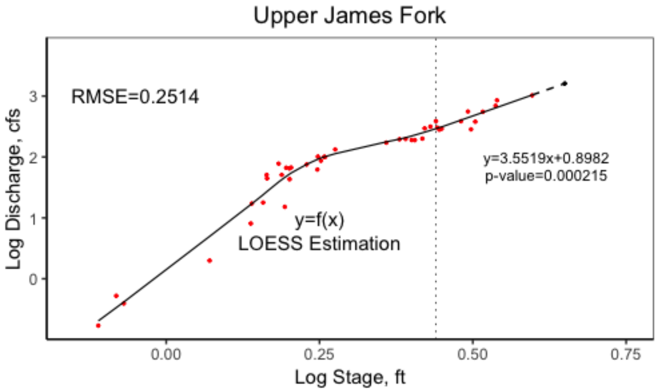

Figure 17: Upper James Fork with extrapolation of a log transformed stage value x=0.65 ft, indicated by the black dashed line and black data point.

Hinkle Jones Creek:

A total of 11 iterations were used in developing the final Hinkle Jones Creek rating curve. The total RMSE decreased as subsequent iterations were performed, until reaching the final total RMSE of 50.18 (Figure 18).

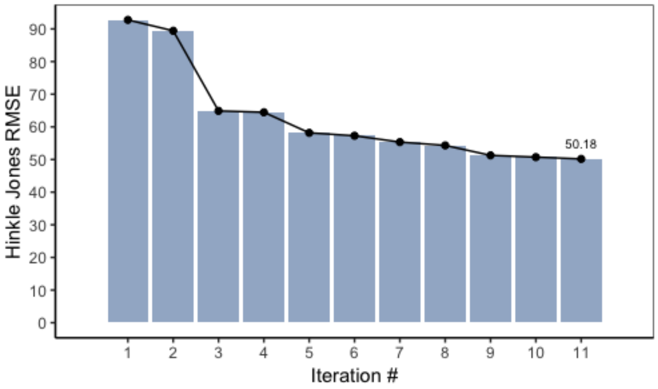

Figure 18: RMSE vs. Iteration Number for Hinkle Jones

The Hinkle Jones Creek gauging site is located downstream from an outfall of a dam at Lake Hinkle. Due to this gauging location, hydrologic behavior at Hinkle Jones Creek is markedly different than that at the Upper and Lower James Fork, especially during base flow conditions. Discharge during base flow conditions ranged from 0-39 cfs, at stage values of 0.5-1.4 ft. The maximum base flow discharge did not occur at the corresponding maximum stage discharge (2.57 ft), and instead occurred at a stage value of 1.44 ft. Once stage exceeded a value of 3.40 feet, the relationship between stage and discharge increased in a linear fashion (Figure 19).

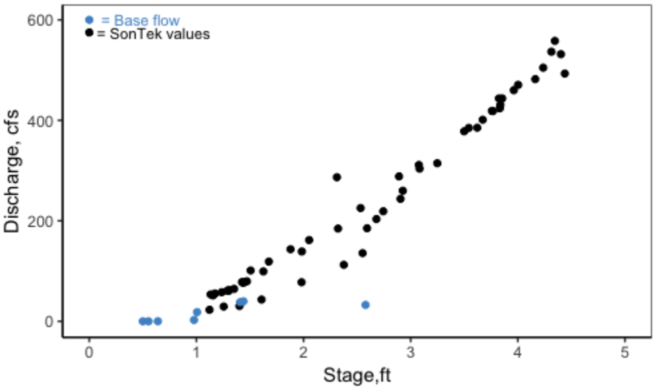

Figure 19: Raw discharge and stage data at Hinkle Jones Creek from October 2017-January 2019

Unlike the procedure followed for the Upper James Fork and Lower James Fork, the discharge and stage data at Hinkle Jones was not log transformed before performing regression analysis. This was primarily due to the unique hydrologic behavior and base flow conditions at the Hinkle Jones gauging location. The Hinkle Jones data was separated into two groups, with the break point occurring at a stage value of 3.40 ft (Figure 20).

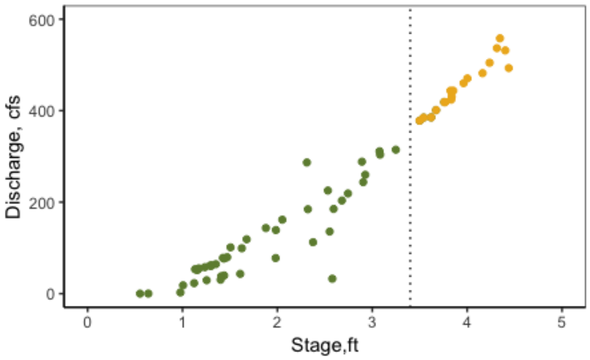

Figure 20: Rating curve data for Hinkle Jones, with break point indicated

The final rating curve resulted from applying a LOESS fit with a smoothing value of *f=0.5* to the first group, and a simple linear regression to the second group (Figure 21). The use of a LOESS fit and then a linear regression in that order also resulted in a much smoother curve, and more flexibility for prediction of base flow values by using a LOESS fit over a regression fit for stage values below 3.4 ft.

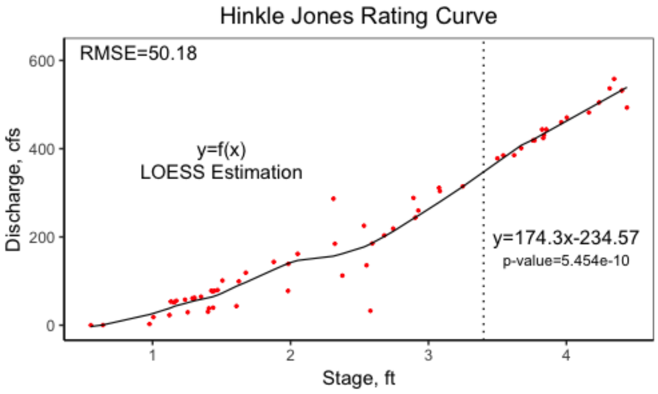

Figure 21: Final Hinkle Jones Rating curve (non-log transformed data)

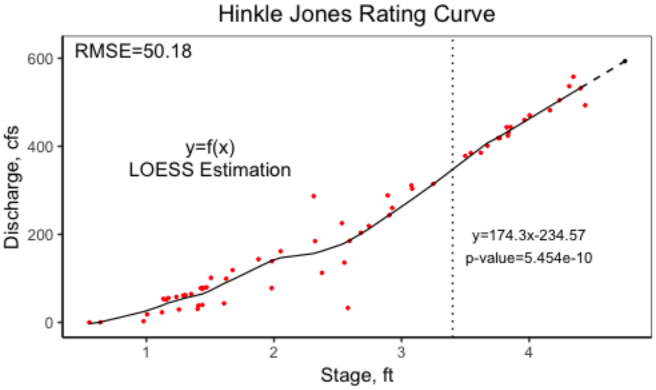

Figure 22: Hinkle Jones with extrapolation of a log transformed stage value x=4.5 ft, indicated by the black dashed line and black data point.

Discussion/Conclusion:

The rating curves developed in this paper will be used to estimate stream discharge for the Upper James Fork, Lower James Fork, and Hinkle Jones creek in the UPRW. For Hinkle Jones creek, the predicted rating curve seems to be less accurate for discharges corresponding to stage values ranging from 2.0-3.4 ft. This likely occurs because the base-flow characteristics at Hinkle Jones Creek are different than that of a typical stream, due to its location below the outfall of a dam. When generating rating curves, it is important to consider that an understanding of environmental and operational influences on data quality is required (Hamilton et al., 2019). For example, while the SonTek acoustic doppler profiler may produce the most accurate measurements for particular flow conditions in a stream, if those conditions are altered, the accuracy may suffer (e.g., if the water depth is below 1.5ft).

Future work for this project could include the consideration of generalized additive models (GAM) as a regression technique, in addition to the LOESS and simple linear regression fits already applied. An advantage of using GAM over LOESS is that GAM includes an R^2 value and P-value, whereas LOESS does not (Wood et al., 2015). GAMs allow the nonlinearity of a trend to be express as an arbitrary shape, and therefore have greater potential for more complex modeling (Morton and Henderson, 2008). Additionally, more work could be performed on optimizing the LOESS smoothing parameter *(f)* when being applied to portions of a rating curve. Another area for improvement is regarding the determination of the separate data sections used in this rating curve development. The different groups could also have been determined using methods other than a visual or manual inspection. For example, a change-point analysis could be used, especially if a larger data set was being used to create a rating curve. This consideration also underscores a unique aspect to rating curve development; the need for balance between quantitative and qualitative approaches for transforming the rating curve.

It also must be acknowledged that discharge in a channel is inherently dependent upon factors other than stage. For future work, characteristics such as surrounding topography or local geology could be taken into consideration when developing rating curves. Creating a more specialized and site-specific approach to the development of each rating curve also has the potential to be applied to other sites, where streams share similar characteristics outside of their general hydraulic behavior. Specifically, consideration could be given to the bankfull geometry of the channel. Future work could look into potential patterns in stage-discharge data based on whether stormflow exceeds bankfull discharge. This could lead to more definite thresholds for different data groups, which would also be supported by the physical behavior of the stream.

All final rating curves were comprised of a combination of regression techniques, as opposed to solely using a LOESS fit or linear regression over the entire data set. If the only goal in developing the rating curve were to minimize the RMSE, then the LOESS only fit would be the best option. However, in doing this, the visual fit and smoothness of the rating curve is sacrificed. Likewise, only using a LOESS fit limits the ability to extrapolate beyond the observed stage and discharge values. When performing a LOESS fit, there is no output equation, or means to extrapolate data; instead, a series of predicted values are directly generated. On the other hand, a linear regression allows for extrapolation of values not included in the observed data set, by creating a linear equation that relates the independent and dependent variables. When generating these rating curves for this report, applying a linear regression the second group of data allowed for extrapolation outside of the observed data range. Rating curve development requires a combination of personal, site-specific experience with the necessary mathematical analysis of the site data (Hamilton et al., 2019). The importance of this personal awareness is a unique and valuable factor in the overall process of rating curve development process.

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