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Error Assessment for Height Above the Nearest Drainage Inundation Mapping

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Error Assessment for Height Above the Nearest Drainage Inundation Mapping

by

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Dedication

To my mother Kim

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Abstract

Error Assessment for Height above the Nearest Drainage Inundation Mapping

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Floods are natural events that can have disastrous impacts in terms of loss of life and damage to property. Flood modelling and mapping allow cities, emergency response and individuals to better prepare for and react to these potential disasters. While detailed flood models and maps are available at some locations in the U.S., many locations are left without. Automatic flood modelling and mapping using remote sensed data allows the possibility of providing flood maps on a large scale without the need for field studies on each and every river. As of 2016 the National Water Model is using rainfall forecasts from the National Weather Service to predict discharge estimates for approximately 2.7 million reaches across the entire continental U.S. To use these discharge values for inundation mapping, relationships between discharge and stage height known as rating curves are used.

While rating curves are typically derived for river cross sections using detailed field studies, the proposed methodology for the National Water Model is to derive rating curves purely from remote sensed data. Manning's equation is applied to derive a relationship between discharge and stage height using topographic data to estimate reach geometry, known as “synthetic” rating curves. The focus of this thesis is to assess the accuracy of these synthetic rating curves and to propose possible improvements. The synthetic rating curves are assessed for 527 reaches across four rivers in Texas, and the effect of terrain characteristics such as slope and reach length on accuracy are explored. An approach to recalculate the slope for Manning’s equation is proposed and evaluated using our method to quantify synthetic rating curve performance.

Table of Contents

List of Figures x

Chapter 1: Introduction 1

Motivation 1

Background 2

Project Overview 4

Research Questions 5

Chapter 2: Literature Review 7

Chapter 3: Study Areas 12

Chapter 4: Synthetic Rating Curve Accuracy Assessment 15

Objective 15

Method 15

Results 17

Discussion 32

Chapter 5: Moving Window 34

Objective 34

Method 34

Results 35

Discussion 38

Chapter 6: Discussion and Conclusion 41

Research Questions 41

Recommendations for Improving HAND Inundation Mapping 43

Final Remarks 45

Appendix..47

Glossary 55

References..57

List of Figures

Figure 1: Real-time discharge predictions from the National Water Model 2

Figure 2: Height Above Nearest Drainage relative to NHDPlus channels 3

Figure 3: Study area consisting of the San Antonio, Guadalupe, Lower Colorado and Blanco rivers in Coastal Texas. 13

Figure 4: Example comparison between synthetic rating curve in blue and HEC-RAS average rating curve in red. Error is calculated at each point of discharge shown and aggregated into a mean single value. 17

Table 1: Statistical measures for the four rivers detailing mean normalized RMSE and overall percent bias 19

Figure 5: The departure of HAND SRCs from HEC-RAS reach averaged rating curves as a function of reach length and slope for the San Antonio River ...19

Figure 6: The departure of HAND SRCs from HEC-RAS reach averaged rating curves as a function of reach length and slope for the Guadalupe River 20

Figure 7: The departure of HAND SRCs from HEC-RAS reach averaged rating curves as a function of reach length and slope for the Lower Colorado River 21

Figure 8: The departure of HAND SRCs from HEC-RAS reach averaged rating curves as a function of reach length and slope for the Blanco River 22

Figure 9: Box plot of the relationship between reach length and SRC accuracy for Blanco river 24

Figure 10: Box plot of the relationship between reach length and SRC accuracy for Guadalupe river 25

Figure 11: Box plot of the relationship between reach length and SRC accuracy for San Antonio river 26
Figure 12: Box plot of the relationship between reach length and SRC accuracy for Lower Colorado river 27
Figure 13: Box plot of the relationship between reach slope and SRC accuracy for Blanco river 28
Figure 14: Box plot of the relationship between reach slope and SRC accuracy for Guadalupe river 29
Figure 15: Box plot of the relationship between reach slope and SRC accuracy for San Antonio river 30
Figure 16: Box plot of the relationship between reach slope and SRC accuracy for Lower Colorado river 31
Figure 17: Box plot of the relationship between bankfull width and SRC accuracy for Blanco river 32
Figure 18: Scaling analysis for comparison of reach-averaged normalized RMSE against moving window length for the Blanco river 36
Figure 19: Scaling analysis for comparison of reach-averaged normalized RMSE against moving window length for the rivers. 38
Figure 20: Elevation profile along the Guadalupe river thalweg 40

Chapter 1: Introduction

MOTIVATION

Flood maps provide crucial information that can assist in planning for disasters before they happen, and can allow emergency responders to react to the disaster with knowledge of current and forecasted conditions. Severe floods can occur with very little warning, with weather forecasts days in advance often not conveying the level of danger that arises. Weather forecasts can also be misleading in situations such as intense rainfall upstream which causes flooding far downstream as in the 2015 Memorial Day Flood of Austin. Flood models can utilize rainfall forecasts to predict the extent and severity of the resultant flooding, and convey this information as a flood map to be used by cities, emergency response, and individuals looking to protect life and property.

Flood inundation maps have traditionally been prepared by cities to build flood resilience and better prepare for emergency response. However, these inundation maps have generally only been produced for densely populated areas, and are usually not produced at all for less populated and rural areas. The agency historically responsible for producing and aggregating flood maps is the Federal Emergency Management Agency, but their flood maps cover less than half of continental USA. An automatic process using remote sensed data and algorithms for flood modelling and inundation mapping would allow flood maps to be produced for the entire country, without the need for detailed field studies. Producing coverage of flood maps to the entire continental U.S. would be incredibly beneficial, providing access to information that can improve disaster resilience and emergency response efforts. This thesis can be read in the context of a large scale collective effort in flood forecasting to help protect life and property.

Background

The National Water Model (NWM), a recent effort of the National Oceanic and Atmospheric Administration (NOAA), produces daily and sub-daily discharge forecasts for over 2.7 million reaches spanning continental USA. The NWM takes precipitation forecasts from the National Weather Service and simulates snowmelt and surface runoff to predict discharge values. To convert these discharge values to inundation extent, rating curves are used to convert reach discharges into corresponding stage height, and then a process called Height Above Nearest Drainage (HAND) is used to convert stage height to inundation extent, using elevation data from the National Elevation Dataset (NED). The NWM uses a network of rivers and reaches from the National Hydrography Dataset, with the current iteration known as NHDPlusV2 (*McKay et al*., 2012). A snapshot of real time river discharge across continental U.S. is shown in Figure 1.

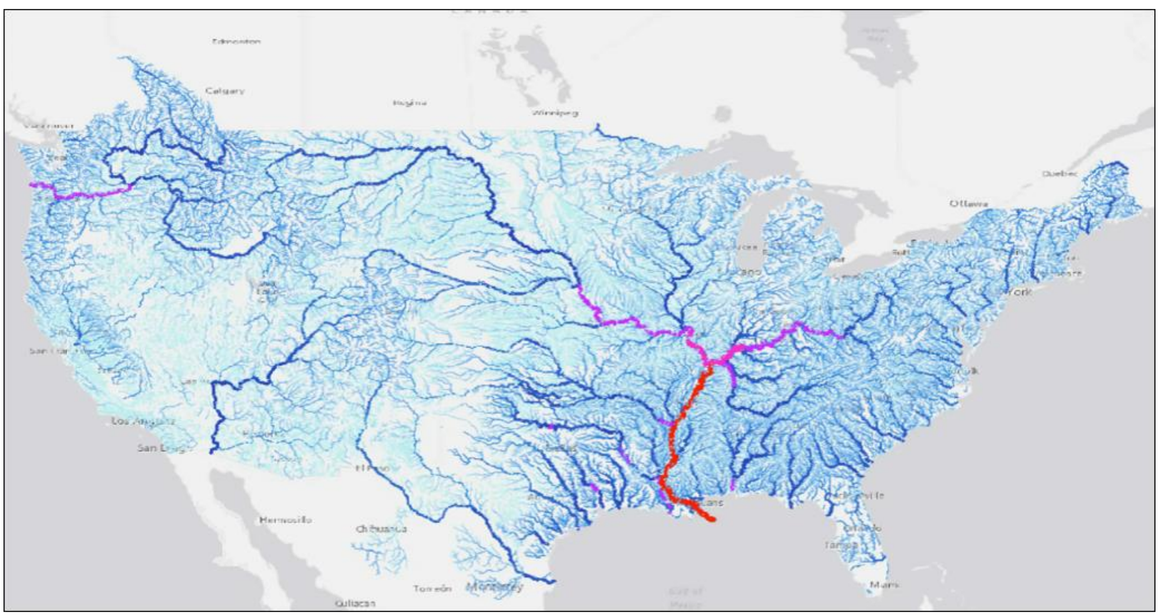

Figure 1: Real-time discharge predictions from the National Water Model

Image credit: NOAA National Water Center

While traditional rating curves have related discharge to stage height using river cross sections measured in field studies, for automatic flood mapping we use only remote sensed data. Hydrodynamic models such as HEC-RAS are often used at the local scale, but the field data requirements are prohibitive to produce inundation maps for the entire USA. Instead, we derive reach-averaged rating curves using channel geometry and Manning's equation, and call these Synthetic Rating Curves (SRCs) (*Zheng et al*., accepted). SRCs are combined with the HAND method which is a measure of relative elevation, calculated as the vertical difference between a given location and the bed of the channel that it drains into. HAND has been calculated for continental U.S. as shown in Figure 2. The ability to generate inundation maps using HAND and SRCs from a digital elevation model (DEM) has recently been demonstrated at the national scale (*Liu et al*., accepted).

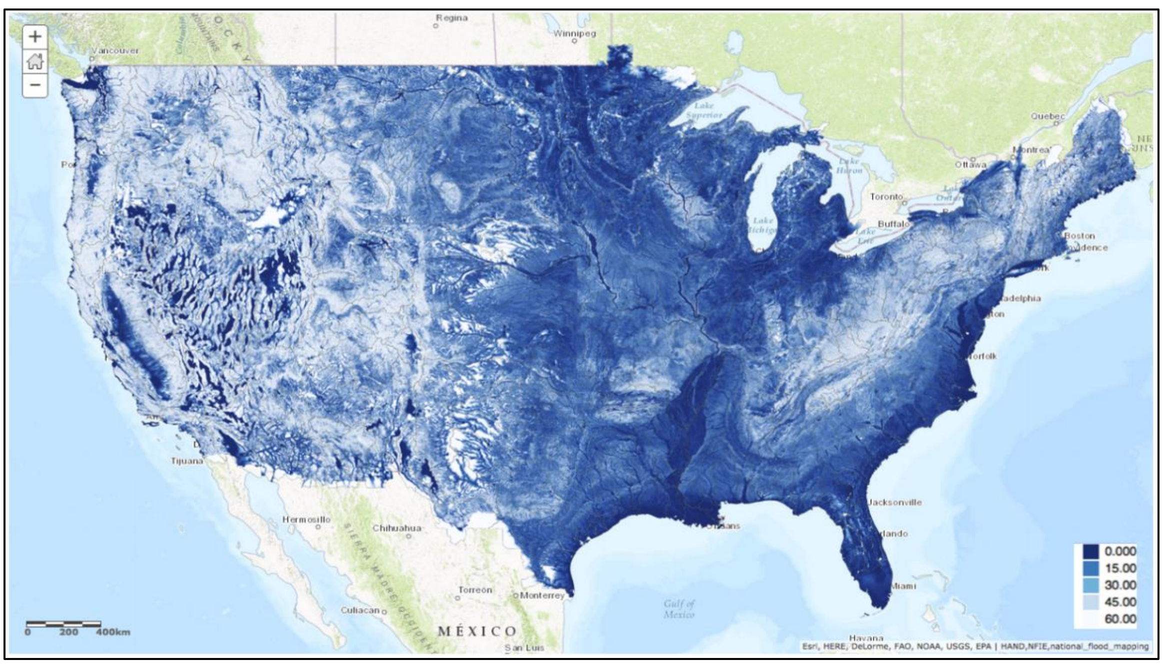

Figure 2: Height Above Nearest Drainage relative to NHDPlus channels

Image credit: Xing Zheng

PROJECT OVERVIEW

The accuracy of the NWM flood maps must be assessed to have confidence in releasing them publically. The focus of this thesis is the accuracy of synthetic rating curves (SRCs), one of the three key steps in the NWM's flood mapping process. SRCs use Manning's equation to convert discharge values for reaches into a corresponding stage height, and their key advantage is that they do not require any field data and rely only upon remotely sensed data. However, this also means that they are likely to be less accurate than traditional rating curves. SRCs are used in conjunction with Height Above the Nearest Drainage (HAND), a measure of relative elevation between a location and the bed of the channel it drains into. We assess SRC accuracy by comparing them to existing, calibrated rating curves. The primary aim of this thesis is to produce a method and framework to quantify rating curve performance with appropriate metrics to assess SRC accuracy.

We also look to investigate the relationship between SRC performance and terrain characteristics as well as channel features. Channel flow patterns are affected by local and overall slope of the channel bed, any form of friction caused by vegetation, rock and soil, as well as the geometry of the channel. Narrower and steeper sections of the channel will result in different hydraulic conditions than wider and flatter sections. Characteristics of the overbank terrain will also affect the discharge to stage height relationship as there can be different slopes and aggregate friction. We look to quantify the effect of these different characteristics on SRC performance.

The aim of this thesis is to assess the accuracy of modelling this process using only remote sensed data, so all of these complex physical processes and interactions are bulked into only a few measurements and one equation. We hope to measure the accuracy of our calculated relationships between discharge and stage height in an effort to quantify uncertainty and allow improvements to be made and assessed on the performance of the model.

RESEARCH QUESTIONS

1. What is the overall accuracy of the synthetic rating curves?

First we want to characterize the overall accuracy of the SRCs on a large aggregate scale and for individual rating curves. We assume that the performance will be worse than for rating curves derived from detailed cross sections measured in field studies, and we look to quantify this difference in performance. We know that the channel geometry from remote sensed data is going to be less accurate, and that the roughness values we use will similarly be less accurate. Furthermore, we are assuming a uniform water surface level across an entire reach, which can range in length from a meter to over ten miles in some circumstances. These issues with flood modelling using remote sensed data will contribute to worse rating curve performance, so to improve future SRC performance we look to quantify their current performance.

2. Do terrain characteristics and channel features affect synthetic rating curve accuracy?

We expect terrain characteristics and channel features such as reach length and reach slope to have a significant effect on the accuracy of SRCs. We hypothesize that SRC accuracy is likely to decrease for reaches that are very short as channel geometry will be inaccurate, and similarly for long reaches where the assumption of a uniform water surface level no longer holds. We also hypothesize that performance will decrease for extreme slope values where Manning's equation under the assumption that flow is controlled by the slope of our reach may no longer be accurate. We would also like to test for roughness and stream order, but due to the limited availability of calibrated hydrodynamic models to test our SRCs against we are largely unable to draw conclusions about these terrain characteristics and channel features.

3. How can the performance of synthetic rating curves be improved?

Since we produce a methodology to quantify SRC performance, we look to apply a change to the SRC calculation and test for improvement in SRC accuracy. As the current calculation of SRCs uses simple channel geometry from remote sensed data and Manning's equation, we assume that many improvements could be made. Possible improvements include utilizing lidar data with a better resolution, varying roughness values and altering geometry calculation for applying Manning's equation. We look to the results of research question 2 to identify terrain characteristics or channel features that predict poor accuracy, and use these to inform changes to the SRC calculation. We suggest a process to recalculate reach slope as a pilot study to demonstrate how future improvements can be evaluated.

Chapter 2: Literature Review

Hydrological models have improved significantly in the past century and flood maps are one of the products of this modelling that can have a significant positive impact in our society. Flood inundation maps communicate the severity and spatial extent of the disaster in a form that can be quickly and easily understood by emergency response [*Maidment*, 2017]. Predictions of conditions days in advance and estimates of current conditions help inform decision making in these time sensitive situations.

Simulation of the hydrological cycle was first envisioned by *Freeze and Harlan* (1969) with the continual improvement of computing power and understanding of the different aspects of the hydrological cycle. While flood modelling has traditionally been conducted on local scales, the idea of continental and global scale flood modelling has been gaining traction in recent years. *Dottori et al*. (2016) note that developing high resolution flood hazard models is now feasible and present a procedure for flood hazard mapping that can be applied globally. The recent wide spread availability of high resolution topographic elevation data is key for large scale flood modelling using both hydrological (*Liu et al*., accepted) and hydrodynamic methods [*Wing et al*., 2017].

One key example of using this high resolution topographic data for large scale flood mapping is the NOAA National Water Center (NWC) which runs the National Water Model (NWM), a real time flood forecasting product (*Maidment,* 2017). The NWM uses WRF-Hydro to convert rainfall predictions from the National Weather Service to discharge estimate for approximately 2.7 million reaches for the entire NHDPlus continental channel network [*Maidment*, 2017]. The method used to convert discharge to inundation extent by the NWM is a combination of synthetic rating curves (SRCs) (*Zheng et al*., accepted) and the Height Above Nearest Drainage (HAND) [*Rodda*, 2005; *Renno et al*., 2008]. The conversions from rainfall to runoff, channel flow and finally to overbank flow and flooding are conducted at different resolutions suitable for each individual process.

A dense network of gauging stations or applying hydrodynamic models such as the Hydrologic Engineering Center's River Analysis System (HEC-RAS) for every river in the country would provide very accurate flood maps, but would be prohibitively difficult and expensive. As *Fekete and Vorosmarty* (2007) note, while gauging stations produce the most accurate values, “they are expensive to maintain and in many cases the sites and resulting data can be technically, logistically, and politically difficult to access.” Similarly, conducting detailed field studies to produce cross sections along 2.7 million reaches is also unrealistic.

Therefore, the specific methods that the NWM uses to simulate these processes such as SRCs and HAND are chosen due to the suitability for remote sensed data and efficiency to run on a continental scale. These two methods both use topographic elevation data, with SRCs converting discharge to stage height using Manning’s equation, and HAND converting stage height to flood extent using relative elevation [*Zheng et al*., accepted]. The HAND is a measure of relative elevation, as the vertical elevation difference between some location and the channel bed that it drains into [*Rodda*, 2005; *Renno et al*., 2008]. When the stage height of the reach that a location drains into is greater than the HAND value, that location is flooded. The depth of inundation is equal to the stage height minus the HAND value. The application of HAND has previously been demonstrated (*Nobre et al.,* 2011, *Nobre et al*., 2016) and is relatively computationally inexpensive which is suitable for continental scale inundation mapping.

The use of rating curves with elevation data as input rather than a series of river cross sections is a new application. Rating curves are an approximation of the relationship between discharge and stage height for a given cross section or stretch of river (*Kennedy,* 1984), and have traditionally been produced using detailed field studies. Rating curves have typically been used in the U.S. by the U.S. Geological Survey (USGS) at gauging stations where discharge values are measured (*Kennedy*, 1984), but the application of discharge to stage height relationships has been expanded in recent years. In addition to SRCs derived purely from remote sensed data (*Zheng et al.*, 2016), *King et al*. (2018) use rating curves in the reverse manner using stage height from remote sensed data to predict discharge with Manning's equation. Similarly, *Kean et al*. (2005) produce rating curves based on hydrodynamic models, circumventing using Manning's equation to relate stage height to depth.

As the application of rating curves of SRCs in conjunction with HAND relative elevation for flood mapping is still new, the accuracy of this process has not yet been thoroughly tested [*Zheng et al*., accepted]. The focus of this thesis is to assess SRC accuracy in addition to test for relationships between terrain characteristics or channel features and SRC performance. Factors that affect SRC performance include terrain characteristics like slope, channel features such as channel geometry and roughness from vegetation, as well as the accuracy of the elevation data used.

Terrain characteristics and channel features play a significant role on the flow of water through channels and floodplains. *Fleischmann et al*. (2016) examine the effect of floodplain characteristics on hydrograph skewness, where regions with larger floodplains and more vegetation produce higher aggregate friction and therefore attenuate the hydrograph. *Montgomery et al*., (1997) find that characteristic slope, grain size, shear stress and roughness ranges for different reaches affect flow patterns and sediment transport. The relationship between terrain characteristics or channel features and SRCs at this point has not been investigated.

The accuracy of models based on topographic data are strongly tied to the resolution and accuracy of the elevation values. Remote sensed topographic data has played an increasing role in hydrological simulation over recent decades. A simplistic algorithm using digital elevation grids to extract channels and calculate flow accumulation was introduced by *Tarboton et al*. (1991) in the form of TauDEM. The fundamental idea is that water will flow in the direction of steepest descent, initially in the D8 model (*O'Callaghan et al*., 1984) to one of eight flow directions such as north or northwest. This was later extended by *Tarboton et al*. (1997) to a model where the flow can be in any direction, and the role of topographic data in hydrological modelling and flood mapping has only increased since then.

The increasing availability of lidar provides new opportunities for improvements in flood inundation mapping using SRCs and HAND. The hyper-resolution detail that lidar provides allows for identification of topographic features that would otherwise be indistinguishable [*Roering et al*., 2013]. Lidar has been used to analyze terrains and more accurately extract channel networks using channel extraction tools such as GeoNet [*Passalacqua et al*., 2010]. More accurate channel networks and channel geometry have significant potential for application in flood modelling. Utilizing lidar can be used to improve HAND inundation mapping and also validate flood models as in a study by *Chen et al* (2017) where lidar was used to measure the inundation extent of the 2008 Iowa floods.

Lidar can also be used to assess terrain characteristics and channel features, which are shown in this thesis to predict SRC performance. *Ozdemir et al.* (2013) use hyper-resolution lidar measurements to evaluate the effect of roughness in urban flood modelling. This idea can be applied to SRCs, where lidar is used to better approximate inputs used in Manning's equation such as roughness and reach slope.

Finally, it should be stated that the approximations used for global and continental scale flood mapping as by the NWM should be validated by more detailed hydrodynamic models. *Fatichi et al*. (2016) stress the importance of continuing to improve physically based hydrological models, and comparisons between efficient, less accurate methods and less efficient, more accurate measures can lead to insights into how much inaccuracy approximations introduce and in which situations they tend to fail.

Chapter 3: Study Areas[1]

Data used for each study area is in the form of a HEC-RAS model, where for each of the rivers we have detailed cross section geometry information at many points along the river. The study areas were chosen primarily due to the availability of these HEC-RAS models which have been provided by the U.S. Army Corps of Engineers (USACE). The initial aim was to choose a set of rivers that were located in areas with very different terrain characteristics, but HEC-RAS models are only available for a small subset of U.S. rivers. We study four rivers in Texas, located within three HUC6 units. We use HEC-RAS models provided by USACE for the Lower Colorado river, the Guadalupe river, and the Blanco river. For the San Antonio river we use HEC-RAS models provided by the San Antonio River Authority.

The terrain characteristics which we were looking to capture were a mixture of high relief and low relief, a mixture of coastal and inland, and a mixture of main stem rivers and tributaries. While all of the rivers are located near the Texas coast, we have three main stem rivers and one large tributary, and some variations in overall slope. The Blanco river has particularly different characteristics to the three major rivers as a tributary of the Guadalupe river. The Blanco has a far smaller drainage basin, is much shorter, and also has a higher overall relief. The rivers and their drainage basins are presented in Figure 3. Due to the limited availability of HEC-RAS models, we are not able to capture a mixture of coastal and inland terrains, nor do we have any mountainous regions of particular high relief to compare.

[1] Part of study to be submitted as *Godbout et al.* to JAWRA (in preparation)

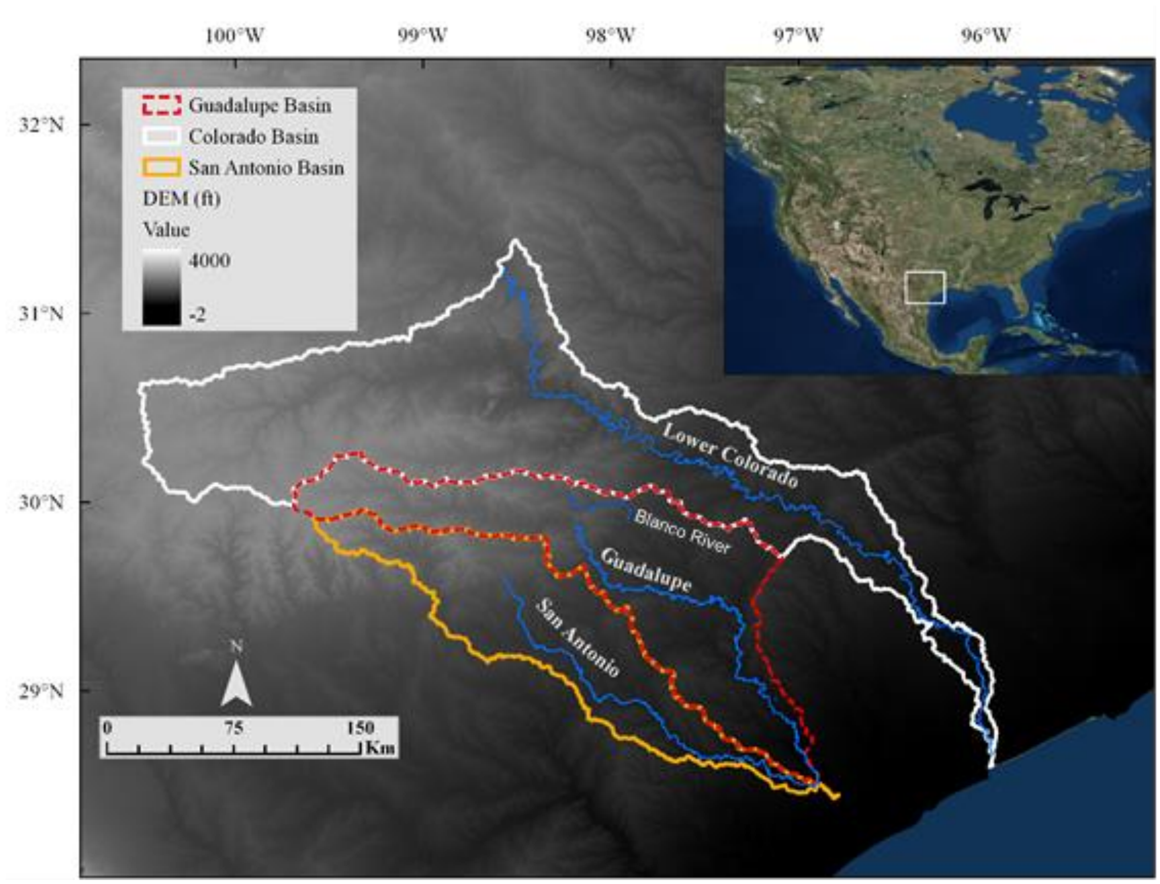

Figure 3: Study area consisting of the San Antonio, Guadalupe, Lower Colorado and Blanco rivers in Coastal Texas.

The total area of the San Antonio River basin is approximately 10,863 square kilometers. The San Antonio River is approximately 390 km or 240 miles, converging with the Guadalupe River before finally flowing into the Gulf of Mexico. The measure of the river extent covered is approximately 76% or 182 miles from downstream. The portion of the river included in our study area contains 96 reaches or unique COMIDs, and the overall relief is approximately 0.04%.

The entire extent of the Guadalupe river is approximately 370 km or 230 miles. The portion of the river extent analyzed in this study downstream of Canyon Lake is approximately 183 miles or 295 km. This portion of the river contains 126 reaches or unique COMIDs, and the average slope or overall relief is approximately 0.08%. For the downstream portion of the Guadalupe River, the HUC06 basin area is approximately 10,000 square kilometers.

The Colorado River is approximately 1,387 km or 862 miles. It flows southeast from its source on the Llano Estacado to Matagorda where it empties into the Gulf of Mexico. The extent of the river covered in this study is considered part of the lower Colorado River and is approximately 666 km or 414 miles. The lower region extends from San Saba (upstream of Lake Buchanan) to Matagorda Bay. The portion of the river depicted as our study area contains 275 reaches, and the overall relief is approximately 0.033%. The area of the HUC04 river basin covering the lower region of the Colorado River is approximately 28,904 square kilometers.

The Blanco river is approximately 90 km or 56 miles. It flows east from its source near Fredericksburg through the town of Blanco until it flows into the San Marcos river which itself flows into the Guadalupe river. It has a much smaller watershed of approximately 1,000 square kilometers, and for our study consists of 30 reaches with an overall relief of 0.19%. It has been chosen for its different river and basin characteristics, in addition to the significance to this study of the deadly flood of 2015 where at Wimberley the river rose over 30 feet in less than three hours with fatalities involved.

HEC-RAS models for the San Antonio River were obtained from the San Antonio River Authority, while the models for the Guadalupe, Lower Colorado and Blanco rivers were provided by the USACE.

Chapter 4: Synthetic Rating Curve Accuracy Assessment[2]

OBJECTIVE

To quantify the overall accuracy of synthetic rating curves and assess whether terrain characteristics and channel features affect synthetic rating curve accuracy.

METHOD

In this part of the study we detail a process to compare a SRC for a reach and a HEC-RAS rating curve which is valid for a particular cross section, the HEC-RAS rating curves must be aggregated into reaches for comparison. We discuss possible ways to aggregate these cross section rating curves to calculate the difference between the SRC and HEC-RAS rating curve. We compare the SRC stage height to the median of the HEC-RAS stage heights for the cross sections contained within that reach, and then use statistical measures of mean normalized RMSE and mean absolute depth difference to evaluate our SRCs. Synthetic rating curve calculation is first conducted as previously discussed in the introduction (Zheng et al., accepted) and is outside the scope of this thesis.

As can be seen in Figure 4, the SRC has a value of stage height for every discharge value, and at a set of discharge values along the rating curve we compute the median of the HEC-RAS rating curve stage height values. We compare the SRC stage height to the median of the HEC-RAS stage heights at the set of discharge values, and take the vertical difference as the error. Median HEC-RAS values were assumed to be more representative of reach averages than their mean (*Zheng et al*., accepted). We then have a set of error values which describe the difference between the SRC predicted stage height and the median of the stage heights of the HEC-RAS cross sections contained within that reach.

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[2] Part of study to be submitted as *Godbout et al.* to JAWRA (in preparation)

To calculate overall rating curve performance rather than rating curve performance for a single discharge value, we then aggregate these values by taking the mean of the normalized RMSE or absolute depth difference.

Currently there is no standardized method for statistics in rating curve comparisons. The SRC performance can be assessed by a variety of statistical measures, each with their particularly biases. A variety could be used including mean absolute error, root mean square error, coefficient of determination, range and percent bias. The primary metric used to assess accuracy in this study is normalized root mean square error (RMSE) as it provides a measure of deviation for the SRCs from the calibrated rating curves that is not affected by the size or scale of a river. The normalized RMSE is defined as

$$\textbf{Normalized RMSE} = \frac{\sqrt{\frac{\sum_{i=1}^{n}(\widehat{y_i}-y_i)^2}{n}}}{y_{max}-y_{min}} \qquad \text{(Equation 1)}$$

Where $\widehat{y_i}$ represents the estimated or predicted stage height obtained from the SRCs, y_i is the measured depth from HEC-RAS derived rating curves, *n* is the number of samples or HEC-RAS measurements in a given reach. The normalized RMSE is then the square root of the sum of squares of the difference in depths normalized by the range of the measured depths. We developed an automatic process to compare SRCs to these HEC-RAS reach averaged rating curves.

We calculate synthetic rating curve accuracy or deviation of the SRC from the HEC-RAS median rating curve for all reaches in our study area. We calculate statistics for each of the three rivers, and then look to test whether terrain characteristics and channel features affect SRC performance. We produce plots for the three rivers of rating curve error against reach slope, and use symbology to display the relationship between error and slope. Reaches are separated into bins based on slope, where low slope is defined as less than 0.01% and steep slope is defined as greater than 0.1%. These bin values are defined arbitrarily with the aim of having a roughly equal amount of observations in each bin, and using cutoff values that highlight the difference in performance that corresponds with different slope values.

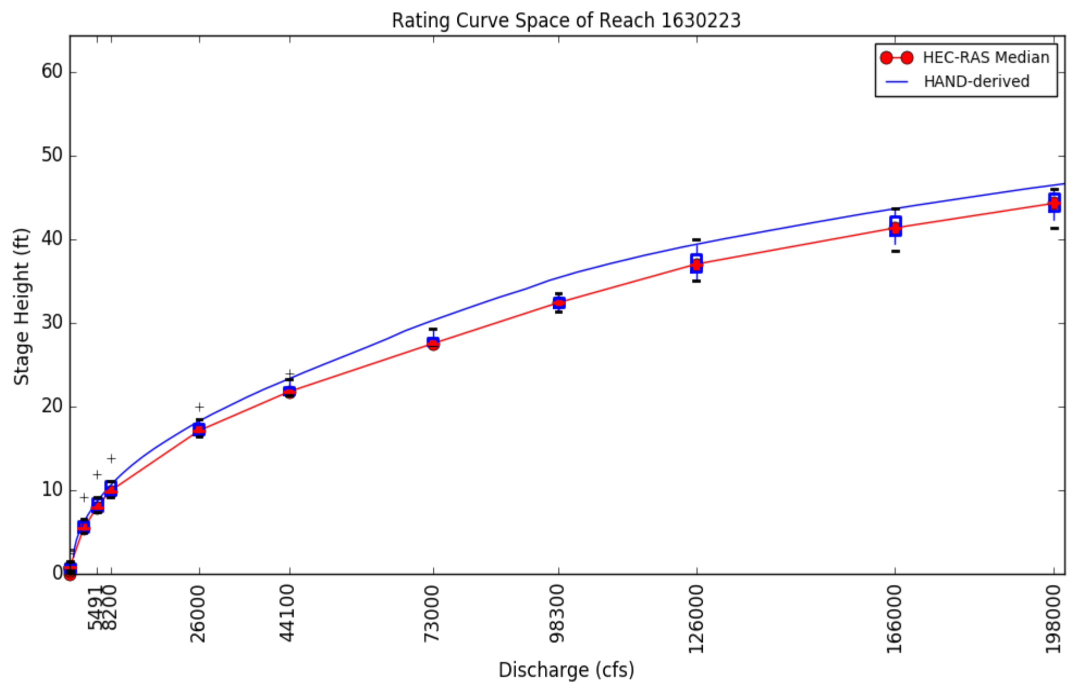

Figure 4: Example comparison between synthetic rating curve in blue and HEC-RAS average rating curve in red. Error is calculated at each point of discharge shown and aggregated into a mean single value.

RESULTS

We evaluate the performance of SRCs by their difference to calibrated HEC-RAS models. First we analyze basic statistics as presented in Table 1. We find that the mean normalized RMSE ranges from 20.6% to 31.2% which shows that the SRCs produced stage height values somewhat similar to the HEC-RAS cross section rating curves, although there is still significant deviation. The Blanco river sees the best performance while the Lower Colorado river has the most deviation of its SRCs to the HEC-RAS median rating curves.

We also see that three of the rivers have a positive percent bias, with only the Guadalupe overall under-predicting the stage height for a given discharge with a percent bias value of -9.5%. The bias is particularly large for the Colorado river of 35.5%, showing that for this river the SRCs are vastly over-predicting stage height for a given discharge.

We then show two types of plots to highlight trends in the results. We first show scatter plots with length on the x axis using three symbols for low, medium and steep slopes, and then show box plots with reach length or reach slope binned into five bins of equal counts of measurements.

The scatter plots of SRC performance are shown for the San Antonio river, the Guadalupe river, the Lower Colorado river and the Blanco river in figures 5, 6, 7 and 8 respectively. Reaches are separated into bins based on slope, where low slope is defined as less than 0.01% and steep slope is defined as greater than 0.1%. These bin values are defined arbitrarily with the aim of having a roughly equal amount of observations in each bin, and using cutoff values that highlight the difference in performance that corresponds with different slope values. The aim of using these bins is to highlight the effect of low and steep slopes, while in this next set of plots we bin the measurements in a more statistically sound way.

There are a number of similarities and differences in the rating curve performance for the four rivers. All three rivers exhibit worse performance for shorter reaches, and worse performance for reaches with low slope values. The trend between slope and error is most clear for the San Antonio river. Low slope values tend to have a normalized RMSE of greater than 30%, while medium and steep slope reaches tend to have a normalized RMSE of less than 30%. This trend is less visible for the Guadalupe river, where the most visible trend is that short reaches tend to have low or steep slope values which correspond to larger error, while long reaches often have medium slope and perform well. In the Lower

Colorado river the most visible trend is that short slope reaches perform very poorly, while medium slope reaches perform very well and low slope values tend to be somewhere in the middle. Overall, the main trend of the four plots are that short reaches and extreme slope values, particularly low slope, correspond strongly to poor SRC performance.

River	Mean normalized RMSE	Percent Bias
Guadalupe	23.1%	-9.5%
San Antonio	29.0%	21.6%
Lower Colorado	31.2%	35.5%
Blanco	20.6%	15.7%

Table 1: Statistical measures for the four rivers detailing mean normalized RMSE and overall percent bias

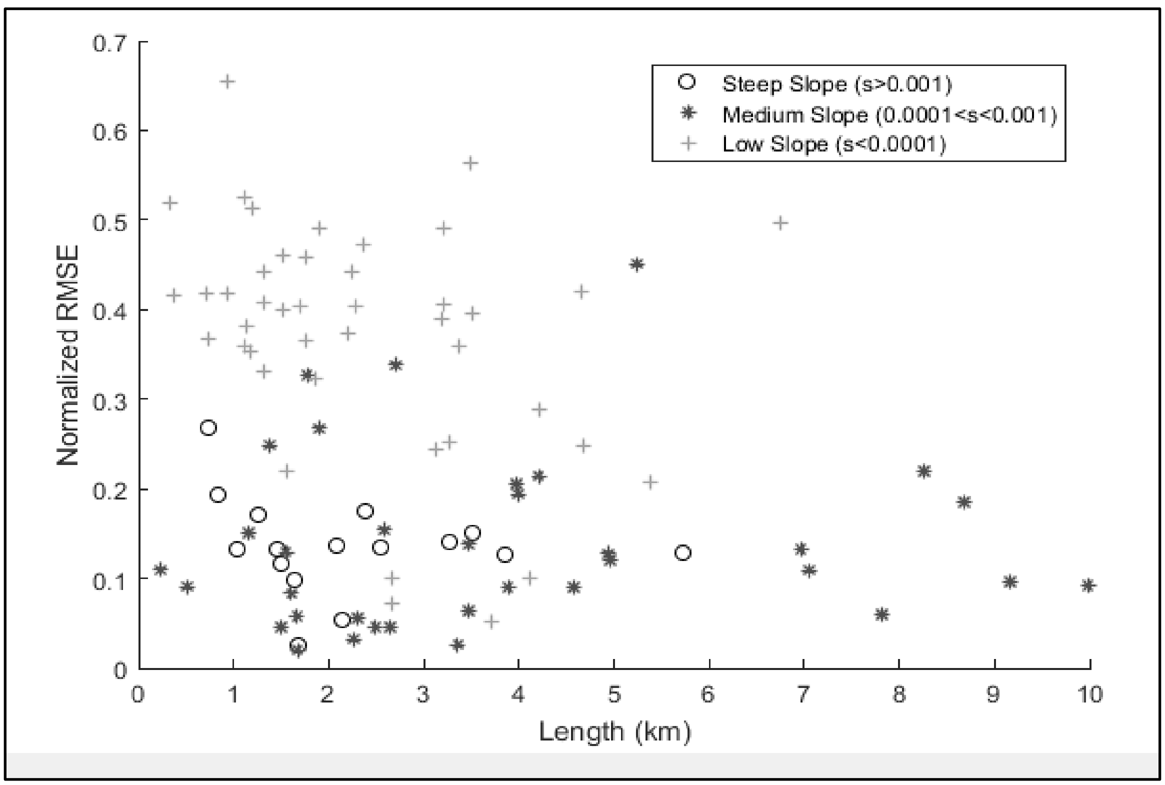

Figure 5: The departure of HAND SRCs from HEC-RAS reach averaged rating curves as a function of reach length and slope for the San Antonio River

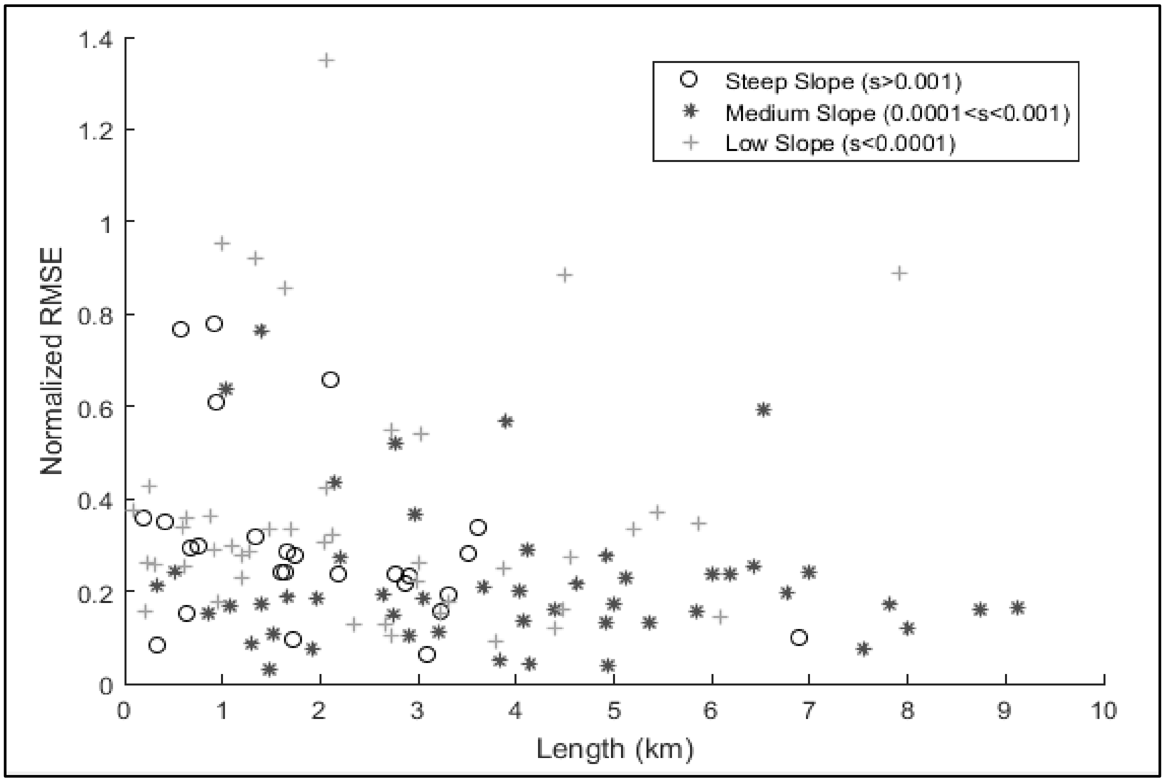

Figure 6: The departure of HAND SRCs from HEC-RAS reach averaged rating curves as a function of reach length and slope for the Guadalupe River

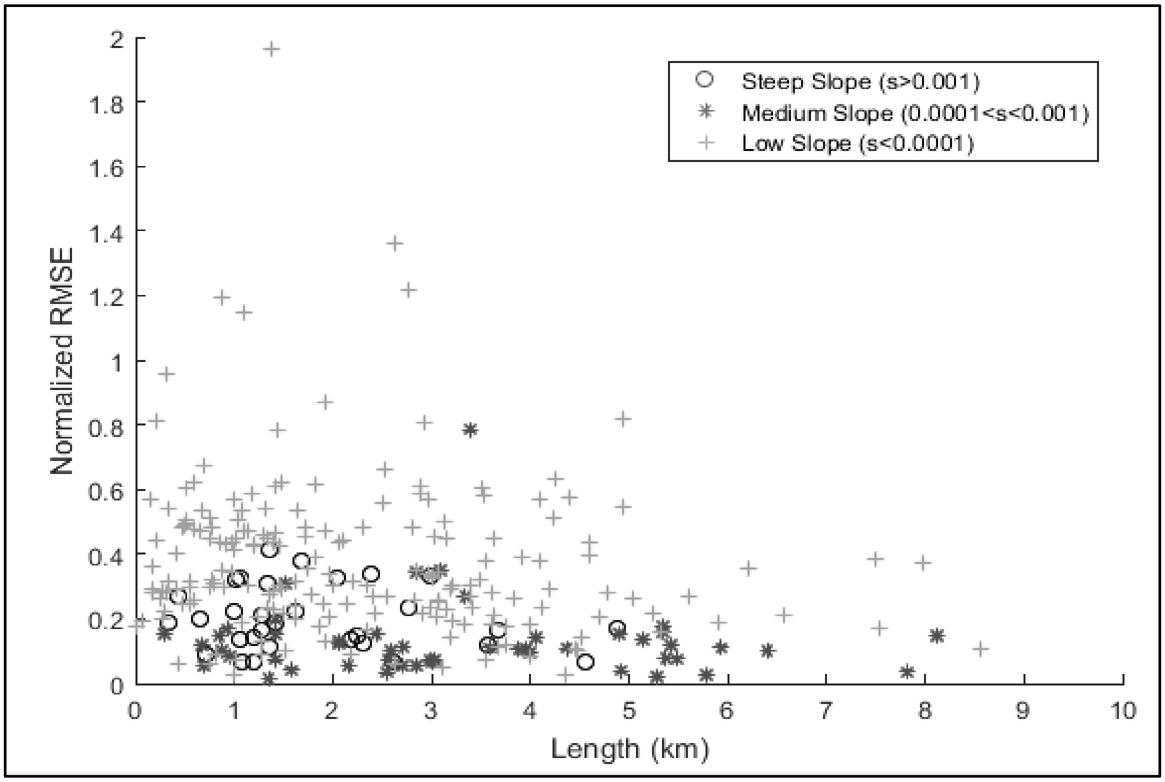

Figure 7: The departure of HAND SRCs from HEC-RAS reach averaged rating curves as a function of reach length and slope for the Lower Colorado River

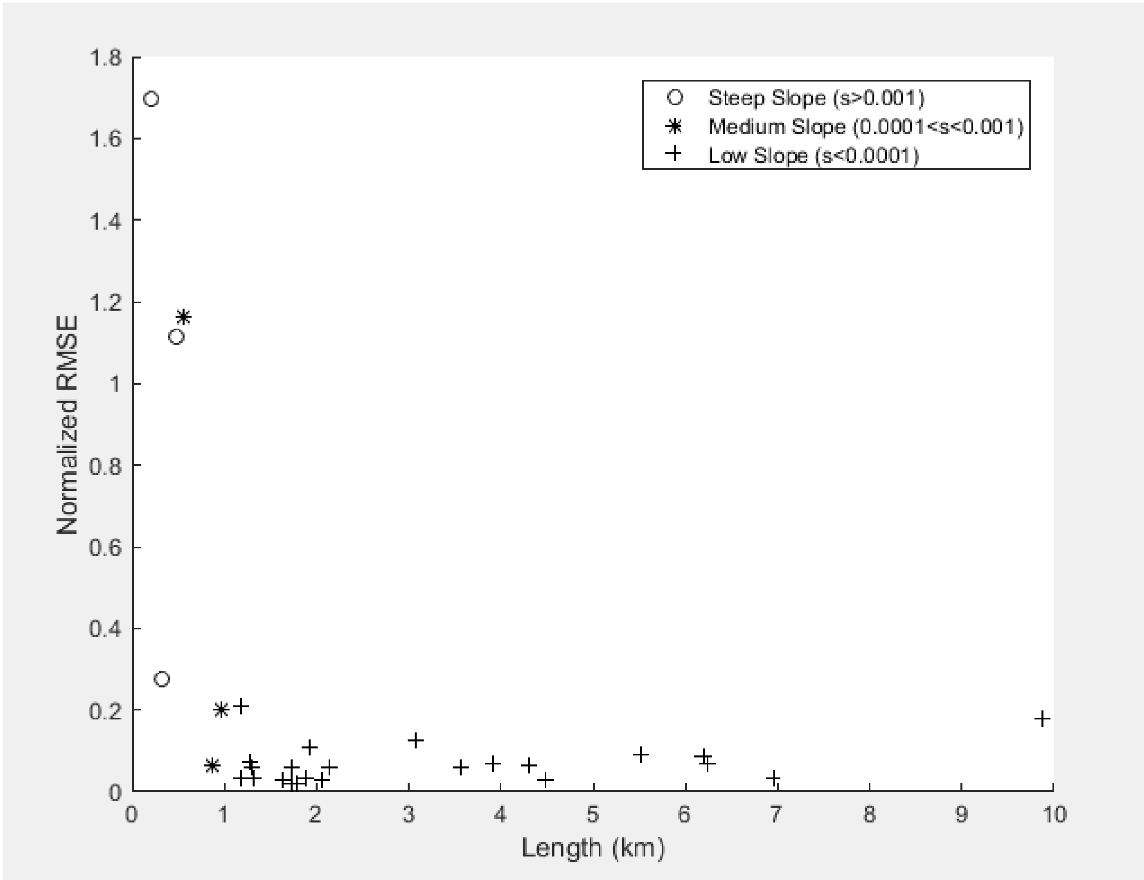

Figure 8: The departure of HAND SRCs from HEC-RAS reach averaged rating curves as a function of reach length and slope for the Blanco River

In addition to scatter plots we have produced box plots to display the significance of the relationship between terrain characteristics or channel features and SRC accuracy. We separate the measurements into five bins by reach length or reach slope, where bin 1 contains the 20% of reaches with the smallest length or slope and bin 5 contains the 20% of reaches with the largest length or slope. The relationship between error and reach length is shown in figures 9, 10, 11 and 12 for Blanco, Guadalupe, San Antonio and Lower Colorado rivers respectively, while the same plots are produced for reach slope in figures 13, 14, 15 and 16. The box plots have been produced by splitting the reaches into five bins of an equal number of observations, ranging from shortest reach length or lowest slope to longest reach length or steepest slope.

We see that the relationship between error and reach length as well as reach slope is most significant for the Blanco river but present for the three other rivers. Short reaches and reaches with low slope exhibit particularly poor performance, while long reaches and reaches with steep slope also perform slightly worse than reaches with medium values.

Figures 15 and 16 are particularly interesting since both the San Antonio and Colorado rivers have many reaches with a slope value of approximately zero. The bins which represent these zero slope reaches with a minimum value of 0.001% have much larger errors than the other bins. The bins that perform the best for both rivers are the ones immediately following the zero slope bins. These are the set of reaches that have a low but non-zero slope, similar to the overall average relief for the entire river.

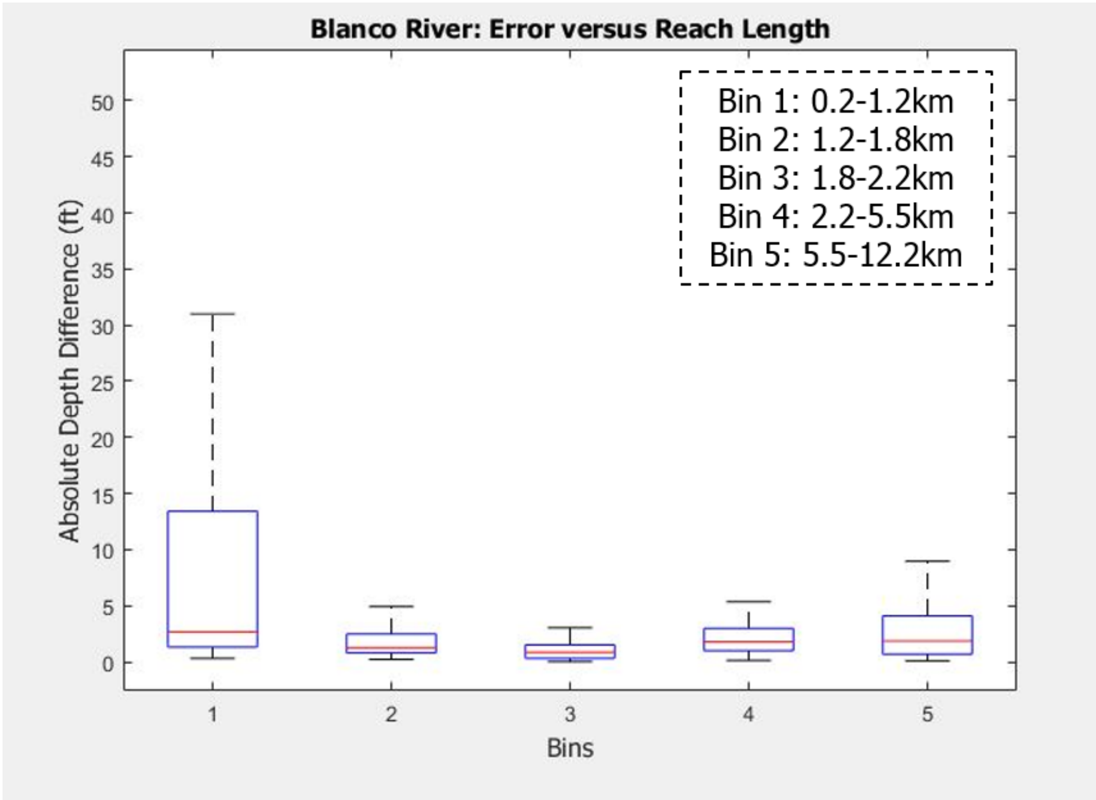

Figure 9: Box plot of the relationship between reach length and SRC accuracy for Blanco river

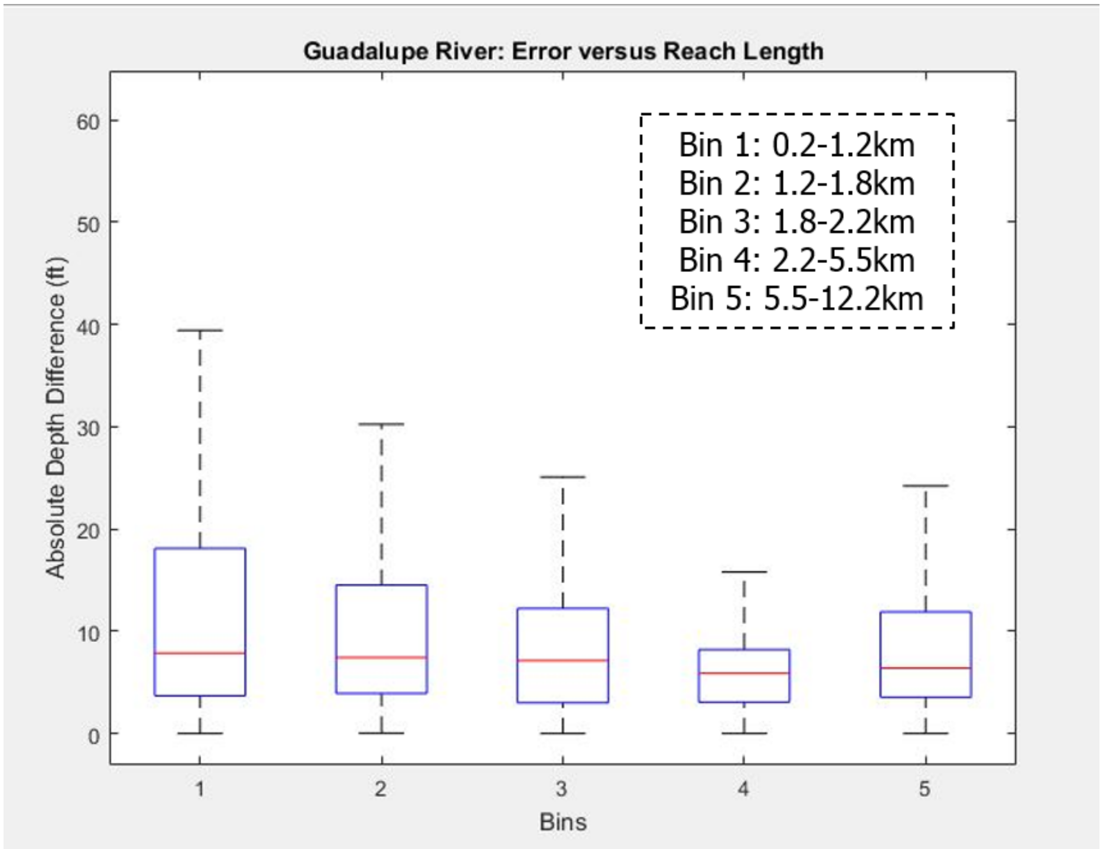

Figure 10: Box plot of the relationship between reach length and SRC accuracy for Guadalupe river

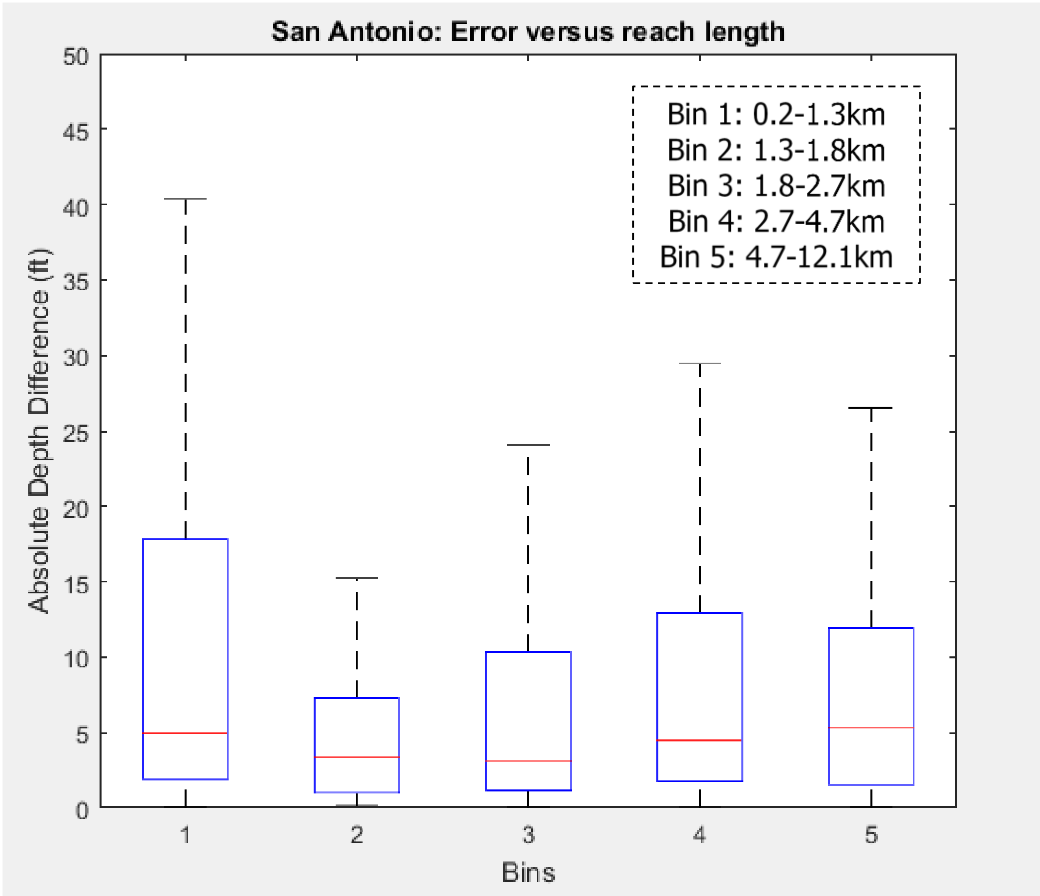

Figure 11: Box plot of the relationship between reach length and SRC accuracy for San Antonio river

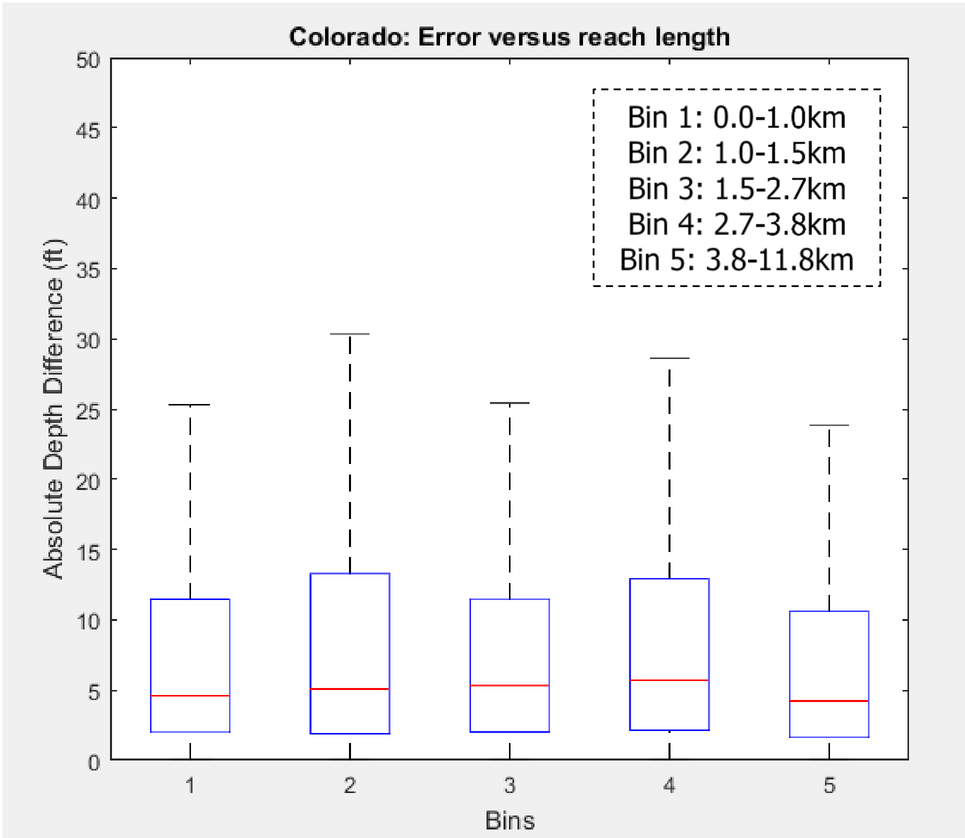

Figure 12: Box plot of the relationship between reach length and SRC accuracy for Lower Colorado river

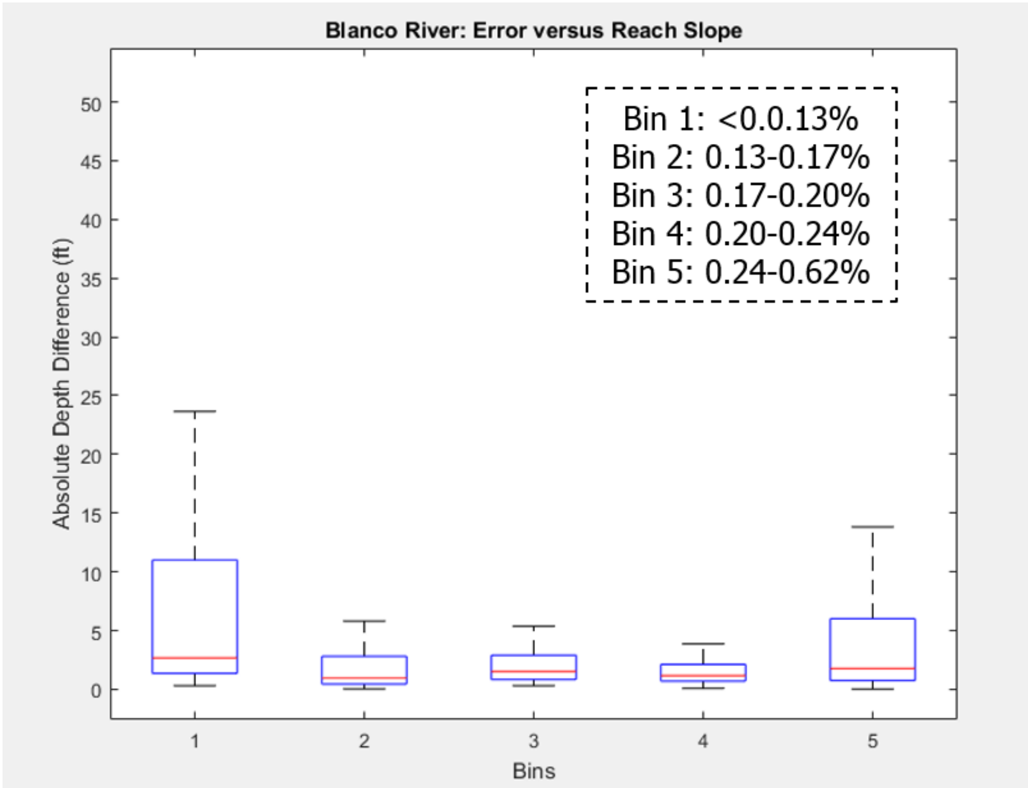

Figure 13: Box plot of the relationship between reach slope and SRC accuracy for the Blanco river

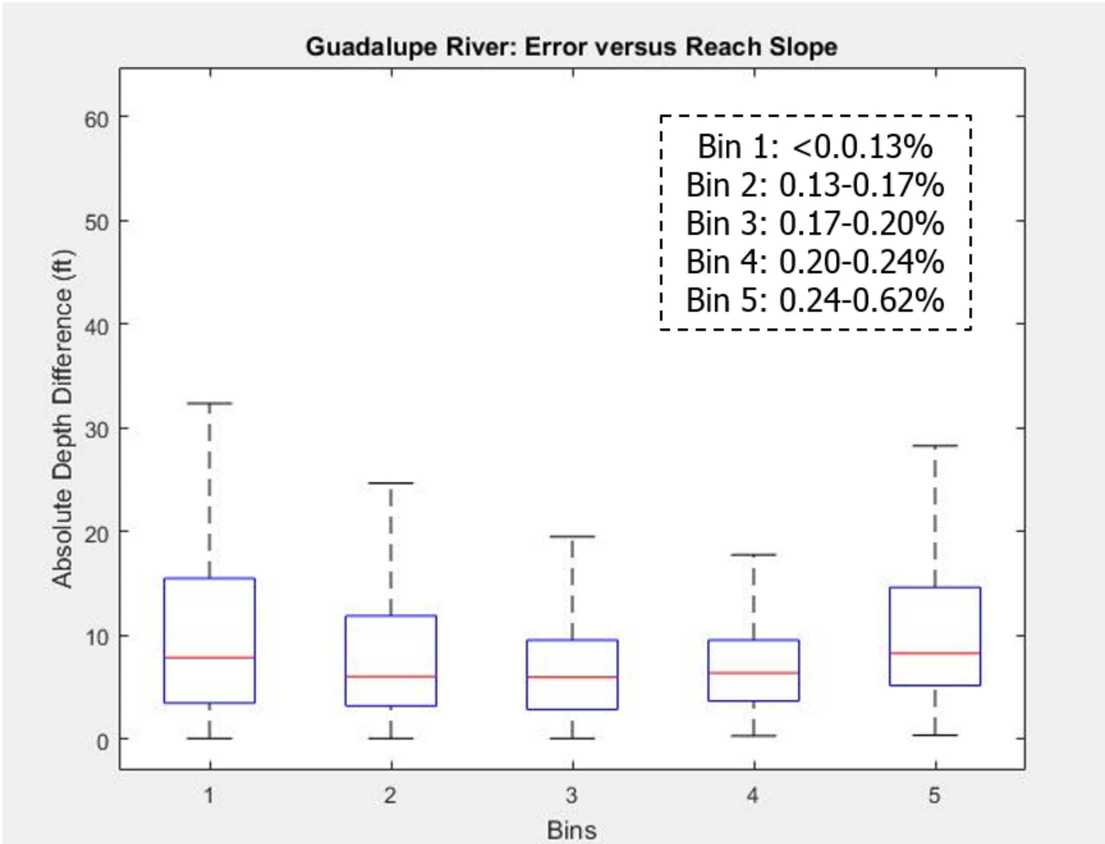

Figure 14: Box plot of the relationship between reach slope and SRC accuracy for the Guadalupe river

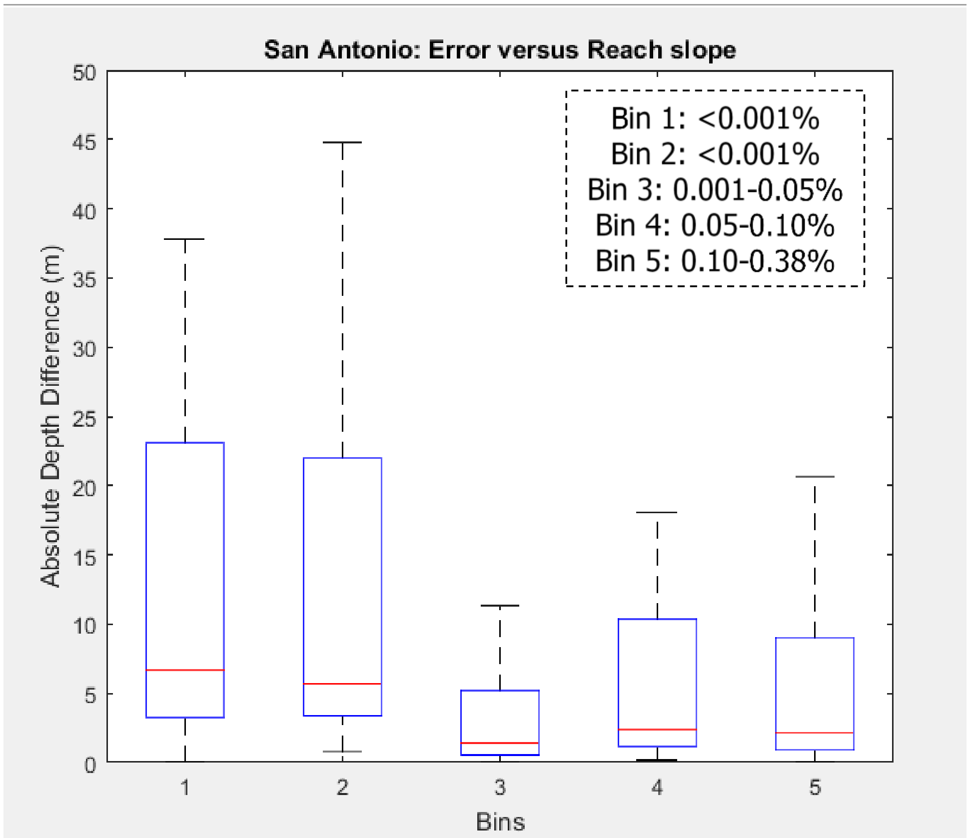

Figure 15: Box plot of the relationship between reach slope and SRC accuracy for the San Antonio river

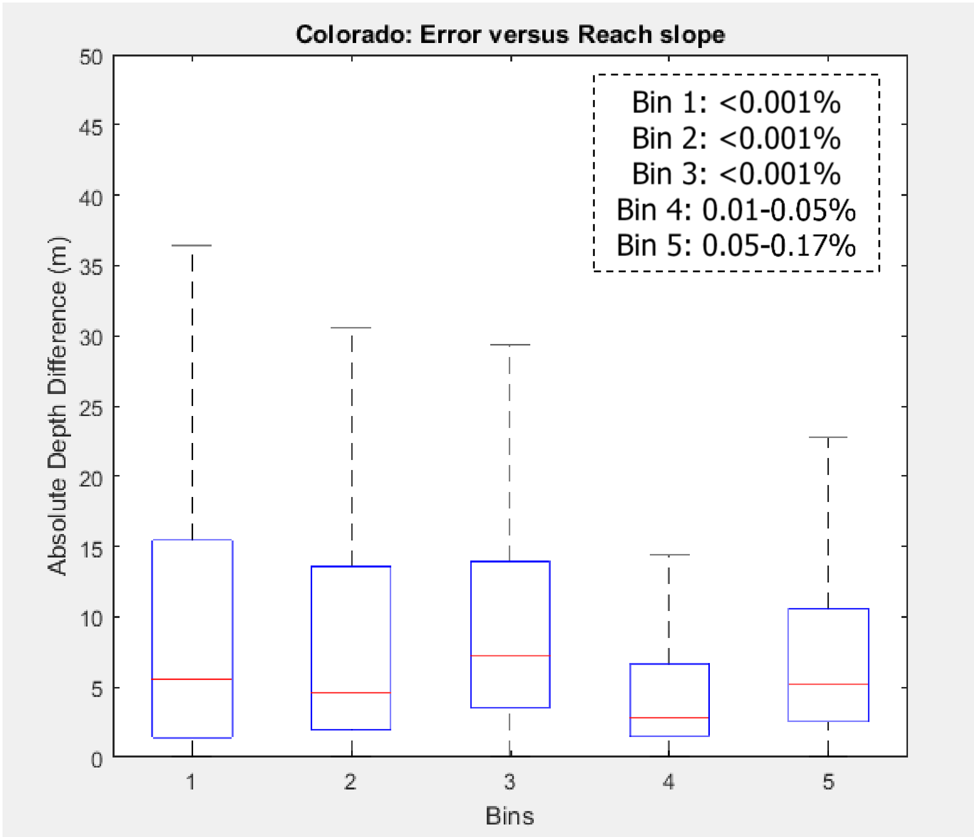

Figure 16: Box plot of the relationship between reach slope and SRC accuracy for the Lower Colorado river

We also test for the effect of other terrain characteristics and channel features including bankfull width, bankfull depth and geographical location of the reach such as distance downstream or upstream. None of these terrain characteristics or channel features are found to have any significant effect on SRC accuracy. Figure 17 is an example plot of this, where for the Blanco river we do not find a relationship between bankfull width and performance.

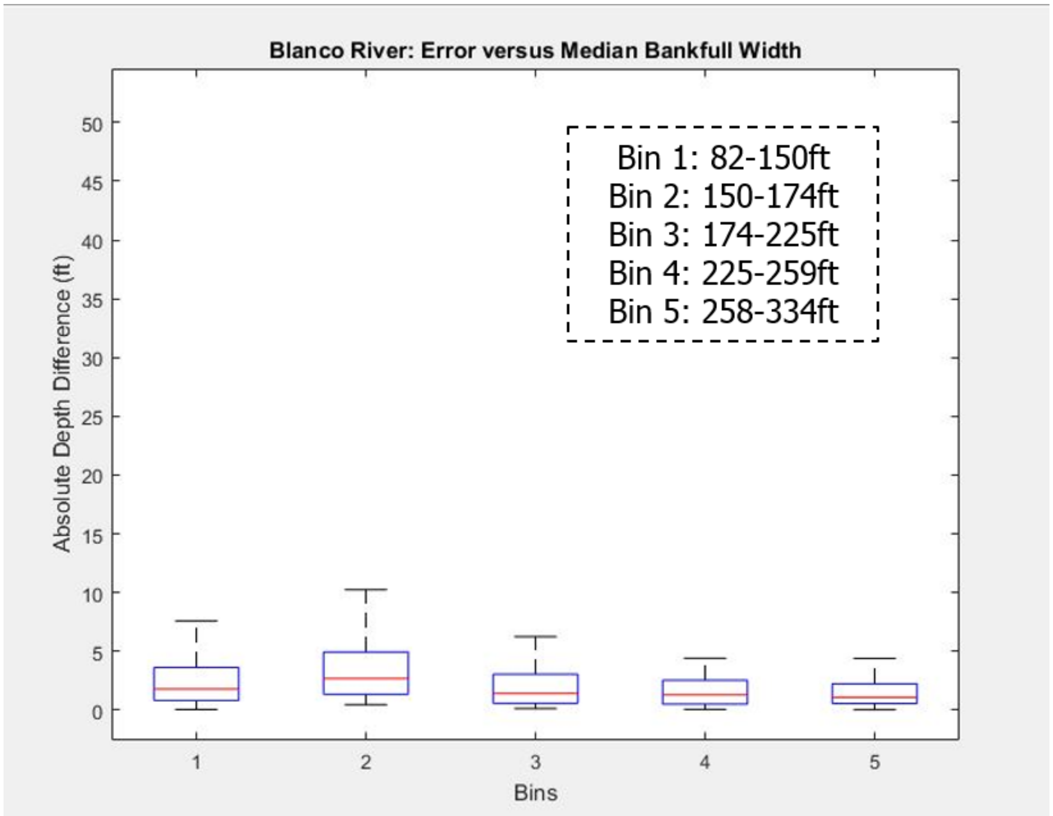

Figure 17: Box plot of the relationship between bankfull width and SRC accuracy for Blanco river

Discussion

The accuracy of the SRCs depends strongly upon the bed slope as was demonstrated in the previous section. A relevant observation is that reaches with medium slope values relative over a given channel network reflect, overall, SRCs that more accurately resemble verified HEC-RAS rating curves. It is important to note that the figures support the overall idea that both slope and reach length are good indicators of rating curve performance. It is also worth noting that for reaches with shorter lengths there is a poorer performance with the SRCs due to higher variability in slope values. Furthermore, depth calculated from

Manning's equation is particularly sensitive to changes in slope. Thus, more accurate values for local bed slope allow for the improvement of SRCs for small reaches.

We see significant differences between the performance of the Blanco river and the three other rivers. The most visible difference is that the SRCs perform particularly well for the medium length and medium slope reaches for the Blanco river, while they do not for the other three rivers. Short and long reaches as well as low slope and steep slopes perform poorly across all rivers. The Blanco river is steeper generally compared to the other rivers, and it may be this higher overall relief that allows for impressive performance of the reaches with regular characteristics in terms of length and slope. Flood inundation mapping, particularly using Manning's equation is more difficult in flat, coastal terrains.

A significant assumption in this analysis is uniform water depth over a reach length. A prospective research topic to pursue and that may augment rating curve comparisons is the extent of which non-uniform water surface level from variability in channel geometry causes poor rating curve performance. Results for this analysis would suggest an advisable upper limit to reach length, which could be used by reorganizing the channel network to something more appropriate for hydraulic modelling.

Chapter 5: Moving Window[3]

Objective

To propose changes to synthetic rating curves and quantify their improvement in performance.

Method

We look to test this framework for quantifying performance and suggest potential changes for the SRC calculation to improve performance. Due to the observation from the previously discussed plots that reaches with low slope have significantly higher mean error than other reaches, we look to recalculate slope for the application of Manning's equation that will reduce the mean error. An initial slope value for each reach was obtained from elevation values from the digital elevation datasets. The slopes were computed by taking the difference in elevation values between the grid cells along each reach of the main stem rivers. These values were compared to averaged slopes from the current version of the National Hydrography Dataset (NHDPlus) attributes table and were found to align accordingly (*McKay et al*., 2012). In an effort to produce more accurate SRCs by recalculating slope we developed a moving window approach. For reaches shorter than the moving window, the new slope value is calculated as a distance-weighted average of the slope of the short reach itself and the slopes of upstream and downstream reaches to the ends of the moving window, as

$$\boldsymbol{S_{new}} = \frac{\boldsymbol{1}}{\boldsymbol{L_{total}}} \sum_{\boldsymbol{i=1}}^{\boldsymbol{N}} \boldsymbol{S_i L_i} \qquad \text{(Equation 2)}$$

[3] Part of study to be submitted as *Godbout et al.* to JAWRA (in preparation)

Where S represents the reach slope and L represents the reach length. For the reaches at the ends of the moving window, the reach length is taken from the previous reach to the end of the moving window rather than the total reach length. L_{total} is by definition the moving window length, and S_{new} is the new slope that is the weighted average slope over the N reaches that are within the moving window.

To find the ideal moving window length for each river we used a scaling analysis approach. We found the optimal length of the moving window for each river by calculating the mean normalized RMSE over all reaches in the river for a variety of moving window lengths and then taking the value that improved the SRC performance most.

Averaging the normalized RMSE over all reaches in the main stem of the river allowed us to assess the effect of moving window length on accuracy, and an ideal minimum length or set of lengths was found for each river. The approach is generalizable for any river and allows for the calculation of an optimal moving window length for SRCs wherever more accurate rating curves are available. An ideal moving window length can be calculated for locations near USGS gage stations and where calibrated HEC-RAS models are available.

RESULTS

The proposed methodology for improving SRC performance using the moving-window approach with recalculating slope was conducted for the Blanco, Guadalupe, Colorado and San Antonio Rivers. The scaling analysis of the moving-window approach of slope recalculation for application in Manning's equation is shown for the Blanco river in Figure 18. The initial performance is shown in a dashed line, while the measure of error is plotted as the length of the moving window increases. The improvement is very significant with an improvement from 20.7% to 7.8% at 1.25km, corresponding to a decrease of 38% of the initial mean SRC error. It is important to remember that the Blanco river has different terrain characteristics and channel features to the other three rivers, being a smaller tributary with steeper overall relief.

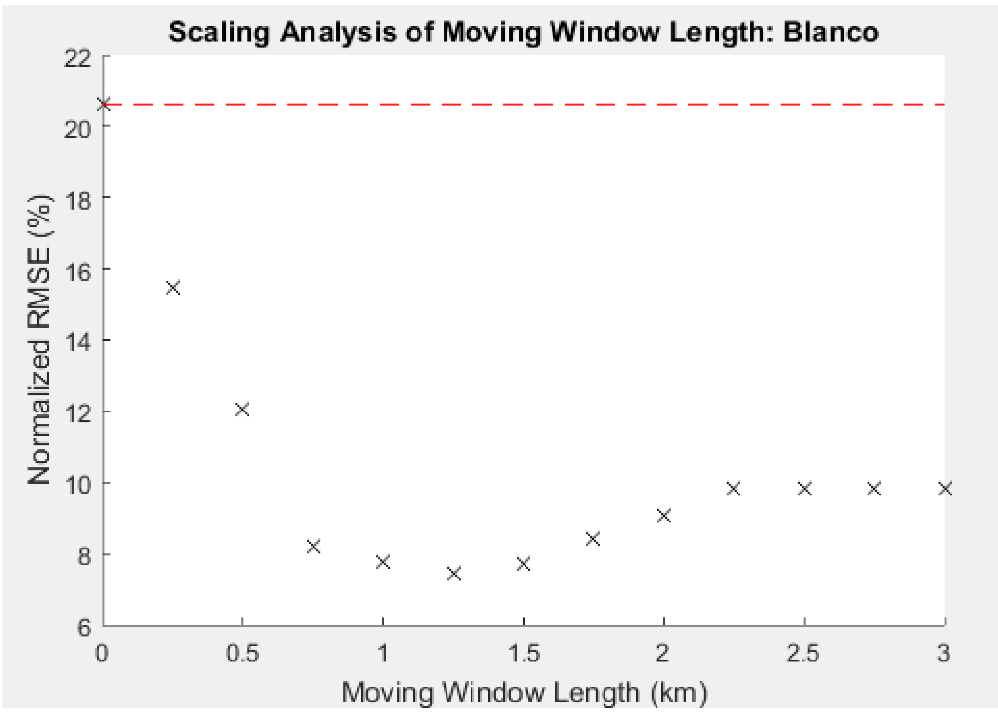

Figure 18: Scaling analysis for comparison of reach-averaged normalized RMSE against moving window length for the Blanco river

However, the performance of the slope recalculation for the other three rivers is not nearly so impressive. These are presented in Figure 19 with the initial performance with no slope recalculation shown in a dashed black line. For the Guadalupe River in green plus signs, the initial average normalized RMSE is 29.00% while the optimal value is found to be 26.43% for a moving window length of 2.25km. For the San Antonio River in blue asterisks, the initial average normalized RMSE is 23.14% while the optimal value is found to be 21.61% for a moving window length of 1.25km. For the Colorado River in red x signs, the initial average normalized RMSE is 30.15% while the optimal value is found to be 29.17% for a moving window length of 0.75km.

Between these three rivers we see some minor improvement in performance. We see particularly minor improvement for the Lower Colorado river with a short moving window, which may be related to the very low overall relief of the river. The Guadalupe and San Antonio see approximately a decrease of 10% of their initial mean normalized RMSE, with a similar moving window length of approximately 2km. These two rivers have a similar overall relief, approximately double that of the Lower Colorado river.

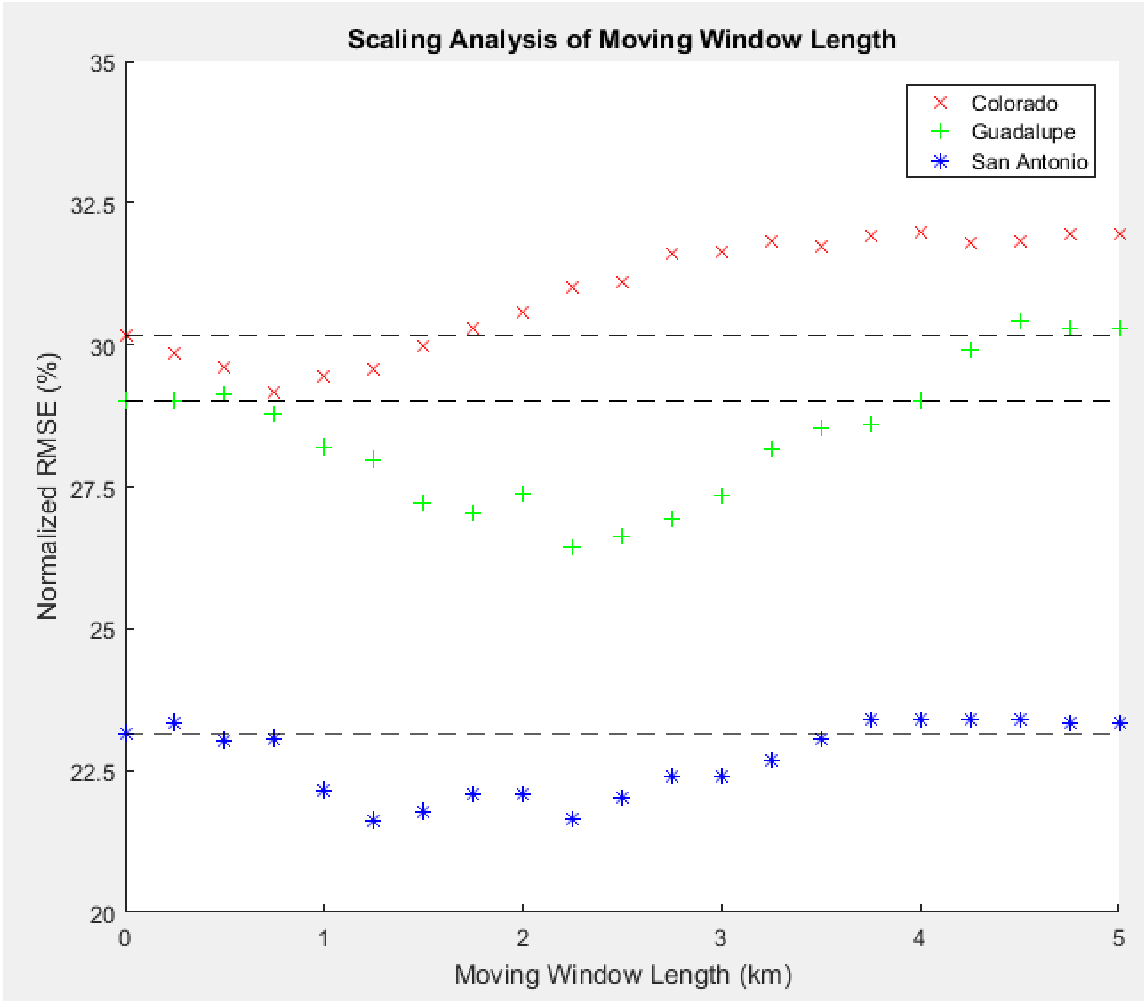

Figure 19: Scaling analysis for comparison of reach-averaged normalized RMSE against moving window length for the rivers.

DISCUSSION

The SRCs for the Blanco, Guadalupe, San Antonio and Lower Colorado rivers are improved by the moving window approach to varying levels of success. This variation may be due to terrain characteristics and channel properties such as overall relief, the distribution and spread of reach lengths and reach slopes, in addition to the bulk channel roughness. Estimating the discharge to stage height relationship using purely remote sensed data as in SRCs is not expected to be as accurate as using rating curves derived from detailed field studies, but this framework has been demonstrated to allow performance improvements to be quantified.

The poor performance of the three major rivers may be due to the low overall relief and long flat stretches of river. The channel bed elevation of the Guadalupe River along the thalweg is presented in Figure 20. The three highlighted areas show stretches of the Guadalupe river that are flat for long areas. There are many stretches that are flat or even slightly uphill along the thalweg over five kilometers or more, significantly longer than the length of many reaches. The channel bed elevations of San Antonio river and Lower Colorado show similar trends, while the channel bed elevation of Blanco does not have any flat stretches longer than a kilometer. These long flat sections may be the reason for the relatively minor performance improvements, where to improve slope values the moving window would have to be made so long that the information contained in local slope values would be largely unused by taking an average slope over such a long distance.

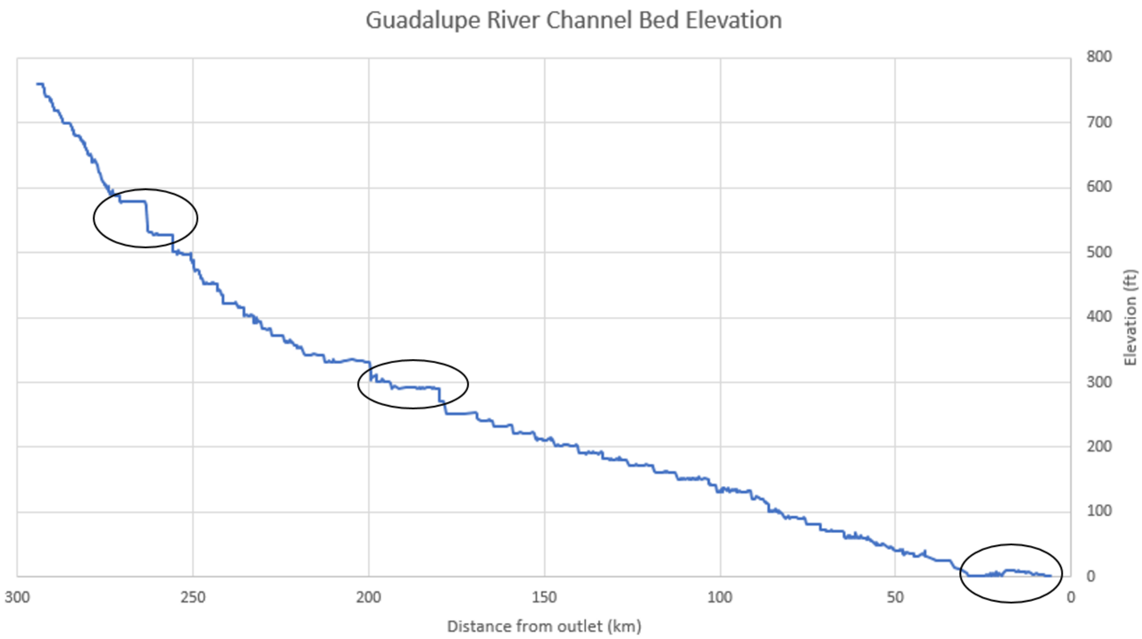

Figure 20: Elevation profile along the Guadalupe river thalweg

Other improvements to the National Flood Interoperability Experiment (*Maidment*, 2017) could be made, such as introducing a new hydraulic network where reaches in the NHDPlus network are recalculated according to some uniform or optimal reach length. The NHDPlus network was not designed for hydraulic modelling, and both short and long reaches pose a significant difficulty to accurate SRCs and inundation mapping, an issue that could be sidestepped by combining short reaches and splitting long reaches.

Using the moving window approach on other study areas or introducing new changes to the SRC calculation would be useful considering the framework applied here to quantify improvements.

Chapter 6: Discussion and Conclusion

Research Questions

1. ***What is the overall accuracy of the synthetic rating curves?***

We presented a framework to validate the performance of SRCs by comparing SRCs computed for a reach to HEC-RAS rating curves for individual cross sections. The results of this comparison for SRCs as they currently exist quantify their current performance. The four rivers are found to have mean normalized RMSE values ranging from 20.6% to 31.2% showing that the SRCs are somewhat close but still have significant room for improvement. The percent biases range from -9.5% to 35.5%, with an overall trend of the SRCs over-predicting stage height for a given discharge compared to the HEC-RAS rating curves.

As previously mentioned, the performance of the SRCs are heavily influenced by the quality of the topographic data from which the rating curves are derived. There is therefore assurance in the notion that improvements in the resolution of topography data may address issues related to the reliability of SRCs. Higher resolution DEMs, which may better represent the shape and length of channels as well as the underlying thalweg, can serve to strengthen the information displayed by synthetic rating curves and adjust to an extent their alignment with calibrated HEC-RAS rating curves (*Zheng et al*., accepted). The employment of better-quality can improve the quality of the SRCs.

2. ***Do terrain characteristics and channel features affect synthetic rating curve accuracy?***

We find that from our study the two terrain characteristics and channel features that predict SRC accuracy are reach length and slope. We suggest that these two are related as the plots of error by reach length show that in particular short reaches with very low slope perform the worst. Similarly, short reaches with very high slope values also perform poorly. Reaches with extreme slope values are unlikely to perform well because Manning's equation is sensitive to slope, and reaches that are flat or slightly uphill are not going to have no flow or flow backwards along the river. Intuitively we know that water will continue to flow down the river even for these sections where the slope is different to the majority of the river. We propose a moving window approach to recalculate slope, but a variety of approaches to account for this issue are possible.

Other terrain characteristics and channel features that were not present in our study area may also have an effect on rating curve accuracy. We know that roughness has a significant effect on Manning's equation, but in this study we assume a uniform roughness for all reaches since we do not have data to take as ground truth for roughness. Rivers or reaches with more or less vegetation may perform worse than areas with a moderate amount of roughness. This issue remains difficult to solve since in channel roughness is difficult to estimate from remote sensed data and changes from year to year in addition to throughout the year.

3. ***How can the performance of synthetic rating curves be improved?***

We suggested a method to recalculate the slope for every reach and tested the effect of this on the overall SRC accuracy. The SRC accuracy assessment was successful, although the increase in performance from the slope calculation was relatively minor. We found that the moving window and scaling analysis was very successful for the smaller Blanco river which is steeper and a tributary, while for the longer flatter major rivers there was less improvement. We hope that the framework for quantifying SRC performance continues to be used in an effort to make SRCs as accurate as possible for inundation mapping. Further suggestions for improvements to SRCs and to the NWM inundation mapping process as a whole are discussed in the following section.

Recommendations for Improving HAND Inundation Mapping

We have seen the ability of the HAND method using SRCs to produce automatic real time inundation maps, and here we suggest improvements to be made to this process. There are many possible improvements that could be made for the second iteration of HAND, some of which are more promising than others. Improvements to SRC calculation and the application of HAND will produce more accurate inundation maps. Some of the inaccuracies stem from terrain differences, some stem from the elevation data used, and other inaccuracies stem from how assumptions are handled by the model. Recommendations are suggested here to reduce or remove these sources of inaccuracy. Any of these SRC changes can be tested using this framework for SRC accuracy assessment, allowing for improvements to be quantified and tracked.

One simple improvement to the NWM process is using higher resolution topography data as previously mentioned. While lidar is not available everywhere, where it is available it can be used in conjunction with advanced channel detection techniques. The automatic feature extraction tool GeoNet (*Passalacqua et al.,* 2010) could be used to automatically map flow paths that more accurately align with the channelized terrain using a nonlinear filtering technique. Lidar will therefore allow both improved channel geometry approximations from the elevation data as well as a more accurate channel network.

Other improvements to the National Flood Interoperability Experiment (*Maidment*, 2017) could be made, such as introducing a new hydraulic network where reaches in the NHDPlus network are recalculated according to some uniform or optimal reach. The NHDPlus network was not produced with inundation mapping or hydraulic modelling in mind, and contains reaches shorter than ten meters as well as reaches over ten kilometers. The NHDPlus network was not designed for hydraulic modelling, and both short and long reaches pose a significant difficulty to accurate SRCs and inundation mapping, an issue that could be sidestepped by combining short reaches and splitting long reaches. A new reach network that contains uniform length or some optimal length of reach for inundation mapping would likely lead to improvements in accuracy for the NWM predicted inundation maps.

One assumption that we can look to challenge is that of a uniform water surface level for each catchment, or all the area that flows into a given reach. While this problem will be improved by the new hydraulic network with uniform or optimal reach lengths, there may still be some locations where the water surface level elevation of two adjacent reaches is drastically different. There are different ways to approach this problem. First, you could enforce a maximum difference in water surface level elevation between adjacent catchments and take a weighted average of the two elevations such that the maximum is never exceeded. Second, you could add an extra step where you use a 2D moving window where the water surface elevation is smoothed out such that it will gradually change from one water surface elevation to another rather than abruptly. Finally, you could leave the system as it is and implement a check where if the water surface elevation difference between two adjacent catchments is more than a specific value such as one meter, a warning will flag, allowing for further investigation.

There are further options for SRC improvement by better accounting for terrain and channel differences. Roughness is an issue that is hard to address as it is difficult to measure and it can change rapidly with vegetation growth and flash floods that remove vegetation from the channel. One initial improvement that could be made is to use composite values of in channel roughness and overbank roughness rather than a bulk value as roughness is expected to increase past the banks where the flow is shallower and more vegetation leads to an increase in friction. A second approach that could be used is to develop an algorithm that estimates the changes in roughness due to seasonality and flash floods, such that during the seasons when vegetation is minimal the roughness value is lower, during seasons when the channel is heavily vegetated the roughness value is higher, and when a flash flood occurs the roughness value drops accordingly. Since Manning's equation is sensitive to roughness, more accurate estimates of roughness or Manning's n may lead to significant improvements in SRC performance.

Another study has been conducted on assessing the overall accuracy of the NWM inundation mapping process (*Zheng et al*, in preparation). The overall accuracy of this process depends upon the rainfall forecasts, the runoff models to calculate discharge, the SRC conversion to stage height and finally the HAND relative elevation to predict the extent of inundation. *Zheng et al* find that the NWM accurately predicted the bulk inundation extent of Hurricane Harvey in 2017. While predictions for specific locations had significant variations between the predicted inundation and measured inundation, the prediction was relatively unbiased. Further studies for floods in different locations could be completed to test whether this assessment of the accuracy and lack of bias for the NWM holds for different situations.

FINAL REMARKS

The HAND methodology with SRCs has the potential to provide real time inundation extents for discharges generated by the National Water Model. The suitability of the HAND methodology with SRCs for continental scale inundation mapping warrants further attention and study to improve their accuracy.

We produced a framework to compare SRC performance to HEC-RAS rating curves. SRC accuracy was assessed for the four rivers with significant differences to the rating curves from detailed field studies as expected from using purely remote sensed information including 10m resolution elevation data.

We proposed a moving window approach to recalculate reach slope and assessed the impact of this change on SRC performance using the proposed framework. The improvement was found to be very significant for one river but relatively minor for the three others. This method or a similar approach should be used to improve accuracy by not simply using only the slope of the individual reach in Manning's equation. This change and other improvements should be used to improve SRC accuracy to provide emergency response with better real time inundation maps to better prepare communities for risks associated with natural disasters.

Lastly, the efforts presented in this thesis can be viewed as initial steps or iterations to investigate optimal reach length and slope. Further exploration of the proposed moving window approach across different terrains and rivers will be necessary for a robust and comprehensive basin scale evaluation under various morphological contexts. Furthermore, there are a variety of possible changes that can be made for the SRCs and National Water Model process that can improve the accuracy of the flood inundation maps, and these improvements can be quantified and tracked.

Appendix

This appendix includes four codes used to recalculate the SRCs using a variety of moving window lengths that produce new slope values. Aggregate statistics are produced using the new SRCs for each moving window length for the four rivers.

Code 1: Recalculate slope for a range of moving window lengths

```
import arcpy
import os
import pandas
import numpy
import gc
import time
start_time = time.time()

# Three input files
# List of COMIDs with their discharge values and maximum station (cross section ID)
comid_max_stn_file = r"C:\Users\Lukas\Miniconda32\HAND_RCs\Scaling_Analysis\San_Antonio\SanAntonio_COMID_max_station.csv"
# Hydroprop table from NFIE for the HUC6 that the river is within
hydro_file = r"C:\Users\Lukas\Miniconda32\HAND_RCs\Scaling_Analysis\hydroprop-fulltable-121003.csv"
# NHD attributes table of the HUC6 that the river is within
NHD_att_table = r"C:\Users\Lukas\Miniconda32\HAND_RCs\Scaling_Analysis\nhd_121003.csv"
# Run this script for each moving window length you want to use, edit only the threshold and output file name
threshold = 1.75 #in km
output_file = r"C:\Users\Lukas\Miniconda32\HAND_RCs\Scaling_Analysis\San_Antonio\Intermediate_outputs\hydroprop-121003_1750.csv"

# Recalculate the slope if the length of the reach is shorter than the moving window length
def main():
    hydroprop_df = pandas.read_csv(hydro_file)
    NHD_att_df = pandas.read_csv(NHD_att_table)
    comid_maxstn_df = pandas.read_csv(comid_max_stn_file)
    output_df = pandas.DataFrame()
    # Track how many reaches we change the COMID slope for
    counter_reaches = 0
    counter_us_changes = 0
    counter_ds_changes = 0

    # Loop through all COMIDs
    for cur_comid in comid_maxstn_df["COMID"]:
        print cur_comid
        cur_length = float(NHD_att_df.loc[NHD_att_df["COMID"] == cur_comid,"LENGTHKM"])
        output_df_tmp = hydroprop_df.loc[hydroprop_df["CatchId"] == cur_comid,]
```

```
        us_skip=0
        ds_skip=0

        # Only recalculate slope if the length of the reach is shorter than the moving window length
        if cur_length < threshold :
            cur_to_node = int(NHD_att_df.loc[NHD_att_df["COMID"] == cur_comid,"ToNode"])
            cur_from_node = int(NHD_att_df.loc[NHD_att_df["COMID"] == cur_comid, "FromNode"])
            cur_slope = float(hydroprop_df.loc[hydroprop_df["CatchId"] == cur_comid, "SLOPE"].unique())
            us_window = pandas.DataFrame({"Length":cur_length/2,"Slope":cur_slope,"LSproduct":cur_length*cur_slope},index=[0])
            ds_window = pandas.DataFrame({"Length":cur_length/2,"Slope":cur_slope,"LSproduct":cur_length*cur_slope},index=[0])
            counter_reaches = counter_reaches + 1

            # Upstream of the reach
            # Continute to iterate until the end of the moving window is reached

            while (us_window.Length.sum() < threshold/2) and (us_skip == 0):

                us_comid = NHD_att_df.loc[NHD_att_df["ToNode"] == cur_from_node, "COMID"].values

                # Fix for if there are multiple upstream reaches such as at a fork
                # Take the higher stream order or take the mean if they are the same stream order
                if len(us_comid)>1:
                    stream_ord =  NHD_att_df.loc[NHD_att_df["COMID"].isin(us_comid),"StreamOrde"].values
                    us_slope = hydroprop_df.loc[hydroprop_df["CatchId"] == us_comid[stream_ord.argmax()], "SLOPE"].unique()
                    us_length = hydroprop_df.loc[hydroprop_df["CatchId"] == us_comid[stream_ord.argmax()], "LENGTHKM"].unique()
                    cur_from_node = int(NHD_att_df.loc[NHD_att_df["COMID"] == us_comid[stream_ord.argmax()],"FromNode"].unique())

                # Trace upstream and record the slope and length of the reach
                elif len(us_comid)==1:
                    us_slope = hydroprop_df.loc[hydroprop_df["CatchId"].isin(us_comid), "SLOPE"].unique()
                    us_length = hydroprop_df.loc[hydroprop_df["CatchId"].isin(us_comid), "LENGTHKM"].unique()
                    cur_from_node = int(NHD_att_df.loc[NHD_att_df["COMID"].isin(us_comid),"FromNode"].unique())

                else:
                    us_slope = hydroprop_df.loc[hydroprop_df["CatchId"].isin(us_comid), "SLOPE"].unique()
                    us_length = hydroprop_df.loc[hydroprop_df["CatchId"].isin(us_comid), "LENGTHKM"].unique()

                if len(us_comid)>0:
```

```
                    us_mw_new = pandas.DataFrame({"Length":us_length,"Slope":us_slope,"LSproduct":us_length*us_slope},index=[0])
                    us_window = pandas.concat([us_window,us_mw_new]).reset_index(drop=True)
                    counter_us_changes = counter_us_changes + 1

                # If no changes have been made then skip ahead
                else:
                    us_skip=1

            # Recalculate slope across the moving window using a weighted average
            if len(us_comid)>0:
                us_length_last = threshold/2 + us_window.iloc[-1, a.columns.get_loc('Length')] - us_window.Length.sum()
                us_window.iloc[-1, a.columns.get_loc('Length')] = us_length_last
                us_window.iloc[-1, a.columns.get_loc('LSproduct')] = us_length_last*us_slope

            # Downstream of the reach
            # Continute to iterate until the end of the moving window is reached

            while (ds_window.Length.sum() < threshold/2) and (ds_skip == 0):

                ds_comid = NHD_att_df.loc[NHD_att_df["FromNode"] == cur_to_node,"COMID"].values

                # Fix for if there are multiple downstream reaches such as at a fork
                # Take the higher stream order or take the mean if they are the same stream order
                if len(ds_comid)>1:
                    stream_ord =  NHD_att_df.loc[NHD_att_df["COMID"].isin(ds_comid),"StreamOrde"].values
                    ds_slope = hydroprop_df.loc[hydroprop_df["CatchId"] == ds_comid[stream_ord.argmax()], "SLOPE"].unique()
                    ds_length = hydroprop_df.loc[hydroprop_df["CatchId"] == ds_comid[stream_ord.argmax()], "LENGTHKM"].unique()
                    cur_to_node = int(NHD_att_df.loc[NHD_att_df["COMID"] == ds_comid[stream_ord.argmax()],"ToNode"].unique())

                    # Trace downstream and record the slope and length of the reach
                    elif len(ds_comid)==1:
                        ds_slope = hydroprop_df.loc[hydroprop_df["CatchId"].isin(ds_comid), "SLOPE"].unique()
                        ds_length = hydroprop_df.loc[hydroprop_df["CatchId"].isin(ds_comid), "LENGTHKM"].unique()
                        cur_to_node = int(NHD_att_df.loc[NHD_att_df["COMID"].isin(ds_comid),"ToNode"].unique())

                    else:
                        ds_slope = hydroprop_df.loc[hydroprop_df["CatchId"].isin(ds_comid), "SLOPE"].unique()
                        ds_length = hydroprop_df.loc[hydroprop_df["CatchId"].isin(ds_comid), "LENGTHKM"].unique()
```

```
                if len(ds_comid)>0:
                    ds_mw_new = pandas.DataFrame({"Length":ds_length,"Slope":ds_slope,"LSproduct":ds_length*ds_slope},index=[0])
                    ds_window = pandas.concat([ds_window,ds_mw_new]).reset_index(drop=True)
                    counter_ds_changes = counter_ds_changes + 1

                # If no changes have been made then skip ahead
                else:
                    ds_skip=1

            # Recalculate slope across the moving window using a weighted average
            if len(ds_comid)>0:
                ds_length_last = threshold/2 + ds_window.iloc[-1, a.columns.get_loc('Length')] - ds_window.Length.sum()
                ds_window.iloc[-1, a.columns.get_loc('Length')] = ds_length_last
                ds_window.iloc[-1, a.columns.get_loc('LSproduct')] = ds_length_last*ds_slope

# pandas.concat([moving_window,aaa]).reset_index(drop=True)
# mw_new = pandas.DataFrame({"Length":cur_length,"Slope":cur_slope},index=[0])

            if us_slope.size > 0 and ds_slope.size > 0:

                # Recalculate slope across the moving window using a weighted average
                us_avg_slope = float(us_window.LSproduct.sum() / us_window.Length.sum())
                ds_avg_slope = float(ds_window.LSproduct.sum() / ds_window.Length.sum())
                us_length = float(us_length)
                ds_length = float(ds_length)
                new_slope = (us_avg_slope * us_length + ds_avg_slope * ds_length) / (us_length + ds_length)
                output_df_tmp["SLOPE"] = new_slope
                output_df_tmp["Discharge (m3s-1)"] = output_df_tmp["WetArea (m2)"]*(output_df_tmp["HydraulicRadius (m)"]**(2/3))*(output_df_tmp["SLOPE"]**(0.5))/output_df_tmp["Roughness"]

        output_df = pandas.concat([output_df,output_df_tmp])

    output_df.to_csv(output_file)
    print("Reach counter:")
    print(counter_reaches)
    print("Upslope change counter:")
    print(counter_us_changes)
    print("Downslope change counter:")
    print(counter_ds_changes)

if __name__ == '__main__':
    main()
```

Code 2: Rating Curve Comparison which takes the median of the HEC-RAS rating curves at a set of discharge values to compare to the SRC

```
import numpy
import pandas as pd
import numpy as np
import os

def interpolation(x, y, X, negative_extrapolate=False):
    if not np.array_equal(x, np.sort(x)):
        y = y[np.argsort(x)]
        x = np.sort(x)
    if X < x[0]:
        if negative_extrapolate == False:
            Y = y[0]
        else:
            Y = y[1]+(y[0]-y[1])/(x[0]-x[1])*(X-x[1])
    elif X > x[-1]:
        Y = y[-2]+(y[-1]-y[-2])/(x[-1]-x[-2])*(X-x[-2])
    else:
        Y = np.interp(X,x,y)
    return int(Y)

def main():

    # Four input files
    # Specify this as the output from the previous moving window script
    HydroProp_file = r"C:\Users\Lukas\Miniconda32\HAND_RCs\Scaling_Analysis\San_Antonio\Intermediate_outputs\hydroprop-121003_1750.csv"
    # HEC-RAS rating curve profiles
    HECRAS_RCs_file = r"C:\Users\Lukas\Miniconda32\HAND_RCs\Scaling_Analysis\San_Antonio\SanAntonio_FinalRCs.csv"
    # Attributes of each HEC-RAS rating curve
    NHD_xs_file = r"C:\Users\Lukas\Miniconda32\HAND_RCs\Scaling_Analysis\San_Antonio\SanAntonio_NHD_xs.csv"
    # List of COMIDs with their discharge values and maximum station (cross section ID)
    NHD_Max_Station_Input = r"C:\Users\Lukas\Miniconda32\HAND_RCs\Scaling_Analysis\San_Antonio\SanAntonio_COMID_max_station.csv"
    # Specify an output file for each moving window length
    output = r"C:\Users\Lukas\Miniconda32\HAND_RCs\Scaling_Analysis\San_Antonio\Intermediate_outputs\SanAntonio_MedianRCs_1750.csv"

    hydroprop_raw = pd.read_csv(HydroProp_file)

    NHD_xs_data = pd.read_csv(NHD_xs_file)
    COMID_unique = NHD_xs_data.COMID.unique()

    output_df = pd.DataFrame()

    for com_id in COMID_unique:
        # This poart handles the HECRAS reach average RC
        output_df_tmp = pd.DataFrame()
        XS_info = NHD_xs_data.loc[NHD_xs_data['COMID'] == com_id]
```

```
        XS_info = XS_info.reset_index(drop = True)
        HECRAS_RCs_data = pd.read_csv(HECRAS_RCs_file)
        RC_info = HECRAS_RCs_data.loc[HECRAS_RCs_data.Station.isin(XS_info.RIVSTATION), ["Station", "Profile" ,"Discharge" , "Stage Height"]]
        RC_info = RC_info.reset_index(drop = True)
        output_df_tmp["Discharge"] = RC_info.Discharge.unique()
        output_df_tmp["COMID"] = com_id

        for cur_discharge in RC_info.Discharge.unique():
            RC_filt = RC_info.loc[RC_info["Discharge"] == cur_discharge, ["Station", "Stage Height"]]

            output_df_tmp.loc[output_df_tmp["Discharge"] == cur_discharge, "Median Stage Height"] = RC_filt["Stage Height"].median()
            output_df_tmp.loc[output_df_tmp["Discharge"] == cur_discharge, "Mean Stage Height"] = RC_filt["Stage Height"].mean()

        # This part is for interpolationg synthetic rating curve
        SRC_cur = hydroprop_raw.loc[hydroprop_raw["CatchId"] == com_id,["CatchId","Stage"]]
        SRC_cur["Stage"] = SRC_cur["Stage"]*3.28084
        SRC_cur["Discharge_RC"] = hydroprop_raw.loc[hydroprop_raw["CatchId"] == com_id,"Discharge (m3s-1)"] * 35.3147
        output_df_tmp2 = InterpolateRC(SRC_cur,output_df_tmp)
        output_df = pd.concat([output_df,output_df_tmp2])
        print com_id

    output_df.to_csv(output)

def InterpolateRC(RC1, RC2):
    # RC1 is SRC, RC2 is HEC-RAS
    # This function caculated the depth as per RC1 for flows from RC2
    RC_comparison = RC2
    RC_comparison["SRC_Depth"] = 0
    for flow in RC2.Discharge:
        if flow<=RC1["Discharge_RC"].max():
            row_index = RC1.loc[RC1["Discharge_RC"]>=flow,"Discharge_RC"].idxmin()
            Q2 = RC1.Discharge_RC[row_index]
            Q1 = RC1.Discharge_RC[row_index - 1]
            y2 = RC1.Stage[row_index]
            y1 = RC1.Stage[row_index-1]

            if Q1 == 0 or y1 == 0:
                # Do linear interpolation
                depth_interp = (y2-y1)/(Q2-Q1)*(flow-Q1) + y1
                # Print flow
            else:
                b1 = (numpy.log10(y2) - numpy.log10(y1))/(numpy.log10(Q2) - numpy.log10(Q1))
                b0 = y2/(Q2**b1)
                depth_interp = b0 * (flow ** b1)
            RC_comparison.loc[RC_comparison["Discharge"]==flow,"SRC_Depth"] = depth_interp
        else:
            RC_comparison = RC_comparison.drop(RC_comparison.loc[RC_comparison.Discharge == flow].index)
```

```python

    return RC_comparison

if __name__ == '__main__':
    main()
```

Code 3: Rating Curve Evaluation, calculates the mean normalized RMSE for each pair of SRC and HEC-RAS median rating curve

```python
import numpy
import pandas
import numpy
import os

# Use the output of the rating curve comparison
input_file = r"C:\Users\Lukas\Miniconda32\HAND_RCs\Scaling_Analysis\San_Antonio\Intermediate_outputs\SanAntonio_MedianRCs_1750.csv"
# Output one csv for each moving window length
output_file = r"C:\Users\Lukas\Miniconda32\HAND_RCs\Scaling_Analysis\San_Antonio\RC_Comparisons\SanAntonio_RC_Comparison_1750.csv"
discharge_col = "Discharge"
SRC_depth_col = "SRC_Depth"
Std_depth_col = "Median Stage Height"
RC_ID = "COMID"

# Calculate a range of statistics for the comparison of the SRC and HEC-RAS median rating curve
def main():
    data_raw = pandas.read_csv(input_file)
    id_list = data_raw[RC_ID].unique()
    output_df = pandas.DataFrame()
    output_df[RC_ID] = id_list
    for cur_id in id_list:
        cur_data = data_raw.loc[data_raw[RC_ID] == cur_id,[discharge_col,Std_depth_col,SRC_depth_col]]
        output_df.loc[output_df[RC_ID] == cur_id,"RMSE"] = ((cur_data[SRC_depth_col] - cur_data[Std_depth_col]) ** 2).mean() ** .5
        output_df.loc[output_df[RC_ID] == cur_id,"N_RMSE"] = output_df.loc[output_df[RC_ID] == cur_id,"RMSE"]/max(cur_data[Std_depth_col])
        output_df.loc[output_df[RC_ID] == cur_id,"Max Error"] = max(cur_data[SRC_depth_col] - cur_data[Std_depth_col], key = abs)
        output_df.loc[output_df[RC_ID] == cur_id,"Range"] = max(cur_data[SRC_depth_col] - cur_data[Std_depth_col]) - min((cur_data[SRC_depth_col] - cur_data[Std_depth_col]))
        output_df.loc[output_df[RC_ID] == cur_id,"PBias"] = sum(cur_data[SRC_depth_col] - cur_data[Std_depth_col])/sum(cur_data[Std_depth_col])*100
        output_df.loc[output_df[RC_ID] == cur_id,"R_Squared"] = coefficient_of_determination(cur_data[SRC_depth_col],cur_data[Std_depth_col])

    output_df.to_csv(output_file)

def coefficient_of_determination(ys_orig,ys_line):
```

```python
    y_mean_line = ys_orig.mean()
    squared_error_regr = sum((ys_orig - ys_line)**2)
    squared_error_y_mean = sum((ys_orig - y_mean_line)**2)
    return 1 - (squared_error_regr/squared_error_y_mean)

if __name__ == '__main__':
    main()
```

Code 4: Calculate mean normalized RMSE for all of the moving window lengths

```python
import numpy
import pandas
import numpy
import os

# Point the input to the folder where all outputs from the rating curve evaluations
input_folder = r"C:\Users\Lukas\Miniconda32\HAND_RCs\Scaling_Analysis\San_Antonio\RC_Comparisons"
# Final output which shows the scaling analysis of the moving window lengths
output_file = r"C:\Users\Lukas\Miniconda32\HAND_RCs\Scaling_Analysis\San_Antonio\SanAntonio_Scaling_Analysis_RMSE.csv"

def main():
    pass

    file_list = os.listdir(input_folder)
    output_df = pandas.DataFrame()
    output_temp = pandas.DataFrame()

    for i in range(len(file_list)):
        cur_path = os.path.join(input_folder,file_list[i])
        cur_values = pandas.read_csv(cur_path)
        cur_mean = cur_values.RMSE.mean()
        output_temp = pandas.DataFrame({"cur_mean":cur_mean},index=[0])
        output_df = pandas.concat([output_df,output_temp]).reset_index(drop=True)

    output_df.to_csv(output_file)

if __name__ == '__main__':
    main()
```

Glossary

DEM Digital Elevation Model, a 3D representation of the surface of the Earth.

HAND Height above nearest drainage, a measure of relative elevation between a location and the bed of the channel that it drains into. When the stage height exceeds the HAND value, that location is flooded.

HEC-RAS Hydrologic Engineering Center's River Analysis System, software that uses the 1D shallow water equations to simulate channel flow.

HUC Hydrologic Unit Code, a sequence of numbers that identify a hydrological feature, organized by delineating drainage areas or watersheds in a hierarchical manner.

Lidar Light detection and ranging, a similar technology to radar that uses light to measure topography.

NED National Elevation Dataset, a seamless dataset produced by the USGS that covers continental U.S. with 10m resolution.

NHDPlusV2 The current iteration of the National Hydrography Dataset, a catalogue of watersheds, rivers, and lakes produced by the US EPA and USGS.

NOAA National Oceanic and Atmospheric Administration, an agency of the U.S. Department of Commerce responsible for applications of hydrology and meteorology.

NWC National Water Center, the organization responsible for producing and running the National Water Model.

NWM National Water Model, a hydrological model that predicts discharge for 2.7 million reaches spanning all of continental USA.

Rating Curve A relationship between discharge and stage height that is valid for a single river cross section or reach.

Reach A section of river that can be assumed to be level. In our study reaches are defined by the NHDPlus network.

RMSE Root mean square error, a statistical measure used to aggregate a set of error values.

SRC Synthetic rating curve, a relationship between discharge and stage height valid for a reach that is derived using Manning's equation and elevation data.

Stage Height The vertical difference of the water surface level and the channel bed along the thalweg.

Thalweg A line that follows the deepest section along the course of a river

USACE U.S. Army Corps of Engineers, a branch of the defense force responsible for infrastructure. For this thesis they have provided HEC-RAS models of cross section geometry for four Texas rivers.

USGS U.S. Geological Survey, the federal organization focused on science and technology, in particular on earth sciences.

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