

DISSERTATION

HYDROLOGICALLY CONNECTED FLOODPLAINS AND WOOD-RICH STREAMS
PROMOTE GREATER ATTENUATION OF FLASH FLOODS

Submitted by

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ABSTRACT

HYDROLOGICALLY CONNECTED FLOODPLAINS AND WOOD-RICH STREAMS PROMOTE GREATER ATTENUATION OF FLASH FLOODS

Flash floods are a significant threat, destroying infrastructure and claiming lives. Management of river corridors within the past ~200 years has mainly involved building in areas which frequently flood and then attempting to control floods through local infrastructure projects. We have accelerated floodwater through channels (increasing conveyance) in populated areas and stored flood water behind dams to reduce flooding. Increasing floodwater conveyance is achieved by two main methods, often done in tandem. The first method, termed “snagging,” removes obstructions to flow including wood, riparian vegetation, and boulders. The second method of increasing conveyance is channelization, wherein the river channel is deepened and widened. These practices come at a heavy cost monetarily and environmentally.

Global efforts have been made to explore alternatives to these historical flood-control practices. One of the leading ideas is termed “Natural Flood Management,” which involves strategically restoring the natural ability of rivers and floodplains to attenuate floods with highly obstructed wood-rich channels and well-connected floodplains. The rapid floods with high intensity but a relatively low total volume experienced by these systems make them prime candidates for this style of management. I quantified the flood control benefits provided by wood-rich streams with connected floodplains in Colorado headwater systems.

To fully understand the ability of healthy rivers in Colorado to attenuate flash floods, I studied them at multiple scales. Firstly, I created a highly physics-based two-dimensional model of three reaches of streams to understand which processes are key to adequately represent the ability of a reach to attenuate flow. I then created novel simplified models which encapsulated the important processes I identified with the 2-D hydrodynamic models while being easily applied at large scales. Finally, I used this newly developed model to represent a full watershed in northern Colorado to test the impacts of different management strategies on the propagation of flash floods throughout the system.

I quantified flood attenuation at the reach scale utilizing two-dimensional hydrodynamic models simulating flash floods in three stream reaches located in the Colorado Rocky Mountains of the United States. I quantified the (a) magnitude of attenuation, (b) total accessible floodplain volume, (c) volume of floodwater stored in floodplain depressions, (d) variability of flow path travel times, (e) floodplain heterogeneity, and (f) relative importance of these mechanisms in flood attenuation. I found unprecedentedly high discharge attenuation with an average 13.8% reduction in peak flow per kilometer reach length and continued attenuation up to the 100-year recurrence interval flood. For the studied sites, the strongest correlations were between attenuation and storage in floodplain depressions. Flow path diversity metrics correlated best with attenuation for floods with a time-to-peak greater than 1 hr. My findings also indicated that maintenance of high floodplain roughness and accessibility are effective strategies for bolstering attenuation of flash floods at the reach scale in mountain systems.

To extend these findings to larger scales, I developed five numerical models varying in detail and physical realism for these same streams to identify a simple, effective, and efficient method of routing floods. These models included spatially uniform 1D hydrodynamic models

and four variations of Muskingum-Cunge hydrologic routing models. For each model I compared output hydrographs using Kling Gupta Efficiency, Nash Sutcliffe Efficiency, difference in peak flow attenuation, and differences in predicted total volume retained within the models. I found that standard Muskingum-Cunge routing methods are insufficient in reproducing flood hydrographs because they underpredict water retention within the floodplain and overpredict peak outlet discharge. The model that most effectively reproduced flood routing when compared to 2D hydrodynamic models was a new method I developed to account for floodplain storage of water, which I refer to as the Muskingum-Cunge Augmented Floodplain (MCAF) method. This method scales the volume of water retained on the floodplain by the overall inundated floodplain volume. My results indicate that hydrologic routing algorithms, such as the classic Muskingum-Cunge approach, need better methods to account for mass storage of water in floodplains to accurately predict the attenuation of flash floods in mountain streams, and my Muskingum-Cunge Augmented Floodplain routing scheme improves predictions of flood routing.

Finally, I applied the MCAF method in a full watershed hydrologic model of the Elkhorn Creek watershed in northern Colorado. The studied watershed has recently been the site of reach-scale wood additions. I installed hydrologic instruments throughout the watershed and observed two flash floods driven by convective storms over two years. I used the larger of the floods to calibrate a Monte-Carlo event-based watershed model and validated model performance on the smaller observed flood. This produced six behavioral models which I used to simulate floods with different river corridor management scenarios by changing routing of flood waters within the river corridor parameters. I simulated four routing scenarios: the existing conditions, snagged conditions, conditions before the recent restoration efforts, and complete restoration of in-

channel wood. The simulated snagging had drastic impacts on the system, accelerating the flood wave propagation through the system and increasing the peak discharge across the watershed. The largest impacts of snagging were at the outlet of the watershed, with a mean 34.9% increase in peak discharge and a 1.44-hour reduction in time to peak. Adding more obstructions to the channel minimally impacted flood propagation, with a small, inconsistent delay in peak timing and no meaningful reduction in peak magnitude. The recent wood additions contributed to the attenuation of the site, with an average 5.2% reduction in peak flows in the headwater reaches after implementation. In certain flood scenarios the recent wood additions reduced peak discharges by up to 35%. My results indicate that maintaining wood supply in mountain streams may reduce the risk of deadly flash floods through reductions in peak discharge magnitude and delay flood propagation.

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Chapter 1 Introduction

Flooding remains one of the most dangerous and damaging extreme events (Saharia et al., 2017). In mountainous headwater streams, floods are generally flashy and spatially isolated (Wohl et al., 2024). This flashy nature can be intensified by widespread wildfires (Kean et al., 2019; Moody et al., 2013; Shakesby, 2011). These flash floods are dangerous and can cause immense damage to downstream infrastructure (Chrysovergis et al., 2021). Natural floodplains have been shown to attenuate floods, preserving infrastructure and protecting people downstream (Dadson et al., 2017; Lane, 2017; Puttock et al., 2017; Wyzga, 1996). In headwater mountain streams, unconfined reaches with low gradients, often referred to as river beads (e.g., Wohl et al., 2018), have the potential to attenuate floods and also provide other floodplain services, including soil organic carbon storage (Wohl & Knox, 2022), floodplain-groundwater exchange (Schulz et al., 2024), and sediment storage (Kemper et al., 2024, Figure 1.1). The short duration of these floods makes them particularly sensitive to attenuation in well-connected floodplains (Lininger & Latrubesse, 2016).

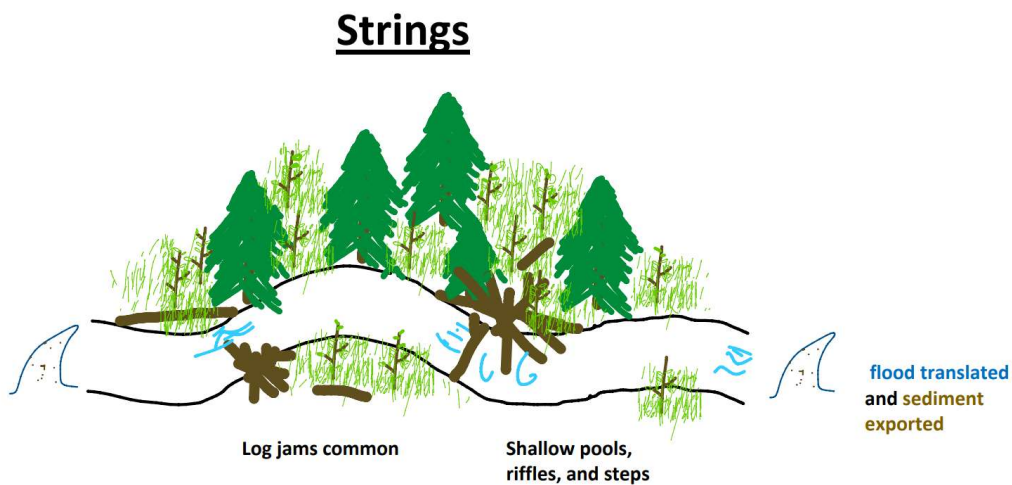
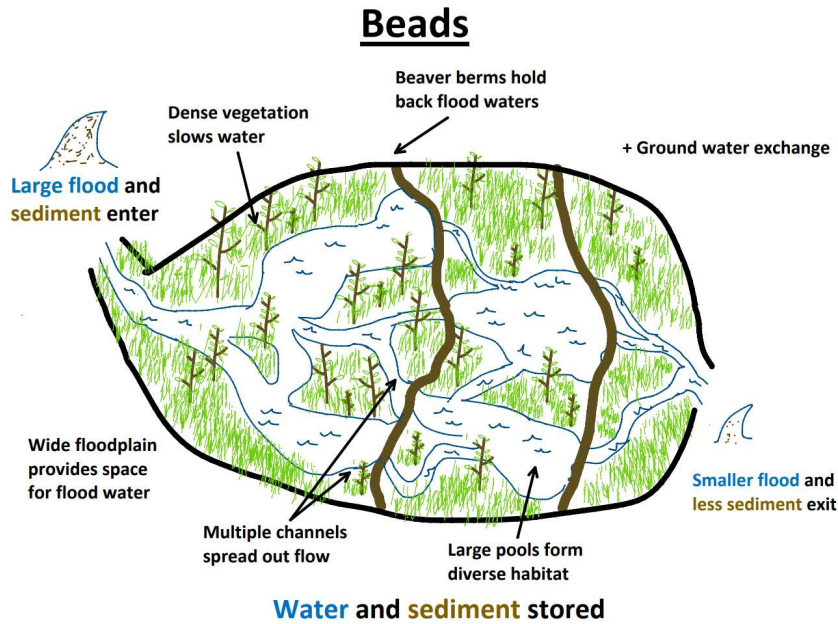


Figure 1.1: conceptual diagram of the general characteristics and services provided by beads and strings.

Despite their ecosystem services and flood attenuation, floodplains have been disconnected from rivers to increase dry arable land, prevent local flooding, and increase conveyance (Knox, Morrison, et al., 2022; Knox, Wohl, et al., 2022). This has had the unintended consequence of magnifying downstream flooding, severely altering riparian ecosystems, and elevating sediment transport through concentrating flow (Hupp & Simon, 1986;

Knox, Wohl, et al., 2022). To restore some of the services provided by floodplains, global efforts have been made to reconnect rivers with their floodplains. Some of the goals of these projects include modulating in-stream temperatures, increasing forage for juvenile fish, and importantly to this work, increasing flood attenuation (Christensen et al., 2024; Opperman et al., 2010; Sholtes, 2009). Several efforts have been made to understand the ability of these projects to increase flood attenuation, but key considerations have been missing which I aim to address through my work. The existing studies of attenuation in headwater streams mainly focus on floods with comparatively long (>10 hours to days) flood hydrographs resulting from persistent, moderate intensity rainfall, which is often generated by frontal convergence (Federman et al., 2023; Follett & Hankin, 2022; Neumayer et al., 2020; Puttock et al., 2017; Sholtes, 2009).

Existing knowledge of interactions between hydrograph shape and attenuation indicates that reductions in hydrograph duration should increase attenuation (Lininger & Latrubesse, 2016; Metcalfe et al., 2018). Some studies have investigated convective storms, which have increased intensity and occur more rapidly, yielding compressed hydrographs (duration of several hours), but the events they simulate are much longer than the floods I have observed in the Colorado Front Range, especially those following wildfires (Metcalfe et al., 2018; Wohl et al., 2024). An example of such a flood in my study catchments is the 2022 Little Beaver Creek flood, in which hydrophobic soils turned a relatively common convective storm into a flood larger than the regional curve estimation for the 1,000 year recurrence interval flow with a rising limb of only 1.25-hour (Wohl et al., 2024). Flash floods also occur in unburned areas and may achieve similar magnitudes and durations without wildfire given intense enough rainfall (Saharia et al., 2017).

Flood attenuation can be achieved through two major mechanisms: the storage of floodwaters and the dispersion of flood waves (Barry & Bajracharya, 1995; Chow, 1959;

Lininger & Latrubesse, 2016). Storage of floodwaters occurs when water is separated from the wave and can occur through storage in retention basins, reservoirs, or within floodplains (Acreman & Holden, 2013; Thomas & Nisbet, 2007). Studies have shown that storage losses for floods in arid environments can be major drivers of attenuation, but studies are lacking discussing losses for floods in semiarid mountain streams (Elfeki et al., 2015). Dispersion of a flood wave occurs throughout river systems as portions of the wave move at nonuniform speeds, causing a dampening effect without removing any of the mass from the wave (Barry & Bajracharya, 1995; Chow, 1959). The dispersion of flood waves is generally higher in well-functioning floodplains because there are more diverse flow paths and wave speeds, creating additional dampening of the wave (Chrysovergis et al., 2021; Lane, 2017; Lininger & Latrubesse, 2016). Floodplain storage of flood flows should also be elevated by well-functioning floodplains as these systems have numerous depressions which remove water from the main wave and return it slowly to the stream through subsurface processes (Puttock et al., 2017).

River beads have characteristics that lend themselves to flood dispersion and storage, including wide and topographically complex floodplains that can be heavily vegetated (Turner-Gillespie et al., 2003; Wohl et al., 2018). Dense vegetation increases the hydraulic roughness of the floodplain, while the topographic complexity forces flow paths to be tortuous and creates storage in depressions. These mechanisms are not represented uniformly throughout the different methods of modeling and measuring flood attenuation (Dixon et al., 2016; Elfeki et al., 2015; Paiva & Lima, 2024). Direct, in-situ measurement of flood attenuation captures the total effect of all mechanisms of attenuation but fails to explicate the individual impacts of floodwater storage, dispersion by roughness, and dispersion by flow paths. A major disadvantage of in-situ measurement of flood wave attenuation is that the observer must be ready to measure real-world

flooding events, which are rare and very destructive to the instruments used to measure them (Wohl et al., 2024). Aside from in-situ measurement of flood attenuation, we are left with simulating these events. One-dimensional hydrologic routing often requires the consideration of a reach as uniform. This simplification precludes one-dimensional models from considering the impact of nonuniform cross sections within a reach or the consideration of tortuous floodplain flow paths. One-dimensional models can represent losses of water to storage elements and consider the impact of dispersion through roughness elements if calibrated. Two-dimensional hydrodynamic models allow us to simulate these properties, including moving water over the microtopography of the floodplain, which creates tortuous pathways and storage elements (Chen et al., 2020; Tull et al., 2024).

2D hydrodynamic models are excellent tools for understanding reach-scale attenuation, but I am not aware of any existing studies that have used a fully 2D hydrodynamic model to represent routing for an entire watershed. Some studies have used hydrodynamic models at watershed scales (Dixon et al., 2016), but this necessitates large cells and a scheme to combine 1D models for the channel with 2D models. Dixon et al. (2016) used 20 m cells in a fully distributed hydrologic and hydrodynamic model along with a scheme to determine whether flow overtopped the channel banks by using the reach averaged channel characteristics as calculated by hydraulic geometry relationships (Leopold & Maddock, 1953). Although paired 2D-1D models with the full dynamic wave represent the physics of flood propagation most thoroughly of the watershed scale methods explored, their large cells alter the impact of floodplain topography and the use of average channel cross sections greatly simplifies channel-floodplain connection. This misrepresentation of floodplain topography which occurs using large cells eliminates the impact of dead storage in microtopography and severely hampers the ability of the

model to produce accurate representations of live floodplain storage. Studies of model type and resolution's impact on prediction of flood attenuation are severely lacking. Some studies have addressed the importance of model resolution on performance but did not study how attenuation changed through decreased resolution. Peña & Nardi (2018) studied the impact of resolution on predicted inundation for steady state events and simulated a large river with a 5 m-700 m cell size. The hydrodynamic model was used to calculate water surface elevation and then that was draped over the fine DEM to calculate metrics. Channel capacity was calculated moving downstream for each model resolution, but attenuation was not addressed. This leaves a significant knowledge gap as there are no direct conclusions which can be drawn from the existing work on the relationship between model resolution and predicted attenuation.

Alternatively to reducing model resolution, the diffusion wave and kinematic wave approximations are the two simplifications commonly used to reduce computation time (Fenton, 2019). The diffusion wave assumes that inertial and acceleration terms in the St. Venant equations are negligible (Chow, 1959). The kinematic wave assumption goes a step beyond the diffusion wave assumption by also ignoring pressure differences (Barry & Bajracharya, 1995). The kinematic wave is best applied for fast, shallow, subcritical flow with gradual changes in space and time. Examples of kinematic wave solutions include Muskingum and all derivative methods. These assumptions are generally not appropriate for rapid flooding events (flash floods or dam breaks) or for any area where there is a mixed flow regime (steep mountain streams): “Both approximations, advection-diffusion and Muskingum [kinematic wave], especially the latter, are vulnerable to shorter period fluctuations as they are small-diffusion approximations and rapidly-rising floods and/or shorter components present in a general input hydrograph have larger effective diffusion.” (P 252, Fenton, 2019). Despite the assumptions necessary to

optimally utilize kinematic wave solutions, this solution has been applied through Muskingum routing to rivers of all types, from the mainstem Amazon to the mountainous headwaters of the Colorado River (Paiva & Lima, 2024; Schulz et al., 2024).

The diffusion and kinematic wave methods have the added benefit of relatively easy modification to incorporate lumped losses, which are usually calibrated to field data. Elfeki et al. (2015) used a 3 parameter Muskingum method to simulate attenuation including transmission losses of a flood on an ephemeral stream and made a useful tool for applying 3-parameter Muskingum models. Bharali & Misra (2022) used a variety of Muskingum methods to create a range of estimations on an ungauged site. The diffusion wave is usually solved numerically, but can be solved analytically to further reduce computation time for calculating flood attenuation along a corridor (Paiva & Lima, 2024). This analytical solution has been applied to large floods in large rivers in the Amazon with 0.1-0.01% slopes. There are many empirically determined weighting factors including those for floodplain storage, additional inflow, and total flood volume. While this is a useful tool for reducing run times, this tool is not commonly applied and is best applied for gradually varying flow conditions.

Some of the most widely applied routing methods for hydrologic modeling are derivatives of the Muskingum method. These have the advantage of being integrated into standard hydrologic modeling software including HEC-HMS and SWAT, and are readily modifiable in terms of both routing diffusion and transmission losses (Neitsch et al., 2011; USACE, 2025). Many studies have been developed attempting to improve Muskingum routing for different applications but attenuation comparisons between these methods are lacking, especially for mountain streams. Previous studies compare field data to diffusion wave model results and then adjust the routing methods to match their data (Barati et al., 2012; Elfeki et al.,

2015; Paiva & Lima, 2024). Although there is no shortage of papers studying this, the literature is focused on large rivers with low slopes, leaving a gap for us to study these issues in smaller mountain streams. Some comparisons include the simplified and full shallow water equations for peak flow attenuation, but I have only found them on massive, low slope rivers (Dazzi et al., 2021; Paiva & Lima, 2024). This work has found reasonable agreement between the simplified models and the refined 2D models, but this may not hold true for the steep, rapidly varying, and mixed regime flows I observe in the mountains. The only effort I am aware of testing the different attenuation predictions of varying model types compared 1D and 2D representations of a large river (100 km² drainage area) with long flood duration (20 hr rising limb) and found small increases in attenuation for the 1D model (Ghavasieh et al., 2006). I have yet to find a comprehensive study comparing the computed attenuation of varying 2D model resolutions and the simplifications discussed above for mountain rivers and streams. This knowledge is essential to informing which modeling strategies should be used for developing watershed-scale understanding of mountainous flood propagation. Through testing and development of alternative routing schemes, I aim to identify the most efficient and effective methods for routing flash flood flows through mountainous watersheds.

Investigation of the watershed-scale impacts of different management strategies is essential to our ability to prioritize reaches for restoration, yet the watershed-scale investigations have been conducted on a very limited set of systems with vastly different properties to the systems I study. The most comprehensive modeling effort to ascertain the impact of elevating roughness on attenuation was conducted for a humid temperate watershed at low elevation (Dixon et al., 2016; Goodman et al., 2026). The events they simulate occur over many hours to days, characteristic of the area in which they work, but dissimilar from the flash floods

experienced in high elevation semi-arid mountain streams of the Intermountain West. This investigation found moderate increases in attenuation for recurrence interval storms between 2-10 years, but not for the largest storms. Knowing that shorter duration flows are better attenuated by rough systems (Woltemade & Potter, 1994), the flash floods generated in semiarid mountains should be attenuated effectively and be more sensitive to changes in roughness, but explicit testing of these events is lacking. I will fill this knowledge gap by simulating flash floods throughout mountainous watersheds using my newly developed routing methods.

One disadvantage of increasing roughness and slowing flood movement in the watershed is the potential to synchronize previously desynchronized runoff contributions, causing higher peak discharge (Dixon et al., 2016; Jefferson et al., 2017; McCuen, 1974). This issue has been observed in both simulated forested watersheds and in urban stormwater management where retention basins exacerbate flooding (Birkinshaw & Kristov, 2022a; McCuen, 1974). This synchronization of flows is a function of the watershed shape and properties, so findings for my scale analysis watersheds will not extend universally, and watershed-specific studies are necessary to extend any conclusions drawn in this work (Rinaldo et al., 1991). With these considerations in mind, my objectives for this work are:

- 1) Investigate reach-scale attenuation for flash floods in mountain streams.
 - a. Quantify the range of attenuation attainable during flash floods.
 - b. Identify the relative importance of the underlying floodplain mechanics that drive attenuation in these systems (storage and dispersion of flood waves).
- 2) Adequately simulate reach-scale attenuation with methods that can be readily upscaled to watershed models.
- 3) Determine the watershed-scale impact of management changes.

- a. Determine whether attenuation of flash floods can be significantly influenced at the watershed scale through floodplain reconnection and roughness additions.
- b. Identify reaches in a real watershed that can produce the largest impact on attenuation through floodplain reconnection and roughness addition.
- c. Determine the impact of “snagging” on the propagation of flash floods at the watershed scale.

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Chapter 2 The relative importance of floodplain storage and flow path dispersion on flood attenuation in mountain streams*

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2.1 Introduction

Accurate quantification of the attenuation of floodwaters through beads at the reach scale is essential to prioritize areas for management decisions that may influence attenuation, including wood additions, riparian buffer planting, or cattle enclosures (Dixon et al., 2016; Lane, 2017; Wohl et al., 2018). Efforts to investigate reach-scale flood wave attenuation have occurred, but work investigating these properties in river beads in flashy headwater streams is lacking. The existing studies of attenuation in mountain streams mainly focus on floods with comparatively long (> 10 hours to days) hydrographs resulting from persistent, moderate intensity rainfall, which is often generated by frontal convergence (Federman et al., 2023; Follett & Hankin, 2022; Neumayer et al., 2020; Puttock et al., 2017; J. Sholtes, 2009). Existing knowledge of interactions

between hydrograph shape and attenuation indicates that reductions in hydrograph duration should increase attenuation (Lininger & Latrubesse, 2016; Metcalfe et al., 2018). Some studies have investigated moderately flashy floods (duration of several hours) driven by convective storms, but the events they simulate are much longer than the floods I have observed in the Colorado Front Range, especially those following wildfires (Metcalfe et al., 2018; Wohl et al., 2024). An example of such a flood in this study catchments is the 2022 Little Beaver Creek flood, in which hydrophobic soils turned a relatively common convective storm into a flood larger than the regional curve estimation for the 1,000 year recurrence interval flow with a rising limb of only 1.25 hr (Figure A1) (Wohl et al., 2024). Flash floods also occur in unburned areas and may achieve similar magnitudes and durations without wildfire during intense rainfall (Saharia et al., 2017).

River beads are comparatively lower gradient and have wider floodplains when compared with adjacent reaches (Wohl et al., 2018). Thus beads have large live storage potential in wide floodplains, dead storage potential in floodplain depressions, and complex floodplains which may produce a diversity of flow paths (Turner-Gillespie et al., 2003; Wohl et al., 2018). Direct, in-situ measurements of flood attenuation capture the total effect of all mechanisms but fail to explicate the individual impacts of floodwater storage, dispersion by roughness, and dispersion by flow paths. A major disadvantage of in-situ measurement of flood wave attenuation is that the observer must be ready to measure real-world flooding events, which are rare and very destructive to the instruments used to measure them (Wohl et al., 2024). Aside from in-situ measurement of flood attenuation, I am left with simulating these events.

Simplifying assumptions often are necessary when simulating flood events, but the implications of these simplifications are not well tested for flash floods in mountain streams.

Some of these assumptions include one-dimensional flow, simplified flow physics for hydrologic routing, and the use of uniform reaches (Dixon et al., 2016; Federman et al., 2023; J. Sholtes, 2009). These simplifications neglect the impact of complex flow paths and usually do not include mechanisms for dead storage. Through this work, I minimize the simplifying assumptions with a fine scale, two-dimensional hydrodynamic models, which allow us to simulate and quantify tortuous flow pathways and dead storage elements to determine if these properties impact flow attenuation at the reach scale (Chen et al., 2020; Tull et al., 2024).

Given the gap in literature on flood attenuation in mountain streams and the relative importance of the different mechanisms of attenuation, my objectives are to 1) quantify the range of attenuation of flash floods attainable in headwater beads and 2) identify the relative importance of the underlying floodplain mechanics that drive attenuation in these systems. To accomplish these objectives, I use a combination of field data and two-dimensional hydrodynamic models for three headwater streams located in the Front Range Rocky Mountains of Colorado, United States.

2.1 Methods

2.2.1 Site description

To determine the ability of headwater beads to attenuate flash floods and the mechanisms driving attenuation, I studied three reaches of different headwater streams in the Colorado Front Range, United States (Figure 2.1): Little Beaver Creek (LBC), Elkhorn Creek (EH), and Beaver Creek (BC). The observed sites are all in the subalpine region ranging in elevation from 2,440 m to 2,740 m above sea level (Table 2.1). The flooding regime is characterized by sustained high flows in May–June from snowmelt and larger magnitude events occurring as flash floods from convective storms in July–August (Jarrett, 1990; Saharia et al., 2017; Triantafyllou & Wohl,

2024). Vegetation in these sections is generally characterized by woody shrubs, grasses, and small deciduous trees due to the relatively wet riparian environment (Wohl et al., 2024). While all the sites have evidence of historic beaver activity, none of the studied sites had active beavers during the period of data collection.

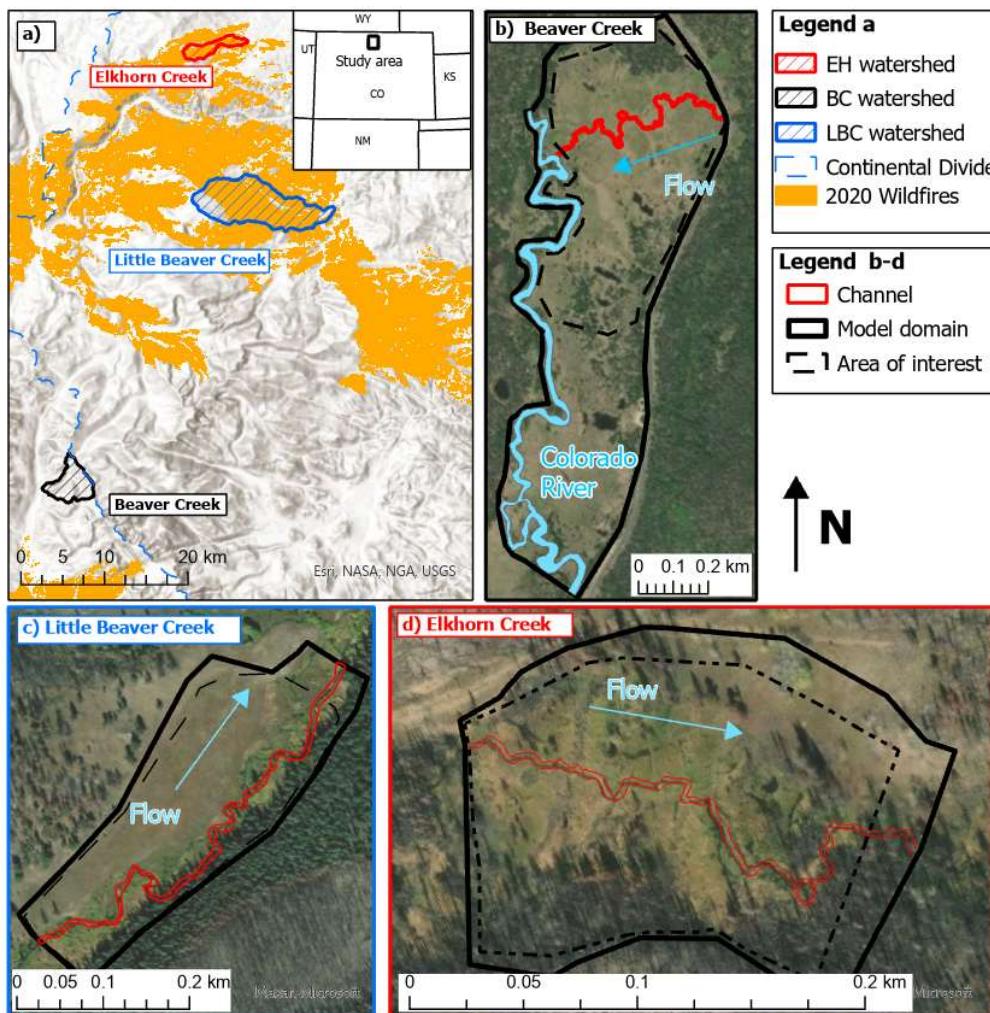


Figure 2.1 Studied reaches and their contributing watershed. Two of the studied watersheds were burned in the 2020 Cameron Peak Fire. The floodplain of Beaver Creek overlaps with that of the Colorado River (seen on the west side of the valley), which gives it an unusual shape with water flowing west and south, down and across the valley, before entering the Colorado River. The labeled area of interest marks the extent of my analysis. I reported the outlet discharge at the end of the area of interest and calculated all floodplain metrics only within the area of interest. ArcGIS Pro imagery from 2021. Sources: Maxar, Microsoft.

Table 2.1 Basic Characteristics of Each Study Site

Site	Little Beaver Creek	Beaver Creek	Elkhorn Creek
Channel slope (m/m)	0.02	0.01	0.03
Valley slope (m/m)	0.025	0.019	0.042
Sinuosity (m/m)	1.27	1.9	1.3
Drainage area (km ²)	37.6	12.5	5.2
Mean elevation (m)	2440	2740	2680
Mean annual precipitation (mm)	500	880	590
Confinement ratio (valley width/ baseflow width)	4.5	15.7	4.2
Bed sediment d50 (mm)	10.5	22.6	9.3
Channel width (m)	3.4	2.1	2.6
Reach length (m)	1070	2160	280

LBC and EH were impacted by the Cameron Peak Fire in 2020, inducing flashy flows and high sediment loads that caused rapid adjustment in the channel morphology (White et al., 2022; Wohl et al., 2022) (Figure 2.1). I modeled these sites in their post-fire conditions in 2023. Both burned sites are located within the Cache la Poudre Watershed on the east side of the Continental Divide. Their position east of the Continental Divide brings a reduction in precipitation compared to BC, which is located west of the Continental Divide (Capesius & Stephens, 2009). In fall 2022, wood was reintroduced into the channel of EH in a restoration effort by a local nonprofit in the form of post-assisted log structures. The general geomorphic characteristics of each site are shown in Table 2.1.

BC is a tributary of the Colorado River and is located within the Kawuneeche Valley in Rocky Mountain National Park. The studied reach of BC is the last 500 m of stream before its confluence with the Colorado River and runs through the floodplain of the Colorado River (Figure 2.1). BC's position within this floodplain provides this reach with a wide floodplain trending south and west before all its floodwaters meet with the Colorado River. The outlet for this site was defined by its confluence with the Colorado River. More information on the representation of the Colorado River in the model can be found in section 2.2.

2.2.2 Model Geometry and Solution Scheme

I used a combination of aerial Light Detection and Ranging (LiDAR) and Global Navigation Satellite System (GNSS) surveys of channel bathymetry to develop topographic surfaces of each site. I used a digital elevation model (DEM) created from the LiDAR data to develop the model geometry for surfaces higher in elevation than the baseflow channel. I used Emlid Reach RS2 GNSS survey equipment to collect channel bathymetry data that were not captured by LiDAR. Within the channel, I surveyed cross sections with irregular spacing, increasing the density of sampled cross sections where changes in bathymetry were more rapid in space and increasing spacing where the geometry was more uniform. I ensured the average cross section spacing for each reach was less than two channel widths for each site. I adjusted the GNSS survey Emlid software (Emlid, Budapest, Hungary) using a continuously operating reference station correction (National Geodetic Survey, 2024). I vertically aligned the GNSS survey and LiDAR by GNSS surveying nearby roads assuming that the elevation of the aerial LiDAR was the correct elevation. The LiDAR and GNSS surveys were offset by a consistent elevation and could be snapped to within +/- 0.01-m precision. I merged the two datasets in ArcGIS Pro with the “mosaic” function to create a DEM with varying resolution between sites

based on the resolution of the available LiDAR datasets. For the EH model I used 0.31-m resolution DEM created from LiDAR flown by Ayres Associates Inc., a civil engineering firm that added wood structures to the channel in 2022 (Ayres Associates Inc., Fort Collins, Colorado, United States). For the BC and LBC models, I used 0.75-m resolution DEM collected by USGS in 2021 and 2024, respectively (USGS, 2021, 2024).

I simulated flood events using the Sedimentation and River Hydraulics - Two Dimension river flow software (Aquaveo, Provo, Utah, United States), henceforth referred to as SRH-2D, to solve the depth-averaged St. Venant Equations with the finite volume method (Lai, 2010). Averaging flow conditions across the depth column introduces dispersion terms which must be approximated using the quadratic friction law. To approximate these terms I used the built in turbulence approximation with a turbulence constant of 0.7 (Lai, 2010). For the model mesh, I used an irregular triangular network, which subsampled the DEM raster with a finer resolution in and near the channel and became progressively coarser farther from the channel up to a cell spacing of 3 m. This coarsening scheme served to maximize resolution where flow was most complex while minimizing model run times. The resolution varied for each site based on the channel size to always achieve at least three mesh cells within the channel. This resolution resulted in a mesh size of 0.3 m for the channel of EH and 1 m for the channels of LBC and BC, progressing to a maximum of 5-m cell sizes on the outer edge of the floodplain for each model. For the model time step, I used 0.1 s to maximize the stability of the model given the fine mesh size in the channel. This fine resolution and the associated small time step resulted in model run times between 3 and 12 hours of real time. I also tested the impact of mesh resolution on the results, the details of which can be found in appendix A.

The model boundary for LBC ranged from the upstream extent of the unconfined section to 5 m upstream of its confluence with a minor tributary (Jack's Gulch). The EH model included the entire reach from the upstream extent of the unconfined section until an unnamed tributary entered. The model boundary for BC included the Colorado River to simplify the boundary condition assumptions at the downstream extent of the model (Figure 2.1b). I did not include the area influenced by the Colorado River in any analysis after model runs were complete (Figure 2.1b). I assumed that flow in the Colorado River was confined to its main channel during the floods simulated for BC so that there was no interference between flow in the two rivers within the area of interest. The LiDAR-derived surface did not include any bathymetric information for the Colorado River, so I needed to set the channel dimensions manually. I superimposed a 1-m deep channel for the Colorado River, assigned it a roughness of 0.04 (Chow, 1959), and set the flow at the inlet of the Colorado River as a constant $0.85 \text{ m}^3/\text{s}$, well below its capacity. With these assumptions, the Colorado River was effectively the outlet for the reach and did not interfere with the hydrodynamic modeling of flow in and around BC.

For each model, I set the downstream boundary as normal depth. I only considered the area highlighted as the Area of Interest (Figure 2.1b – d) in each model simulation to reduce the impact of the downstream boundary on results. For model initial conditions, I assumed that each system was at the summer baseflow and used an observed baseflow from the field. The baseflow used in each simulation was $0.3 \text{ m}^3/\text{s}$ for LBC, $0.05 \text{ m}^3/\text{s}$ for BC, and $0.09 \text{ m}^3/\text{s}$ for EH. I simulated baseflow in each site until steady-state was reached and used the steady-state conditions as the initial condition of each scenario.

2.2.3 Model calibration and validation

To calibrate the roughness coefficient for each site, I utilized pairs of measured water surface elevations and discharge measurements (Bates et al., 1992; Christensen et al., 2024). I visited each site several times over the course of the spring runoff (April-June) to capture calibration and validation data at the highest flows possible. For each site visit, I simultaneously surveyed the water surface across the reach approximately every 10 m longitudinally with an GNSS unit and measured the discharge with a SonTek FlowTracker2 Acoustic Doppler Velocimeter (Xylem Analytics, San Diego, California, USA). During calibration adjusted the modeled channel roughness to minimize the root mean square error (RMSE) between the observed and simulated water surface elevations. To validate the model, I simulated the second largest discharge for which I collected a discharge-water surface elevation pair and again calculated and reported the RMSE between the observed and simulated water surface elevations. Ideally, the observed discharges would be as large as the simulated flows, but due to the rare nature of the simulated flash floods, I was only able to capture flows near the lower end of simulated floods. The relatively small flood flows used in calibration may contribute error to the large flood simulations as roughness is dependent on flow depth and velocity (Barinas et al., 2024; Ferguson, 2007).

The observed data were not sufficient to constrain floodplain roughness (n_{fp}) values with certainty. I chose to complete all the simulations using two floodplain roughness values, producing a high roughness scenario and a low roughness scenario. I set the high and low estimates of n_{fp} values to 0.1 and 0.3, respectively. I chose these values based on the range of roughness values that have been calibrated for large floods through trees and shrubs across the literature (Abu-Aly et al., 2014; Chaulagain et al., 2022; Prior et al., 2021; Straatsma & Baptist,

2008). The use of two roughness scenarios led to two attenuation estimates for each flow scenario (J. Sholtes, 2009; Woltemade & Potter, 1994). Increased roughness in the floodplain or channel will increase attenuation. For the channel roughness calibration, I structured the method to yield a conservative (lower) channel roughness. During this calibration I used the higher floodplain roughness estimate. Using a higher floodplain roughness during calibration necessitates a lower channel roughness to produce the same water surface elevation.

2.2.4 Hydrograph generation

I determined the magnitude of the modeled flood hydrographs for each site using regional regressions for the 2-year (Q2), 10-year (Q10), 50-year (Q50), and 100-year recurrence interval floods (Q100) (Capesius & Stephens, 2009). The peak flows of these events are tabulated in Table A1. I used each peak discharge to generate a Gaussian distribution for the input hydrographs and a time-to-peak ranging from 30 min to 4 hr (Follett & Hankin, 2022). I chose this range in time-to-peak (t_p) based on pressure transducer data that captured the timing of a large flood at LBC (Figure A1). The flood at LBC highlighted with a 1.25 hr t_p was larger than the 500-year recurrence interval flood from the regional curve, while the greater than 4 hr and 0.5 hr t_p floods were relatively minor, indicating that t_p is extremely variable for flash floods. Longer t_p floods generally have reduced attenuation because of their higher flood volume and more gradual spatial gradients in flow conditions (Lininger & Latrubesse, 2016; Woltemade & Potter, 1994).

2.2.5 Flow attenuation

I calculated the peak flow attenuation for each simulated hydrograph at each site using the monitor lines function within SRH-2D. Monitor lines determine the flow moving across a

pre-defined cross section by calculating the velocity perpendicular to the line at each cell within the cross section, multiplying by the cell depth to obtain each cells flow contribution, and then summing the flow contribution of each cell. For each model, I used one monitor line at the downstream end of the area of interest (Figure 2.1b-d) to calculate the downstream outlet discharge series. An example of paired input and output hydrograph is shown in Figure 2.2 with the variables of interest for peak flow attenuation labeled.

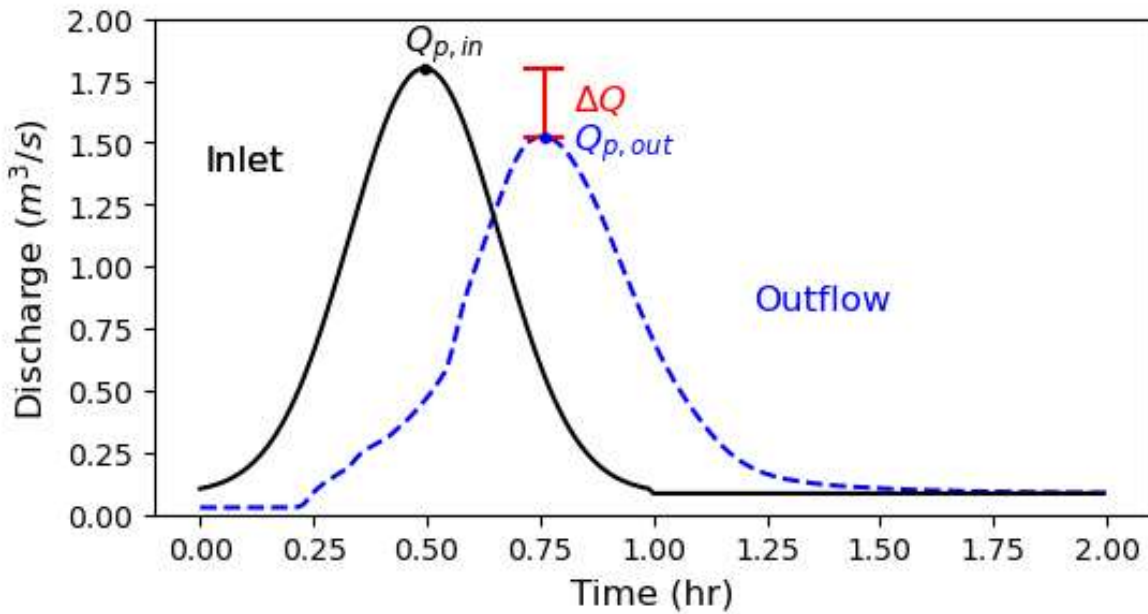


Figure 2.2 Example hydrograph with variables used to calculate peak flow attenuation.

I calculated the fraction of peak flow attenuated per meter stream length ($Q_{a/l}$) as:

$$Q_{a/l} = \frac{\Delta Q_{p,in} - Q_{p,out}}{Q_{p,in} * l} * 100 = \frac{\Delta Q}{Q_{p,in} * l} * 100 \quad (1)$$

where $Q_{a/l}$ is the fractional attenuated discharge (%/km), $Q_{p,in}$ is the peak magnitude of the inflowing discharge (m^3/s), $Q_{p,out}$ is the peak magnitude of the outflowing discharge (m^3/s), and l is the reach length (km). Previous works indicate that attenuation occurs as power function with distance along streams at the scale of 10 –100 km (Barati et al., 2012; Lininger & Latrubesse,

2016; Paiva & Lima, 2024), but I did not find this same relationship at the scale of < 1 km. See Appendix A for more details on my choice to linearly normalize attenuation.

2.2.6 Floodplain characterization

I characterized floodplains according to 1) dead storage for each event, 2) maximum live storage volume and width at each discharge, 3) structural heterogeneity of the inundated area, 4) fraction of flow moving within the floodplain, and 5) floodplain flow path diversity. I calculated the volume retained in the floodplain of each unsteady event simulation $V_{fp,retained}$ by the differencing the total inlet and outlet volume as calculated by a trapezoidal approximation of area under the inlet and outlet hydrographs. For all other floodplain characteristics I simulated a steady-state event at the maximum inlet flow for each event and extracted the steady-state floodplain characteristics. These metrics together will henceforth be referred to as the steady-state floodplain metrics. While the floodplain inundation changes rapidly over the course of a flood event, I chose to quantify them at the steady-state for the peak discharge to reduce the complexity of comparisons and to be consistent with previous calculations of these metrics. Steady-state floodplain metrics have been used by researchers to describe floodplain functions and represent the maximum attainable floodplain activation for a certain discharge (Czuba et al., 2019; Hammersmark et al., 2008). To ensure that I found steady-state conditions, I ran each model with a constant discharge until the active number of cells stabilized and model inflow was within 1% of outflow. Once I achieved steady-state, I calculated several metrics of floodplain function for each flow at each site including relative inundated floodplain width ($W_{fp,rel}$), relative floodplain storage volume ($V_{fp,rel}$), and relative discharge within the floodplain ($Q_{fp,rel}$). The methods for calculating these metrics are shown in equations 3–5. Each metric

represents aspects of the connection between the channel and floodplain in a normalized formulation, which allows for comparison between sites (Christensen et al., 2024).

$$W_{fp,rel} = W_{fp}/W_{ch} \quad (3)$$

$$V_{fp,rel} = V_{fp}/V_{ch} \quad (4)$$

$$Q_{fp,rel} = Q_{fp}/Q_{ch} \quad (5)$$

where, for a given discharge, W_{fp} is the average inundated floodplain width, W_{ch} is the average channel width, V_{fp} is the inundated floodplain volume, V_{ch} is the channel volume, Q_{fp} is the longitudinally averaged flow moving through the floodplain, and Q_{ch} is the longitudinally averaged flow in the channel.

To determine the influence of tortuous two-dimensional flow paths on attenuation, I evaluated differences in flow path distributions through the floodplains using a particle tracing program “PyDorado” (Hariharan et al., 2020). I extracted SRH-2D results for the flow velocity field, water depth, and water surface elevation associated with the final time step within the model. These extracted values were in an irregularly spaced grid due to the refinement of the grid closer to the channel. To place these outputs into a regularly spaced grid, I utilized the PyDorado function “unstruct2grid,” which interpolated the data into a uniform grid with 0.3048 m by 0.3048 m cells (Hariharan et al., 2020). I chose this resolution because it was the finest resolution used in the computational mesh of the hydrodynamic models. The uniform grid allowed us to utilize other tools from PyDorado to simulate particle movement through the floodplain. I simulated the movement of 4,000 particles, all released from the inlet of the model domain, spaced equally across the channel. I chose to simulate 4,000 particles to maximize the

number of flow paths while keeping computation time below 4 hr with my available computational power.

PyDorado simulates particle movement through a steady flow field using a weighted random walk and with 8-directional movement to describe the direction of particle travel (Hariharan et al., 2020). A particle is most likely to move to the cell which the velocity field points towards but also has a chance to drift out of line of the velocity field, simulating turbulent bursts which might alter the movement away from the main current. The chances of a particle to follow the velocity current or drift out of the main current are set with the γ and θ parameters. I used $\gamma = 0.05$ and $\theta = 1.05$ on the findings of (Hariharan et al., 2020) for riverine environments. I defined the end of the study area for these particle simulations as the same area of interest for the attenuation calculations (Figure 2.1b-d). After 2×10^4 iterations, I ended the particle routing simulations, assuming the particles that did not arrive at the outlet became stuck within non-conveyance zones of the floodplain. I calculated the travel time (t_t) through the model domain for each particle and assessed the distribution of t_t using box and whisker plots, the inner quartile range of t_t ($IQR_{flowpaths}$), and the relative variance in t_t ($Var_{flowpaths}$). I included all flow paths in these statistics, including those that remained in the channel completely and those that entered the floodplain. Particles that did not exit the model area of interest in the allotted 2×10^4 steps were not considered in the statistics. In addition to characterizing the particle flow statistically, I visually represented the flow paths by plotting particles which had t_t closest to the 10th, 25th, 50th, 75th, and 90th percentiles.

I assessed floodplain topographic heterogeneity for each site with the boundaries of the steady-state 2-, 10-, 50-, and 100-year return period discharge for the high and low roughness scenarios with an additional two-meter buffer that include the cells immediately next to

inundated cells. Including the cells bordering the inundated cells served to measure heterogeneity for all cells interacting with the flow (higher cells which prevented further inundation). Within this boundary, I calculated the standard deviation of floodplain elevations (SD_{fp}) using a moving window throughout the flooding extents of each event (Scown et al., 2015).

2.2.7 Statistical methods

To identify the relative importance of the underlying floodplain mechanics that drive attenuation (objective 2), I tested for correlation between flood wave attenuations and the floodplain characteristics described above. For the correlation tests of floodplain metrics with flood wave attenuation, I separated the time-to-peak scenarios into two halves, with the $t_p = 0.5$ to 1 hr, representing extremely rapid floods and $t_p = 2$ to 4 hr, representing moderately flashy floods. For the steady-state floodplain metrics (all metrics but $V_{fp,retained}$), I averaged the model runs at the two t_p scenarios in each time to peak class for the same magnitude flood and roughness. For each set of attenuation results, I conducted Spearman correlation tests with each floodplain characteristic. I classified correlations as significant at $p < 0.01$, and insignificant at $p > 0.01$. For the Spearman ρ , there are not clear singular guidelines on categorizing the quality of the fit. I chose to define a moderate positive fit as $\rho > 0.6$, and a strong positive fit as $\rho > 0.8$ based off of various guidelines (Gardener, 2017; Prion & Haerling, 2014, 2014; Zar, 1999).

2.1 Results

2.3.1 Model calibration and validation

With at least one runoff season for each site, I was able to calibrate and validate each model. At LBC and BC, minor floodplain channels were inundated, but the flow was primarily confined to the main channel. The calibration flows at LBC and BC were $1.6 \text{ m}^3/\text{s}$ and $1.5 \text{ m}^3/\text{s}$

(89% and 56% of the 2-year recurrence interval flow based on regression curves (Capesius & Stephens, 2009)). At EH, the calibration flow was $0.6 \text{ m}^3/\text{s}$, 115% of the 2-year recurrence interval flow based on regression curves (Capesius & Stephens, 2009). Calibrating the channel roughness to match the observed water surface elevations for the largest flow at each site resulted in a Manning's n roughness of 0.04 at LBC, 0.055 at BC, and 0.15 at EH. Though all three sites had some large wood in their channels, EH had the greatest density of large wood within the reach, which contributed to the higher calibrated roughness. The large wood distribution was not spatially constant at any site and was concentrated in jams, which elevated the flow resistance locally. I simulated each site with a spatially constant channel roughness to simplify calibration of each model, which may contribute to the larger spread in residuals at EH (Figure 2.3) (Christensen et al., 2024; Hahn et al., 2025; J. Sholtes, 2009). EH and BC both had overhanging banks, which I noticed impeding the flow during the collection of calibration data. Overhanging banks are not well represented through two-dimensional models and likely contributed to the higher residuals at BC when compared to LBC (Figure 2.3). For the validation dataset, I measured discharge-WSE pairs with $1.0 \text{ m}^3/\text{s}$, $0.07 \text{ m}^3/\text{s}$, and $0.25 \text{ m}^3/\text{s}$ at LBC, BC, and EH respectively. The validation discharge for BC was comparatively low due to the difficulty of accessing the site during the spring when months are high resulting in us only able to record one large flow during the study period. The validation dataset for each site indicates similar performance in the model's prediction of WSE across the site.

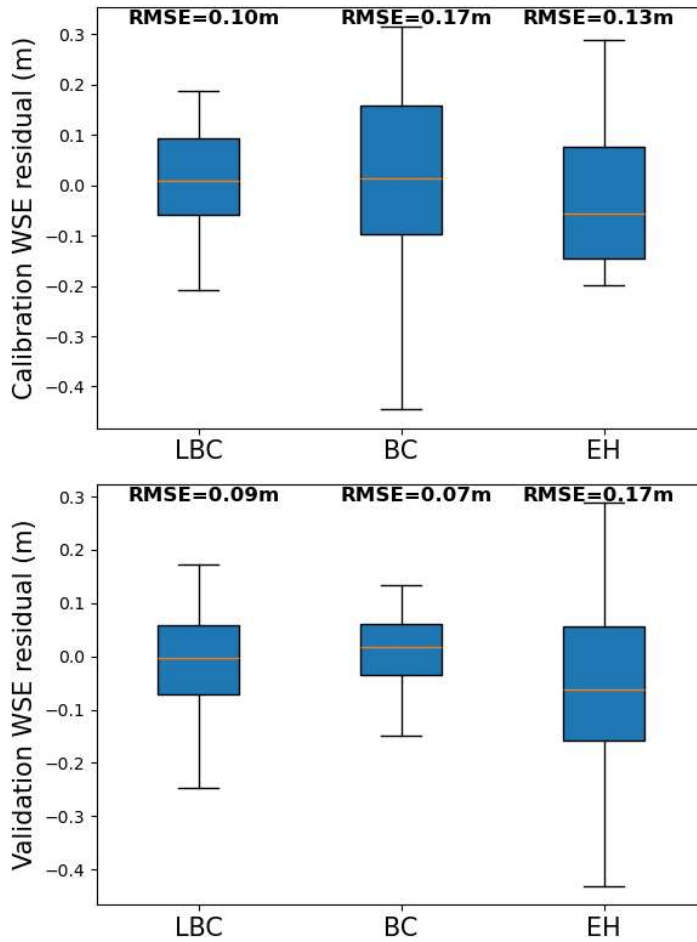


Figure 2.3 Residuals for the calibration and validation datasets represented as boxplots with the inner quartile range, median, and 1.5 times the inner quartile range displayed along with any outliers. The median residuals show minimal bias, and the RMSE for each plot indicates acceptable performance.

2.3.2 Range of modeled attenuation

After completing all hydrodynamic simulations, I produced a range of possible attenuation results using the range of hydrograph and roughness parameters (Figure 2.4). All the scenarios for each site produced a reduction in peak flow, with an average reduction of 13.8%/km. Attenuation was observed over the full range of studied flow magnitudes, including the 100-year flood, but attenuation dropped precipitously at $t_p = 4hr$ for all sites. The relationship between flood magnitude and attenuation was inconsistent across sites, with

attenuation increasing with flow magnitude at BC, and more variable changes in attenuation across flows at LBC and EH. I observed clear differences between each site with respect to their general ability to attenuate flow and how attenuation changed across the range of flood magnitudes, floodplain roughness scenarios, and flood time-to-peak scenarios. When comparing all scenarios at each site, I found the highest attenuation at EH. Attenuation at LBC was consistently lower compared to attenuation at BC and EH. Attenuation at EH was on average 11.3%/km higher than at BC and 22.1%/km higher than LBC.

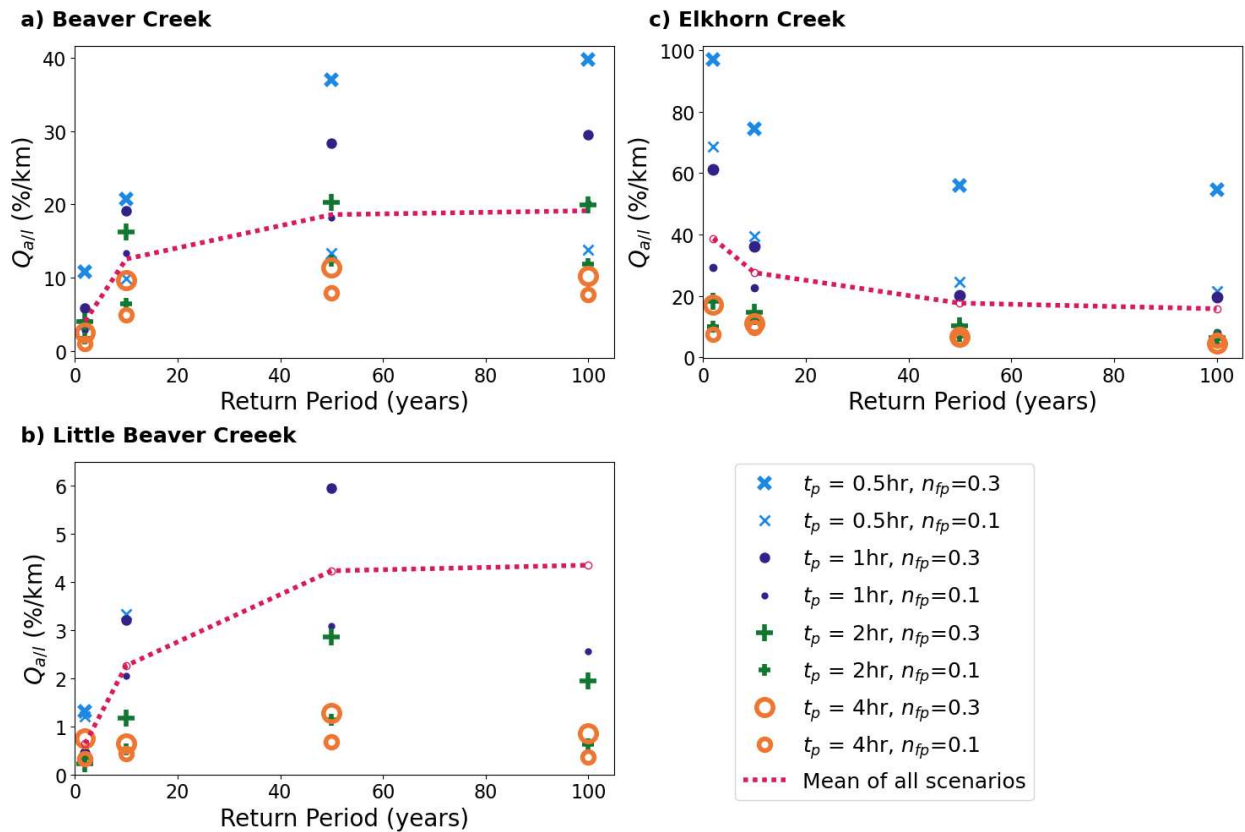


Figure 2.4 Attenuation normalized by reach length for all simulated scenarios. These simulations generally show the highest attenuation at EH followed closely by BC. Increases in attenuation from increased floodplain roughness (n_{fp}) or decreased time-to-peak (t_p).

As expected, increasing floodplain roughness and reducing flood duration both increased flood attenuation (Figure 2.4). The degree of increase from using a higher roughness was

inconsistent, with shorter duration floods gaining more attenuation than longer duration floods for the same increase in roughness. The largest difference created by the high-roughness scenario was a 35%/km increase in attenuation in the EH 10-year flood with $t_p = 0.5$ hr. Reductions in flood duration also caused nonuniform increases in attenuation, with larger changes in attenuation in scenarios with high roughness. The largest difference in attenuation created by reducing time-to-peak was a 79.7%/km increase in attenuation at EH for the 2-year flood with $n_{fp} = 0.3$. The longest duration floods had reduced attenuation (Figure 2.4).

2.3.2 Floodplain characterization

The dead storage calculated for each event followed similar trends to the peak flow attenuation, with a large fraction of the flood inlet volume retained in each reach for the shorter t_p events and generally higher volume retention in the high roughness scenarios (Figure 2.5). For the $t_p = 0.5$ high and low roughness scenarios at LBC, the flood was almost entirely channelized, limiting its access to floodplain depressions and causing a direct translation of all the flood water to the outlet with no volume loss to dead storage (Figure 2.5). The maximum volume retained as dead storage was 14.7% of the inlet flow during a scenario for the 2-year flood with $t_p = 0.5$ and high floodplain roughness at EH.

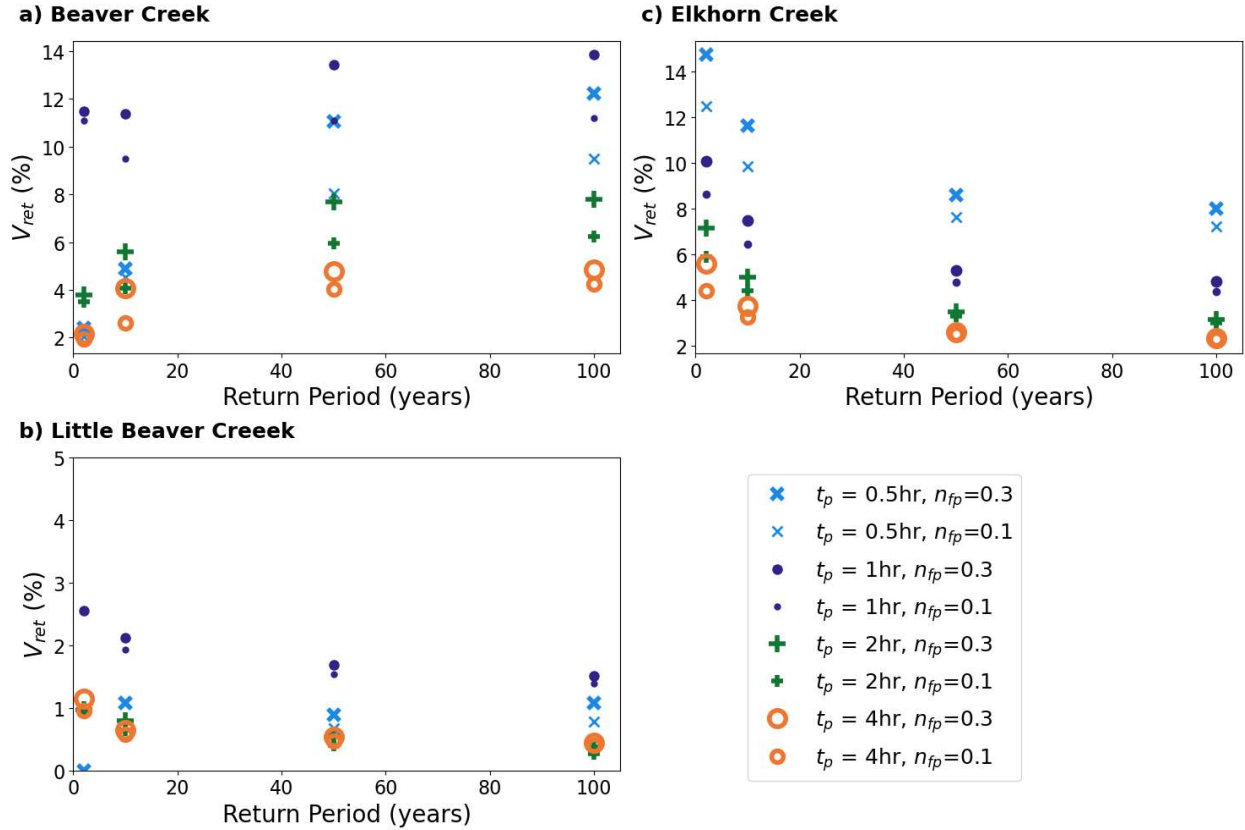


Figure 2.5 Volume retained in the model dead storage for each modeled scenario.

Steady state simulations revealed differences in inundated floodplain characteristics (Figure 2.6). The most striking differences between these sites was the relatively high $V_{fp,rel}$ and $W_{fp,rel}$ of BC (Figure 2.6a). Flow does not begin to inundate the floodplain at BC before the 10-year flow (Figure 2.6a, b), and the $Q_{fp,rel}$ for the site remained low at all flows (Figure 2.6c). The inundated floodplain width of BC continued to grow rapidly as flows increase for all simulated flows (Figure 2.6a). EH exhibited a relatively accessible floodplain with a moderate maximum size, which was nearly filled at the 50-year event (Figure 2.6a). The floodplain at LBC approached its maximum $W_{fp,rel}$ at the 10-year event with little expansion at larger flows (Figure 2.6a). The floodplain of LBC can be characterized as relatively small but readily accessed at all studied flood stages (Figure 2.6b).

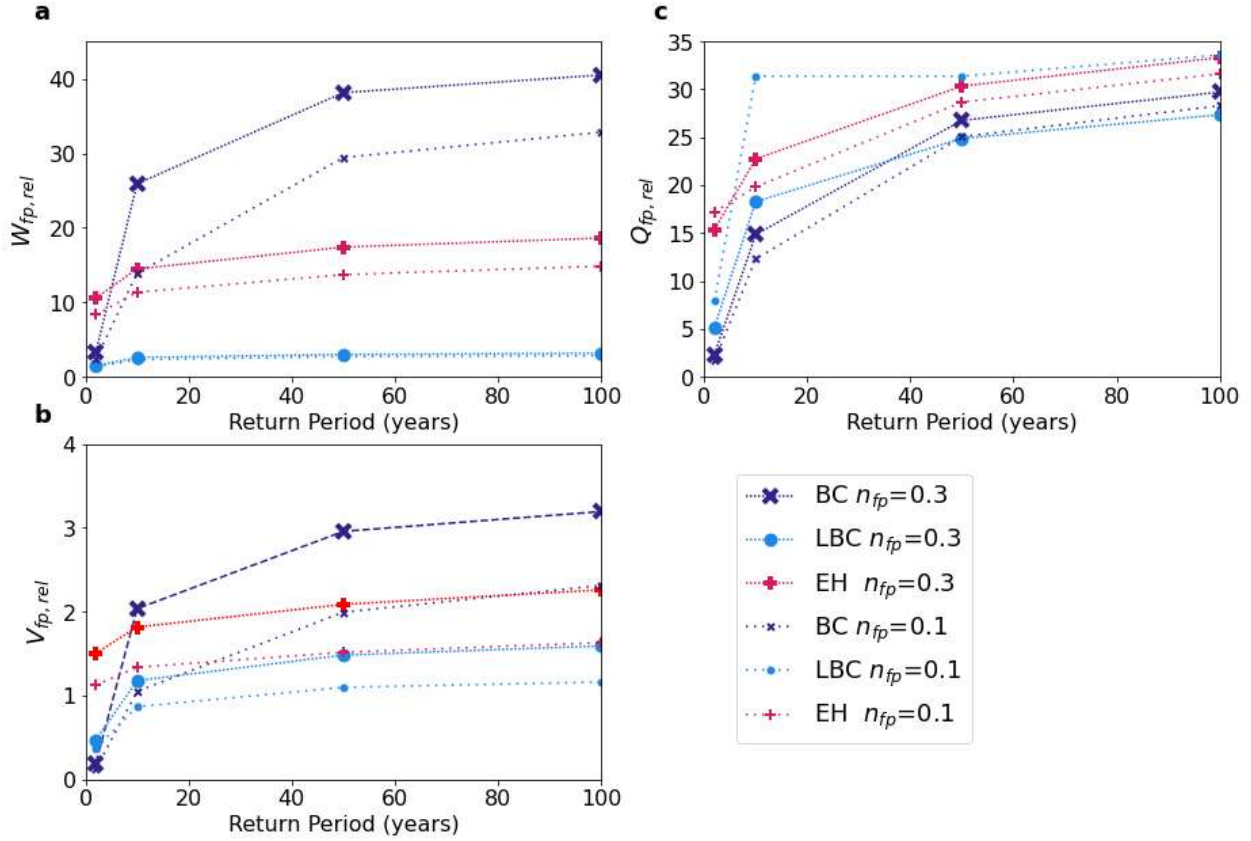


Figure 2.6 a) Relative floodplain width ($W_{fp,rel}$), b) relative floodplain volume ($V_{fp,rel}$), and c) relative flow within the floodplain ($Q_{fp,rel}$) for each site at steady-state for each roughness scenario. Results show that BC has a very large floodplain with an oversized channel (high $V_{fp,rel}$ and $W_{fp,rel}$, low $Q_{fp,rel}$); EH has a moderately large floodplain with low entrenchment (moderate $V_{fp,rel}$ and $W_{fp,rel}$, high $Q_{fp,rel}$); and LBC has a smaller floodplain with low entrenchment (lower $V_{fp,rel}$ and $W_{fp,rel}$, high $Q_{fp,rel}$).

For all sites, increasing the floodplain roughness increased the $W_{fp,rel}$ and $V_{fp,rel}$, although the magnitude of change was different across sites (Figure 2.6a, b). BC experienced the largest increase in $W_{fp,rel}$ and $V_{fp,rel}$ after increasing floodplain roughness, with an average increase of 42% in $V_{fp,rel}$ and 31% in $W_{fp,rel}$ across the studied flows. I observed the smallest changes due to increasing n_{fp} at LBC, where $V_{fp,rel}$ increased by 30% and $W_{fp,rel}$ increased by 10%. Changes at EH due to n_{fp} increases were between those observed at BC and LBC, with a 31% increase in $V_{fp,rel}$ and a 21% increase in $W_{fp,rel}$. The plateau of $W_{fp,rel}$ beyond the 10-year

event for LBC represents the filling of the valley, whereas the floodplain of BC and EH had capacity to extend beyond the inundation extents of moderate floods. Increases in n_{fp} had uneven impacts on $Q_{fp,rel}$ across the sites, with increases for high-roughness scenarios at EH and BC but decreases in $Q_{fp,rel}$ at LBC. This difference is likely tied to the more limited space available for flow in the floodplain of LBC.

Simulation of flow paths for each simulated discharge highlighted the relative ability of each site to disperse flow and influence the residence time of water on the floodplain (Figure 2.7). Graphical representation of the flow paths across a range of t_t show that particles that enter the floodplain experienced a range of fates, with some quickly returning to the main channel and others taking tortuous paths to reach their outlet. The slowest flow paths highlighted in Figure 2.5 (90th percentile for each site) all remain primarily within the floodplain. The fastest flow paths (10th percentile) remained mostly within the main channel but sometimes utilized the floodplain to create meander cutoffs (Figure 2.7c), which reduced the total distance traveled. In this way, both extremes in t_t are controlled by floodplain connection.

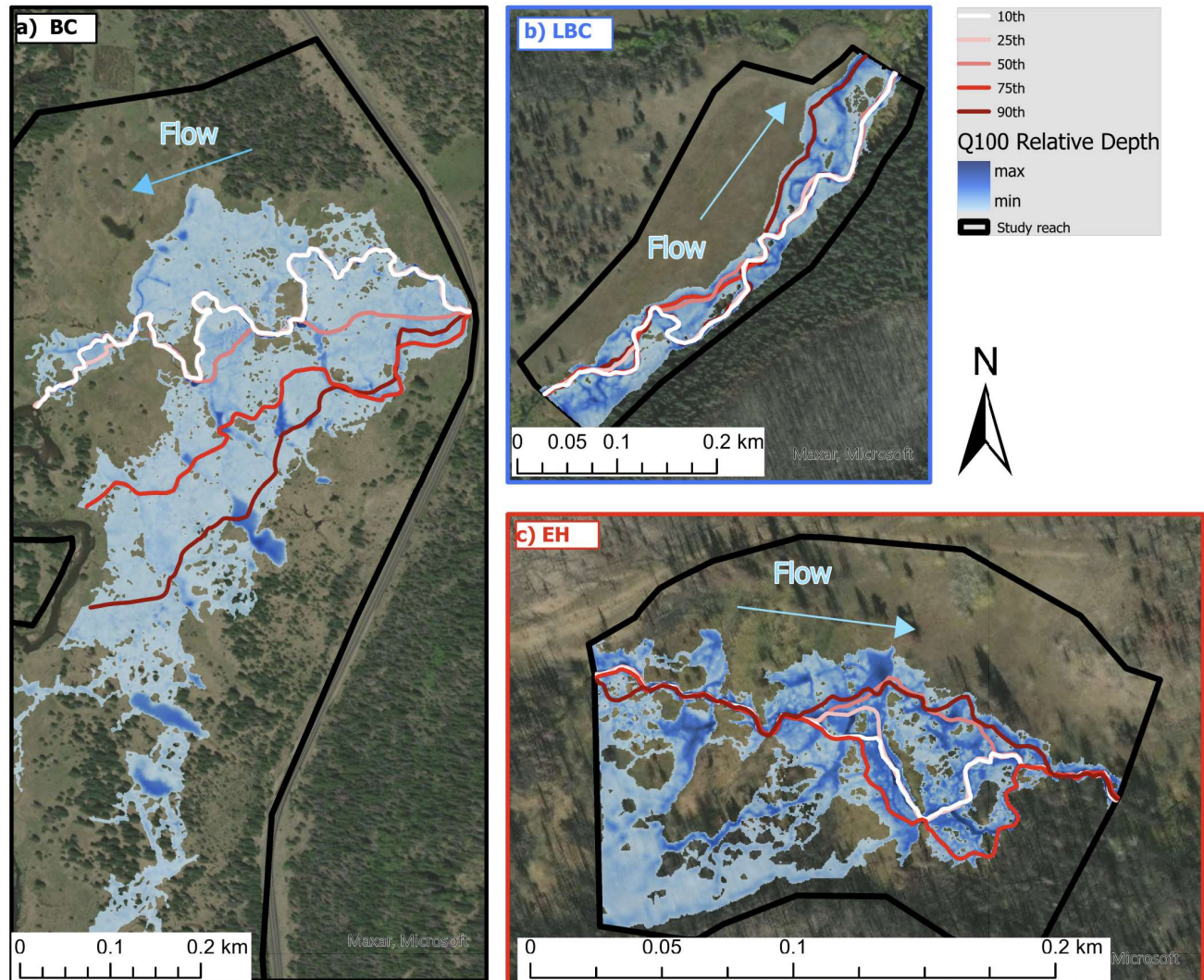


Figure 2.7 Graphical representation of the flow paths that produced the 10th, 25th, 50th, 75th, and 90th percentiles of travel time for all the released particles during the 100-year event (Q_{100}). The highlighted flow paths indicate that floodplain flow paths are drivers of the travel times (t_t) at both extremes of the spectrum, with long floodplain flow paths contributing to the high percentile flowtimes and cutoff channels contributing to low percentiles.

Flow path duration increased with higher roughness across the modeled discharges (Figure 2.8). The relationship between the range of t_t and the magnitude of flow within a site was inconsistent, with a larger spread of flow path durations for the highest flow at BC, and the smallest spread of flow path duration for the highest flow at LBC. The spread in flow path times

at EH increased after flow exceeded the 2-year event but decreased marginally with flows beyond the 10-year event.

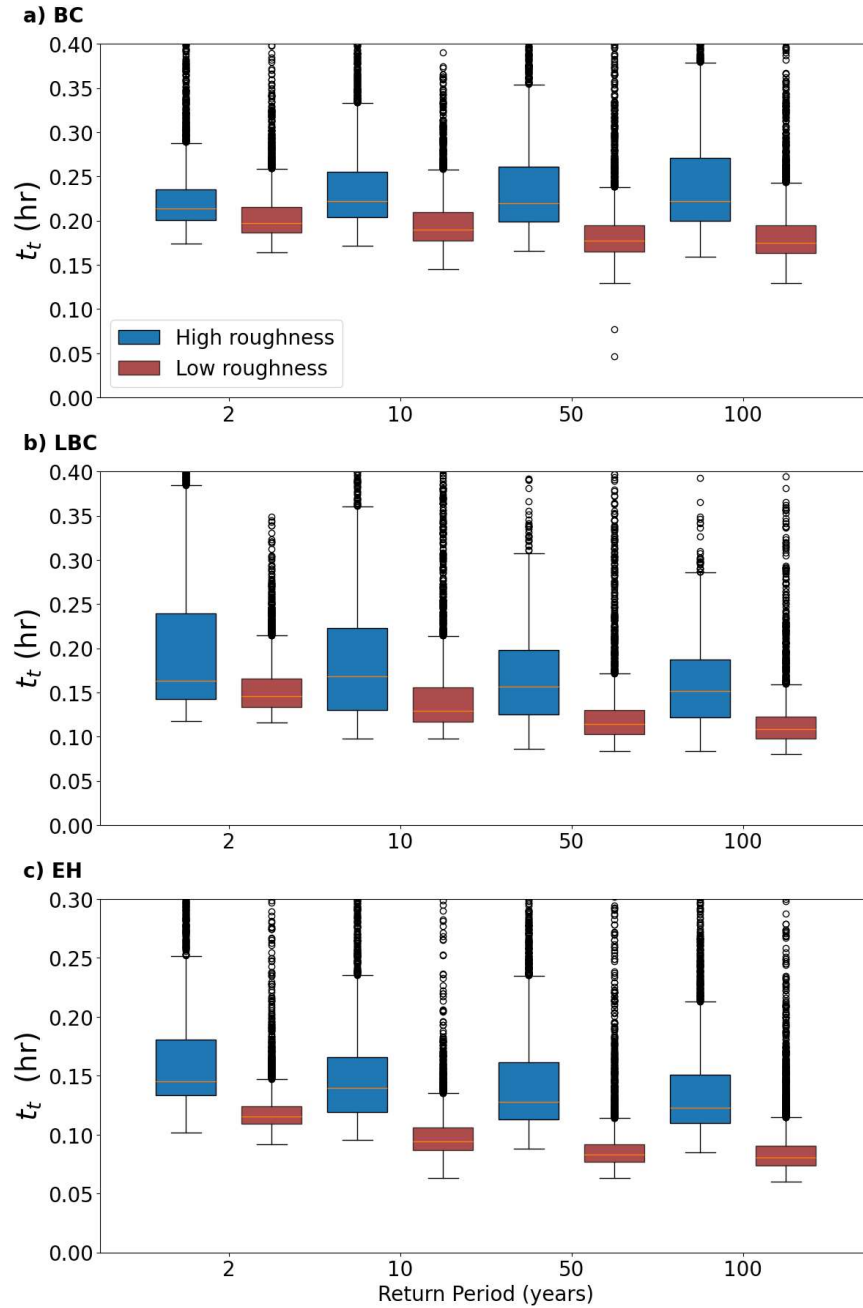


Figure 2.8 Flow path travel time (t_t) for each site indicates clear increases in spread with higher roughness and an inconsistent change in spread with increasing flow.

Topographic heterogeneity varied minimally between the sites and across the considered flood extents (Figure A3). The highest SD_{fp} was 0.072 m, which was measured for the two-year inundation extent with low roughness at EH. There was lower floodplain heterogeneity when considering the larger inundation boundaries (Figure A3). The high SD_{fp} for the low recurrence interval flow can be attributed to the highly variable topography at the interface of the bed and banks. Including more area away from the interface of the channel and floodplain by using a larger inundation extent decreased the overall standard deviation of the floodplain. For a given flow recurrence interval, EH was the most heterogeneous based on SD_{fp} values, followed by LBC and then BC.

2.3.3 Attenuation mechanism statistics

For the longer duration flows ($t_p = 2 - 4hr$), Spearman correlation tests indicated that the metrics for flow path variability, live floodplain storage, and dead floodplain storage were all significant predictors of peak flow attenuation (Figure 9). The most significant relationship was between attenuation and $V_{fp,retained}$ with $p = 3.96 \times 10^{-13}$, followed by $W_{fp,rel}$ with $p = 3.96 \times 10^{-7}$. The significance of the metrics for dispersion was generally lower than that of the storage characteristics, but flow path variance did significantly predicted the peak flow attenuation with $p = 1.65 \times 10^{-4}$. All of the significant relationships were moderate positive associations, mostly ranging ($0.6 < \rho < 0.8$). $W_{fp,rel}$ and $V_{fp,retained}$ both had the strong positive relationships with attenuation with a $\rho = 0.83$.

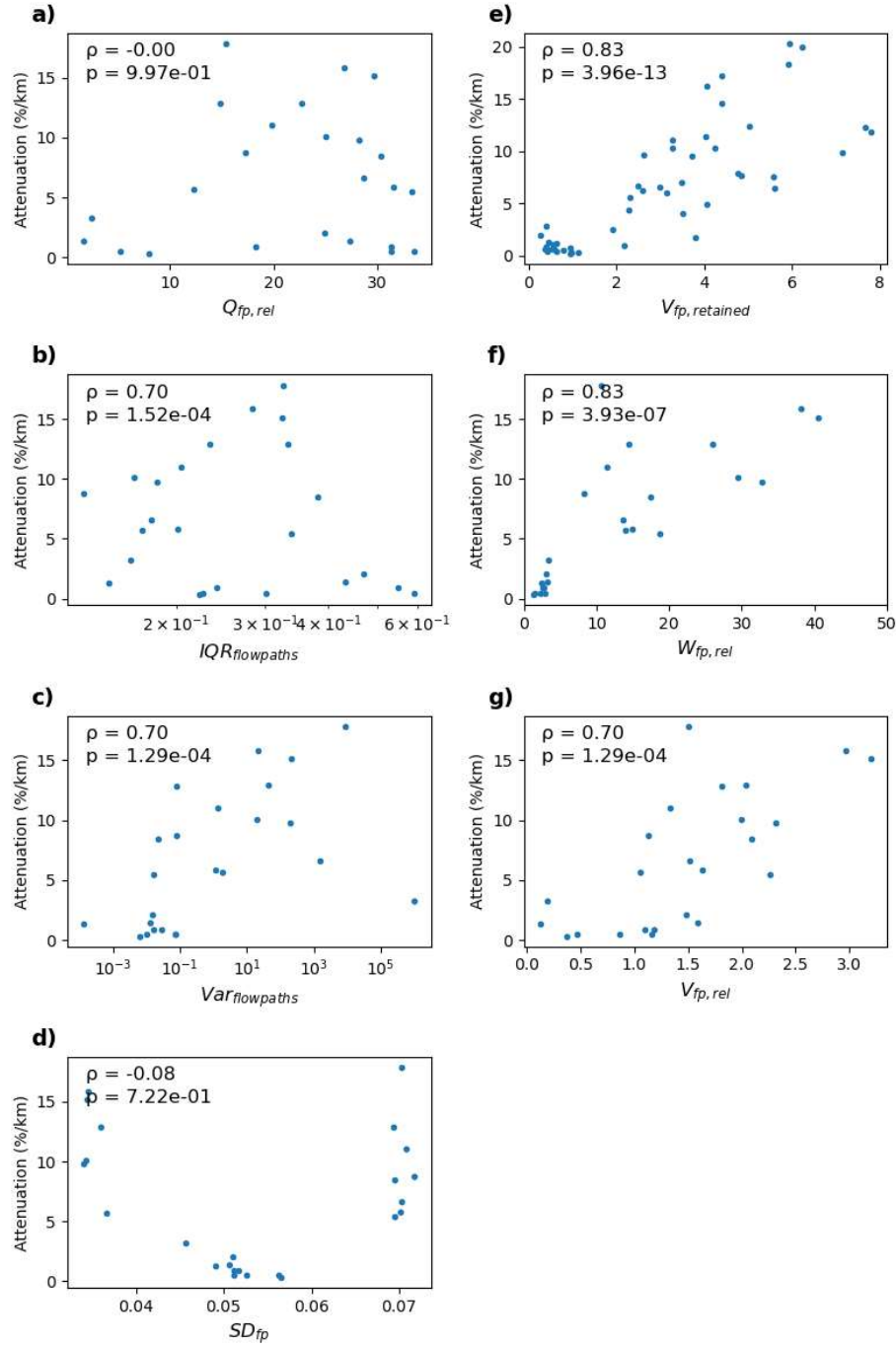


Figure 2.9 Correlations between attenuation and the studied floodplain characteristics for the longer duration floods ($t_p = 2$ to 4 hours). The flow path diversity values ($Var_{flowpaths}$, $IQR_{flowpaths}$) and all of the dead and live storage metrics ($W_{fp,rel}$, $V_{fp,rel}$, and $V_{fp,ret}$) were significant predictors of $Q_{a/l}$. The flow moving within the floodplain ($Q_{fp,rel}$) and the standard deviation of the inundated floodplain topography (SD_{fp}) were not significant predictors of $Q_{a/l}$.

For the shorter duration events, all the live and dead storage metrics remained significant predictors of attenuation, while only one flow path metric ($Var_{flowpaths}$) remained a significant predictor of attenuation (Figure 2.10). The most significant predictor of attenuation was V_{ret} for the short duration floods but its significance decreased compared with the long duration floods to $p = 6.01 \times 10^{-7}$, still well within the limits for a significant predictor. The strength of these predictors was also lower than the long duration floods with a maximum $\rho = 0.75$ between $W_{fp,rel}$ and attenuation.

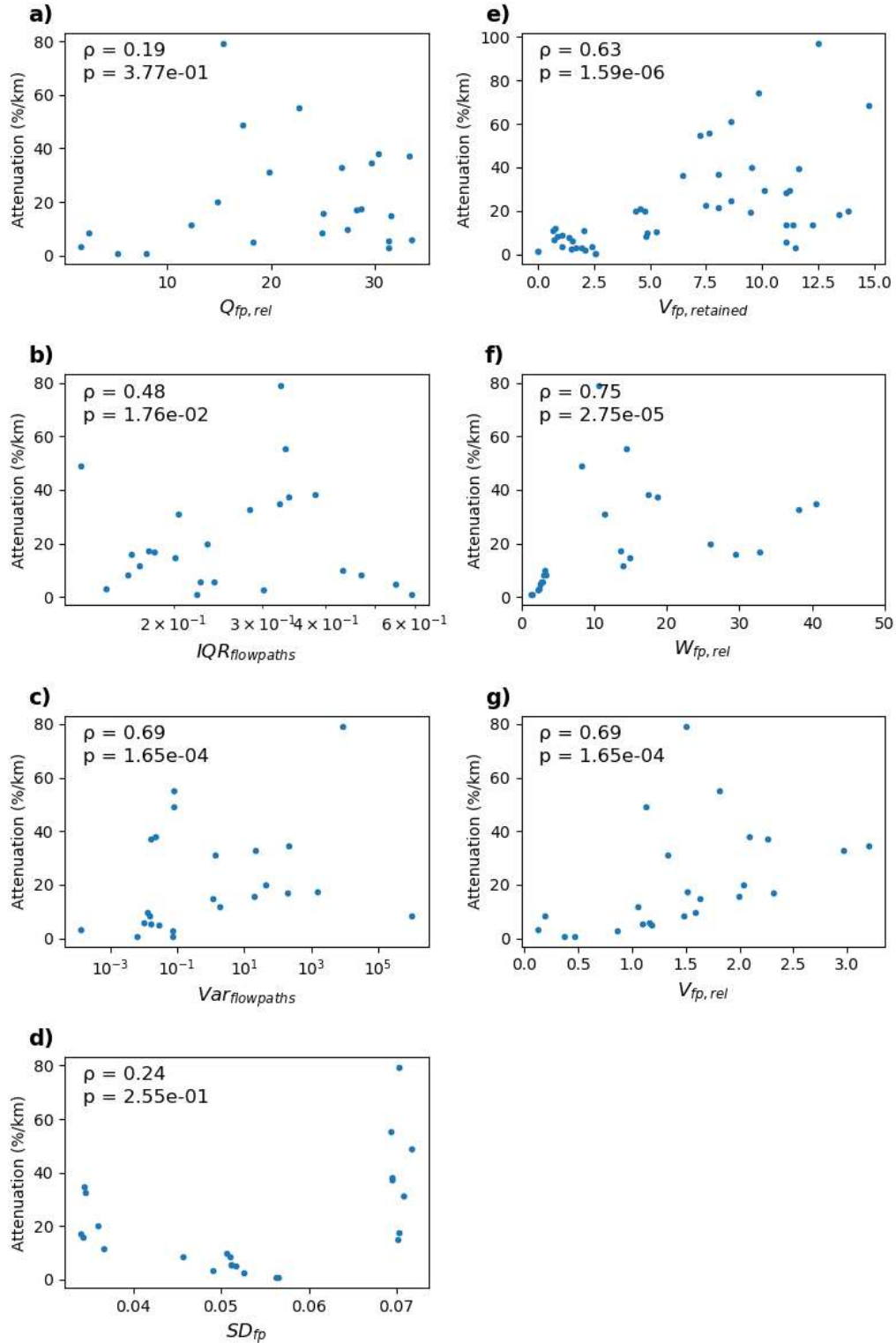


Figure 2.10 Correlations between attenuation and the studied floodplain characteristics for the short duration floods ($t_p = 1$ to 2 hours). All of the dead and live storage metrics were significant predictors of $Q_{a/l}$. The flow moving within the floodplain and the standard deviation of the

inundated floodplain topography were not significant predictors of $Q_{a/l}$. The dispersion through flow path diversity was less clear with $Var_{flowpaths}$ significantly predicting the attenuation but not $IQR_{flowpaths}$.

2.4 Discussion

While floodplains have long been recognized as important buffers for flood attenuation (J. Sholtes, 2009; Wohl et al., 2024; Woltemade & Potter, 1994), I have not found comparable studies in the literature that demonstrate the degree to which the studied reaches attenuate floods. The results of this study suggest that for extreme flash floods, mountain beads with large floodplain volumes and widths may be more capable of attenuating major floods compared to previously studied long duration floods. Previous studies of flood attenuation have found attenuation up to 8%/km (Federman et al., 2023; J. Sholtes, 2009), and many previous studies did not find significant attenuation of floods of magnitude greater than the Q50 (Federman et al., 2023; Neumayer et al., 2020; J. Sholtes, 2009). This is similar to the magnitude of attenuation observed for LBC ($Q_{a/l}$ between 0.2%/km and 11.8%/km), but is much less than the average attenuation at EH and BC (average $Q_{a/l}$ = 13.6%/km, 24.9%/km). In this study, I found some of the highest attenuation at these recurrence intervals (Figure 2.5b,c). The major contrasts in the work compared to previous studies are higher overall attenuation and continued attenuation for floods up to the 100-year recurrence interval. Shorter duration floods have already been identified as more readily attenuated (Woltemade & Potter, 1994), but previous studies of flashier floods have focused on events between several and tens of hours, whereas I focus on those that peak in two hours or fewer, producing even higher attenuation.

Varying the uncertain model parameters (n_{fp} , t_p) produced a range of attenuation results, which aligned with the well-established positive relationship between roughness and attenuation. Multiple studies have all identified roughness as a major driver of attenuation (Federman et al.,

2023; J. Sholtes, 2009; Woltemade & Potter, 1994), and this study agrees, indicating that changes in roughness can increase attenuation by up to 24%/km. The degree of control roughness exhibited in this study is slightly higher than that observed in previous works, with other works citing changes between 4% and 27% over several km (Federman et al., 2023; Woltemade & Potter, 1994). Similar to these previous studies, I find that attenuation is most impacted by changes to roughness in floods with small time-to-peak values (Figure 2.5) (Woltemade & Potter, 1994). However, unlike previous studies (Follett & Hankin, 2022; J. Sholtes, 2009), I find that higher roughness continued to increase attenuation at return periods greater than 50 years (Figure 2.5). Again, this finding is likely due to the short time-to-peak values I studied, resulting in relatively small total flood volume compared with longer duration floods. Another factor contributing to the calculated high attenuation is the large range of roughness values I used. This study included n_{fp} of up to 0.3 while others kept $n_{fp} \leq 0.15$ (Lane, 2017; J. Sholtes, 2009; Woltemade & Potter, 1994). While previous works have been justified in their lower roughness bounds, steep mountain streams have been observed with much higher roughness values of up to $n = 0.9$ in extreme cases (Yochum et al., 2014). Another factor contributing to high estimation of attenuation was my choice to linearly normalize the attenuation by reach length. This choice was most impactful in the calculations of attenuation for EH, which had the shortest reach length. This work highlights that both roughness and time-to-peak are of particular importance in controlling the attenuation of headwater flash floods.

Our work continues to support the well-established link between floodplain width, floodplain volume, and attenuation (Lininger & Latrubesse, 2016; Paiva & Lima, 2024; Woltemade & Potter, 1994) (Figure 9, 10). These floodplain characteristics had strong correlations with attenuation for all the tested flows. Attenuation at BC and LBC increased with

increasing flow while attenuation at EH decreased with increasing flow. This relationship corresponded with continued lateral expansion of floodplain inundation of BC during these floods, while the width of the EH and LBC floodplain inundation was confined by a floodplain terrace and valley wall. This observation aligns with previous works that have identified floodplain width as a major control on flood wave attenuation (De Paiva et al., 2013; Paiva & Lima, 2024; Woltemade & Potter, 1994). These findings suggest that storage of flood waters is a major mechanism for flood attenuation during flash floods.

Dispersion of the flood wave through diverse flow paths exerted a significant control on attenuation, especially for the longer duration floods (Figure 9,10). During shorter duration flows, the volume of water stored in the floodplain depressions is a larger portion of the total flood volume, potentially leading to this reduction in importance of alternate flow paths. A possible complication to these results is that not all flow paths that are simulated with the steady-state model would occur during the unsteady simulation because the lower total flood volume does not fill all floodplain depressions to access all possible paths. The possible discrepancy created by using steady-state models to calculate the flow path diversity could be addressed in future work by creating flow path tracks through snapshots of the unsteady model (Chen et al., 2020).

The results of this study have important implications for the management of floodplains in flash-flood prone mountainous regions. I have demonstrated that floodplain roughness exerts a larger control on attenuation for flashy events in the studied mountain streams than previously studied environments (Federman et al., 2023; Lininger & Latrubesse, 2016; J. Sholtes, 2009), suggesting that maintenance or bolstering of floodplain roughness elements could be particularly effective for downstream flood risk mitigation strategy in these environments (Figure 2.8).

Roughness can be maintained or bolstered through a range of techniques, including responsible grazing strategies (Vernon et al., 2022), ending or modifying de-snagging practices (Lane, 2017), planting of a riparian buffer, or creation of floodplain logjams (Follett & Hankin, 2022). These practices may be especially effective in burned or burn-prone watersheds, as these areas produce particularly flashy and extreme floods (Moody & Martin, 2001; Soulis, 2018; Wohl et al., 2024).

This work also demonstrates that wider floodplains within steep mountain streams are particularly important for preservation. Augmentation or maintenance of roughness and floodplain volume in wider river beads is more effective per unit stream length than focusing on more narrow reaches (Figures 10). Floodplain inundation volume can also be enhanced by increasing channel roughness, leading to more floodplain connectivity. The history of channel simplification and floodplain disconnection is site-specific, but restoration approaches could include regrading techniques such as “stage 0 restoration” or traditional channel reworking (E. Bernhardt et al., 2005; Christensen et al., 2024; J. Sholtes, 2009; Wohl et al., 2015) or the addition of individual wood pieces or large wood jams (Cluer & Thorne, 2014; Follett et al., 2020; Lane, 2017; Wheaton et al., 2019). Though studies indicate the impact of these methods on attenuation is minor, this work indicates that their efficacy may be different for extreme flash floods in mountain streams (Federman et al., 2023; J. Sholtes, 2009). Future studies are needed to understand the impact of these practices on floods similar to those studied here.

In addition to creating flood wave attenuation for flash floods, promoting the storage of floodwaters on floodplains provides numerous other ecosystem services. These services include providing a sink for sediment (Dunn, 2023; Kemper et al., 2024), creating a diverse riparian ecosystem (Bendix & Hupp, 2000; C. R. Hupp, 1982), and recharging shallow groundwater (Schulz et al., 2024). In low gradient mountain valleys, beavers are major drivers in creating

floodplain and channel storage environments (Puttock et al., 2017; Wohl, 2021), and there has been increasing interest from stream restoration practitioners and scientists in mimicking or reintroducing beavers (Wheaton et al., 2019). Previous and ongoing work indicates that beavers and the systems they create can bolster these services (Beschta & Ripple, 2016; Dunn, 2023; Fairfax & Whittle, 2020), although there is uncertainty on the effectiveness of beaver dams in attenuating floods (Neumayer et al., 2020; Pitcairn, 2023; Puttock et al., 2017, 2021). The studies that investigated flood attenuation in beaver complexes used longer duration flows than I studied (Neumayer et al., 2020; Puttock et al., 2017, 2021), and future work should simulate or observe the impact of beaver complexes on flows with the characteristics studied here and must include consideration of structure stability under high-magnitude flooding. Incorporating management like those described above that promote floodplain water storage may be an effective strategy for bolstering these services along with attenuating flash floods, but more work is needed to quantify these potential benefits.

One concern for controlling flood attenuation at the reach scale is the potential to synchronize peak flows from different tributaries (Dixon et al., 2016; Pattison et al., 2014). This synchronization can offset the attenuation provided by reach-scale processes and even exacerbating flooding downstream (Dixon et al., 2016; Guse et al., 2020). The synchronization of floods caused by flash floods is less likely to occur because flash floods are often localized events that mainly influence small catchments (Saharia et al., 2017; Triantafyllou & Wohl, 2024; Yates et al., 2001) especially in the Rocky Mountain Front Range where flash flooding is caused by local convective storms. The flood waves generated from such events are unlikely to compound at large watershed scales and mainly pose threats to infrastructure in relatively small but responsive catchments. Determining the thresholds at which attenuation ceases to reduce

flood magnitudes is a challenge, which is site- and event-specific and complicates the broad applicability of these findings (Dixon et al., 2016; Guse et al., 2020). Future investigation with widespread hydrological data is needed to determine the efficacy of different management strategies on different catchment-wide flooding scenarios. Future investigations should also include consideration of morphological change during events as the geometry of these systems can change considerably after flash flooding events (Hahn et al., 2025; Wohl et al., 2024). Though research has found similar results for attenuation in the same stream reaches before and after major floods (Hahn et al., 2025), the morphological work performed during a flood could potentially impact the ability of the site to attenuate flow within an event, which could be studied using a paired hydrodynamic-morphodynamic model.

2.5 Conclusions

Our work indicates that flash floods can be attenuated effectively within the studied mountain beads, more so than previous studies on longer duration floods. In the study reaches, floodplain dead storage, live storage, and floodplain flow path diversity exerted controls on attenuation. Flow path diversity had a stronger connection with attenuation for the longer duration floods simulated. Attenuation was highest for the shortest duration floods. Floodplain heterogeneity did not correlate with flood wave attenuation. This high attenuation and reliance on floodplain volume and roughness implicate these regions as key sites for management practices that bolster floodplain connection, volume, and roughness. Such management strategies might include wood additions, reduction of grazing intensity in riparian areas, and prevention of development encroachment into floodplains. These management strategies could be of particular importance in wildfire burned and burn-prone regions where low-duration, high-magnitude

floods are common and destructive. These management strategies are likely to be less effective in areas with longer duration floods, lower floodplain access, or lower floodplain roughness.

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Chapter 3 Flash Flood Routing in Headwater Streams is Improved Using a New Muskingum-Cunge Augmented Floodplain Method*

*a version of this has been submitted for peer review at Journal of Hydrology under the same title by Nicholas Christensen and Ryan Morrison but is unpublished as of time of writing.

3.1 Introduction

3.1.1 Flash Floods in Mountain Streams

Flooding remains one of the most dangerous and damaging types of natural events (Saharia et al., 2017). In headwater streams, floods are often flashy and spatially isolated (Wohl et al., 2024). This flashy nature of floods can be intensified after severe wildfires (Kean et al., 2019; Moody et al., 2013; Shakesby, 2011). Floodplains, or unconfined sections of a stream corridor, have been shown to attenuate floods through the dissipation of flow energy and momentum, preserving infrastructure and protecting people downstream (Dadson et al., 2017; Lane, 2017; Puttock et al., 2017; Suddeth, 2014; Wyzga, 1996). When floodplains are disconnected from rivers through channelization or artificial levees, the ability of floodplains to attenuate floods is severely reduced (Knox, Morrison, et al., 2022; Knox, Wohl, et al., 2022).

Not all floods are attenuated equally, however, due to the relative contributions of flow dispersion and water storage in floodplains (Christensen & Morrison, 2026b). For instance, flash floods in headwater streams may be substantially attenuated as energy is quickly dissipated during peak discharge and an appreciable volume of water is stored in floodplain topographic depressions (Christensen & Morrison, 2026b; Elfeki et al., 2015). Conversely, longer duration floods in the same headwater streams may be negligibly attenuated as the volume of water stored in floodplain depressions is quickly overwhelmed by the total floodwave volume (Lininger & Latrubesse, 2016; Woltemade & Potter, 1994). Thus, an effective strategy for reducing downstream flood risks in mountain catchments that experience flash floods is to conserve or

restore river-floodplain connectivity, and this approach is more commonly being applied in the western United States using various restoration strategies (Bernhardt et al., 2005; Wheaton et al., 2019). Adequate modeling approaches for predicting the degree of flash flood attenuation in headwater streams are still missing, however, due to a number of limitations or simplifications of current flood routing algorithms (Teng et al., 2017a).

3.1.2 Modeling Flash Flood Attenuation

Previous studies have evaluated the importance of floodplain connectivity in increasing flood attenuation, but key considerations have been missing that are important for flash floods in headwater streams. For instance, many studies of attenuation in headwater streams focus on floods with long-duration hydrographs (>10 hours to days) that are caused by persistent, moderate intensity rainfall (Federman et al., 2023; Follett & Hankin, 2022; Neumayer et al., 2020; Puttock et al., 2017; J. Sholtes, 2009) rather than flash floods produced by intense convective precipitation events. Furthermore, few studies have considered the impact of water storage in floodplains as a key process in attenuating peak discharges (Dixon et al., 2016; Teng et al., 2017b). By not accounting for these hydrologic processes, flood routing approaches may fail to accurately calculate flood attenuation in headwater stream systems, especially at watershed scales.

Two-dimensional (2D) hydrodynamic models can capture the hydrologic and hydraulic effects of river-floodplain connectivity on flood attenuation, notably energy loss and water storage, but such models are usually too computationally burdensome to apply at large watershed scales without making large simplifications (Dazzi et al., 2021; Ghavasieh et al., 2006; Neumayer et al., 2020). For instance, Dixon et al. (2016) used a 2D hydrodynamic model to evaluate floods at a watershed scale, but their approach required large model mesh sizes and a

scheme to combine one-dimensional (1D) models for channel hydraulics with 2D models of the floodplain hydraulics. Though the paired 1D-2D approach of Dixon et al. (2016) captured the physics of flood propagation, the large cells used in the models limited how floodplain topography can store water, and an assumption of average channel cross sections greatly simplified channel-floodplain connection. Thus, large-scale 2D hydrodynamic models may not be significantly more accurate for predicting flood attenuation than 1D hydrologic models if the river-floodplain connectivity processes are not fully represented.

Hydrologic routing models, which are less computationally intensive than 2D hydrodynamic models, commonly use either the diffusion wave or kinematic wave approximations of the Saint-Venant Equations of unsteady flow (Fenton, 2019). Diffusion wave solutions assume that inertial and acceleration terms in the Saint-Venant equations are negligible (Chow, 1959). The kinematic wave further assumes that pressure differences in unsteady flow can be ignored (Barry & Bajracharya, 1995). The kinematic wave equation is best applied for fast, shallow flow with gradual changes in space and time. Examples of kinematic wave solutions include the Muskingum Equation (McCarthy, 1938) and derivative methods. Assumptions of the kinematic wave equation are less appropriate for floods with rapid changes in time or space (e.g., flash floods or dam breaks) or for any situation that includes a mixed flow regime (e.g., steep mountain streams) (Fenton, 2019). Despite the assumptions inherent in kinematic wave solutions, the ease of using Muskingum methods to predict flow routing means the method is used across a variety of river and flood characteristics, ranging from the mainstem Amazon to the mountainous headwaters of the Colorado River (Paiva & Lima, 2024; Schulz et al., 2024).

3.1.3 Muskingum-Cunge Flood Routing

A benefit of the Muskingum method is the relative ease with which modifications can be made to account for reach-scale processes. An example of such a modification is the three-parameter Muskingum method that includes transmission losses for a flood on an ephemeral stream (Elfeki et al., 2015). Bharali & Misra (2022) used a variety of Muskingum modifications to create a range of estimations of peak discharge on an ungauged site. In most applications the kinematic wave is solved numerically, but it can be solved analytically to further reduce computation time for calculating flood attenuation (Paiva & Lima, 2024). The Muskingum-Cunge method improved on the Muskingum method by using physical parameters based on reach conditions to determine the routing characteristics rather than having to calibrate weighting parameters for each system (Cunge, 1969).

For the Muskingum-Cunge method, one determines the time step (Δt) and spatial step (Δx) using the methods described by Ponce & Yevjevich (1978) and shown in equations (1) and (2), where Δt is one twentieth of time to peak discharge (t_p), and Δx is calculated as the maximum celerity calculated for the inlet hydrograph (c_{max}) multiplied by the time step (equation 2). These constraints serve to maximize model stability by ensuring the wave travel distance in each timestep does not exceed the spatial step.

$$\Delta t = t_p/20 \quad (1)$$

$$\Delta x = c_{max} * \Delta t \quad (2)$$

The Muskingum-Cunge method often assumes no lateral inflow to the unsteady flow system when the reach is short and the inputs throughout are minimal (termed MCv1 for this study). The flow for the next spatial and time step ($Q_{out,i+1}$) is determined using equation (3)

using the known flows ($Q_{in,i}$, $Q_{out,i}$ and $Q_{in,i+1}$) and constants which are calculated based on the reach geometry and inundation extent (c_1 , c_2 , and c_3).

$$Q_{out,i+1} = c_1 Q_{in,i} + c_2 Q_{out,i} + c_3 Q_{in,i+1} \quad (3)$$

The Muskingum-Cunge method can be applied with a constant lateral flow term (termed MCv2 for this study). The MCv2 method calculates outlet flow for a given spatial step using equation 4, where c_4 is a lateral flow constant that requires calibration. More information on this in section 2.3, Model Calibration.

$$Q_{out,i+1} = c_1 Q_{in,i} + c_2 Q_{out,i} + c_3 Q_{in,i+1} + c_4 \quad (4)$$

Previous works on the efficacy of Muskingum-derived methods focus on long duration floods on large rivers, leaving a gap in our understanding of the applicability of these models to flash floods in mountain streams. The existing works which examine the performance of Muskingum-Cunge methods find sufficient performance, but these studies lack comparisons of different model frameworks for flash floods in mountain streams (Dazzi et al., 2021; Paiva & Lima, 2024). The study which comes closest to determining the impact of different modeling strategies on flash flood attenuation simulated a catchment of 100 km² experiencing a flood with a 20-hr rising limb (Ghavasieh et al., 2006). Ghavasieh et al. (2006) found small increases in attenuation for the 1D model compared to their 2D model.

In this study I compare the accuracy of flood attenuation between full dynamic wave 2D hydrodynamic models and the simplifications discussed above for flash floods in mountain streams. This knowledge is essential to informing which modeling strategies should be used for developing watershed-scale understanding of mountainous flood propagation. Thus, the objectives of this study are to: 1) compare the results of calibrated 2D hydrodynamic models to

commonly used hydrologic routing models for flash floods in headwater streams; and 2) develop a modified Muskingum routing method that captures the attenuation processes for flash floods in headwater streams.

3.2 Methods

3.2.1 Site Description

I utilized the same sites as in Chapter 2 so that I could leverage the 2D hydrodynamic model results for this investigation of model performance. For more details on the site, see section 2.2.1.

3.2.2 Modeling Approaches

I developed five models of each study site to cover a variety of hydraulic and hydrologic modeling approaches, including: one spatially uniform 1D hydrodynamic model, and four variations of the Muskingum-Cunge method for hydrologic routing. I represented each site as spatially uniform with reach-average cross-sectional geometry. To calculate the geometry for the spatially uniform models, I determined the average floodplain width, bankfull area, and bankfull hydraulic radius. I then generated an 8-point cross section with these properties. Using an eight-point cross section allowed us to use the “compound channel” calculations which are incorporated in the chosen routing methods. I used this 8-point cross section and the average reach slope to create an unsteady 1D hydrodynamic model in the Hydrologic Engineering Center River Assessment Tool (HEC-RAS) v 6.6 (United States Army Corps of Engineers Hydrologic Engineering Center, Davis, California, United States).

I tested four variations of the Muskingum-Cunge model termed MCv1, MCv2, MCv3, and the Muskingum-Cunge Augmented Floodplain (MCAF). I evaluated how well they

attenuated flash floods compared to calibrated 2D hydrodynamic modeling results. As described in more detail below and in Table 2.2, MCv1 and MCv2 are original versions of Muskingum-Cunge model, and MCv3 and MCAF are new variations that I developed to account for the effects of floodplain water storage on unsteady flow routing. All the models used the same geometry as the 1D uniform hydrodynamic model.

The two novel Muskingum-Cunge routing methods I tested and developed use an internal decision structure to determine the c_4 parameter. The simpler new model (MCv3) switches between two c_4 parameters depending on the flow moving through the section. If the flow at the given timestep (Q_i) is greater than the bankfull discharge (Q_{bkf}), the floodplain lateral flow $c_{4,fp}$ is used to calculate the next discharge (Q_{i+1}). If Q_i is less than Q_{bkf} , the channel lateral flow $c_{4,ch}$ is used. Both $c_{4,fp}$ and $c_{4,ch}$ require calibration. This method improves the physical realism of the routing through the consideration of floodplain inundation but flattens channel-floodplain interactions to a binary active/inactive floodplain.

Table 3.1 Muskingum-Cunge model variations tested for reproducing flash floods

Muskingum-Cunge Method Variation	Description
MCv1	Original Muskingum-Cunge model (Cunge, 1969)
MCv2	MCv1 with the addition of a constant lateral-flow term, c_4
MCv3	The value of c_4 depends on whether flow is contained within the channel or interacts with the floodplain
MCAF	The value of c_4 is a dynamic flow term that represents either storage or release of water to/from the floodplain

The final routing method I developed progressively increases the volume of water stored on the floodplain based on the inundated area at a given time step. I termed this model the Muskingum-Cunge Augmented Floodplain (MCAF) model. In this approach, the water within the floodplain is stored within a reservoir that represents the floodplain depression storage, and the water is released back to the main channel as flows recede. The total storage capacity of the floodplain depressions is a fraction of the maximum predicted floodplain inundation volume (A_{max}) and is determined in equation (5) as:

$$V_{fp,dep,max} = c * A_{max} * \Delta x \quad (5)$$

where c is a calibrated coefficient representing the relationship between dead storage available and the floodplain inundation level. Flow into the floodplain depression storage is calculated based on the inundated floodplain area in equation (6):

$$c_{4,fp} = -a * (A_i - A_{bkf})^b * \Delta x \quad (6)$$

where a and b are calibrated parameters, A_i is the cross-sectional area at the current time and spatial step, and A_{bkf} is the bankfull area. Water volume is transferred from the floodwave to the floodplain depression storage reservoir in equation (7):

$$V_{fp,dep,i+1} = V_{fp,dep,i} + c_{4,fp} \Delta t \quad (7)$$

where $V_{fp,dep,i}$ is the floodplain depression storage volume at the current timestep, and $V_{fp,dep,i+1}$ is the floodplain depression storage volume at the next time step. When the flow stage is below the bankfull threshold, there is no flow transferred to the floodplain depression storage. After water has been stored within the floodplain, it returns to the channel ($c_{4,return}$) according to the general equation for outflow from a linear reservoir in equation (8):

$$c_{4,return} = d * V_{fp} \quad (8)$$

where d is the calibrated linear reservoir outflow coefficient.

3.2.3 Model Calibration

The flashiness, remote locations, and destructive power of flood events at these study sites made field measurements of discharge or velocity infeasible. So, instead of comparing the simulated outlet discharge to measured field data, I compared the results from the 1D hydrodynamic and hydrologic models to calibrated and validated 2D hydrodynamic models, which represent the most physically-based and accurate prediction of flood attenuation at these study sites. This approach has been used in previous studies, such as Ghavasieh et al. (2006). For the model calibrations I leveraged data from Christensen & Morrison (2026b). In Christensen & Morrison (2026), I created fully calibrated and validated 2D hydrodynamic models and simulated a set of flash floods. In this study, I simulated a subset of the flood scenarios completed in Christensen & Morrison (2026) in each of the 1D models for comparison. Specifically, I simulated the 30-minute, 1-hour, and 2-hour time-to-peak (tp) floods for the 2-yr, 10-yr, 50-yr, and 100-yr recurrence interval discharges. This set of flood simulations for the LBC and BC reaches are henceforth referred to collectively as the calibration dataset. I validated the models using the same combination of time-to-peak and recurrence interval discharges at the EH study site.

The 1D hydrodynamic and MCv1 models rely on the same physical parameters as the 2D hydrodynamic model (eg. channel and floodplain roughness), so no calibration was performed on the 1D hydrodynamic or MCv1 models. The MCv2, MCv3 and MCAF models required calibration of one or more coefficients (e.g., c_4 for MCv2). To calibrate these models, I adjusted

the calibration coefficients manually and through assisted calibration with using differential evolution (Storn & Price, 1995) until I reached a maximum average Kling Gupta Efficiency (*KGE*) for the calibration dataset (Althoff & Rodrigues, 2021). My initial approach to calibration was using the differential evolution assisted calibration method, but I found that the assisted calibration consistently fell victim to seeking local maxima as described by Storn & Price (1995). As such, I explored the parameter space manually to narrow the parameter bounds, which I then explored with a differential evolution to maximize the average *KGE* for the calibration set.

3.2.4 Model Validation and Evaluation

I evaluated each model output set for all simulated events including the calibration and validation datasets. For the model evaluation I used several indicators of performance for the full ensemble of simulations: Nash Sutcliffe Efficiency (*NSE*), percent error in attenuated discharge ($\Delta Q_{a/l}$), and difference in water volume retained in the floodplain ($\Delta V_{fp,ret}$). I calculated the error in predicted attenuated discharge as a percentage of the peak inlet discharge per km reach length ($\Delta Q_{a/l}$) as the difference between each 1D model and the 2D hydrodynamic model using equation (9),

$$\Delta Q_{a/l} = \frac{Q_{p,out} - Q_{p,out,2d}}{Q_{p,in} * l} \times 100 \quad (9)$$

where $Q_{p,out}$ is the maximum outlet discharge (m^3/s) predicted by the simplified model, $Q_{p,out,2d}$ is the maximum discharge (m^3/s) predicted by the 2d model, $Q_{p,in}$ is the maximum inlet discharge (m^3/s), and l is the reach length in km.

I also calculated the total volume retained within the floodplain at the end of each flood event ($V_{fp,ret,i}$) using equation (10),

$$\Delta V_{fp,ret} = (\int_{t=0}^{t_{end}} Q_t - O_{t,2d}) / (\int_{t=0}^{t_{end}} I_t - O_{t,2d}) \quad (10)$$

Where t is the model time O_t is simplified model outflow at time t , $O_{t,2d}$ is the 2D model outflow at time t , and I_t is the inflow at time t .

3.2.5 Model Uncertainty

I assessed model uncertainty using the Generalized Likelihood Uncertainty Estimation (GLUE) protocol (Beven & Binley, 1992). For each of the calibrated models (MCv2, MCv3 and MCAF), I generated an initial 3000 parameter sets in the calibration range with a uniform distribution and completed all of the model runs with each set. I set the behavioral model threshold as an average KGE of 0.937 across the calibration dataset based on the performance of the MCv1 model. If the initial 3000 parameter sets did not generate at least 20 behavioral models, I simulated additional model runs with the same parameter distribution and range until at least 20 behavioral models were obtained. For each behavioral model, I weighted the prediction based on the model “likelihood” using equation 11:

$$L_j = \sum_{j=1}^j \sum_{i=1}^i (Q_{obs,i} - Q_{mod,i,j})^2{}^{-1}$$

Where i is the number of simulations within the set, $Q_{obs,i}$ is the outlet hydrograph for simulation i for the calibrated 2D hydrodynamic model, j , is the number of behavioral parameter sets tested, $Q_{mod,i,j}$, is the discharge modeled for simulation i and parameter set j . I recorded

both the total range of predictions from the set and the 95% prediction interval of behavioral models.

3.3 Results

3.3.1 Model Calibration and Validation

The calibrated parameters for MCv2, MCv3, and MCAF are shown in Table 3.2.

Table 3.2 Calibrated coefficients for MCv2, MCv3 and MCAF

Model	Parameters					
	c_4 below bankful ($\text{m}^3\text{s}^{-1}\text{m}^{-1}$)	c_4 below bankful ($\text{m}^3\text{s}^{-1}\text{m}^{-1}$)	a (unitless)	b (unitless)	c (unitless)	d (unitless)
MCv2	2.1×10^{-3}	2.1×10^{-3}	NA	NA	NA	NA
MCv3	6.6×10^{-3}	0.16	NA	NA	NA	NA
MCAF	0	NA	1×10^{-3}	0.344	0.113	3.1×10^{-4}

I simulated 12 floods at each study site for each modeling approach using the calibrated values where applicable. The average *KGE* and *NSE* values for each model are shown in Table 3.3 along with the *KGE* and *NSE* averaged across all sites. Reducing the model detail to a 1D uniform hydrodynamic system produced the lowest average *KGE* and *NSE* across the calibration and validation datasets (average *KGE* = 0.868 and *NSE* = 0.787 for the full dataset, Table 3.3). The *NSE* and *KGE* ranges observed for events simulated with the 1D hydrodynamic model was the largest, with low values for the BC site where there are large floodplains, while the best performance was observed during events with lower floodplain inundation. The simulations at

LBC with the 1D hydrodynamic model produced good agreement with the 2D model, with the highest performance of any 1D model tested ($KGE = 0.98$). Using Muskingum-Cunge routing with no lateral term (MCv1) produced higher accuracy than the 1D hydrodynamic model and with an average $KGE = 0.918$ and $NSE = 0.949$ (Table 3.3). Performance patterns in the MCv1 model runs followed similar trends as the 1D hydrodynamic model with the lowest metrics during the largest flood events at the BC site. Performance decreased with increasing return period for BC and decreased with t_p . Performance increased with increasing return period for EH and LBC but followed the same trend in decreasing NSE and KGE with decreasing t_p , which was observed in the BC model.

Table 3.3 Model performance averaged over all events at each site (LBC, BC, and EH columns) and over all sites (Avg. column). The LBC and BC site were used in the calibration of each model, while the EH site was not. These results indicate that the most effective model in reproducing results was the MCAF model.

Model	KGE				NSE			
	Calibrated		Validation		Calibrated		Validation	
	BC	LBC	EH	Avg.	BC	LBC	EH	Avg.
1D Uniform hydrodynamic	0.81	0.98	0.90	0.868	0.66	0.96	0.91	0.839
MCv1	0.91	0.96	0.88	0.918	0.93	0.97	0.96	0.949
MCv2	0.90	0.97	0.92	0.929	0.93	0.98	0.97	0.955
MCv3	0.94	0.98	0.92	0.944	0.95	0.98	0.96	0.956
MCAF	0.94	0.98	0.92	0.942	0.93	0.98	0.96	0.954

As an example, Figure 3.1 demonstrates the outlet flood hydrograph produced by each model for one large event (100-year recurrence interval discharge with 0.5-hour time-to-peak flood) and a small flood (100-year recurrence interval discharge with 1-hour time-to-peak flood). The various methods of calculating outlet discharge manifested differences during different portions of each simulated event. As shown in Figure 3.1, the MCv1 model overpredicted flow during the peak, the MCv2 model produced a small reduction in outflow over the entire hydrograph, and the MCv3 model created too much attenuation. There is also an additional delay in the peak discharge for the MCAF model of BC.

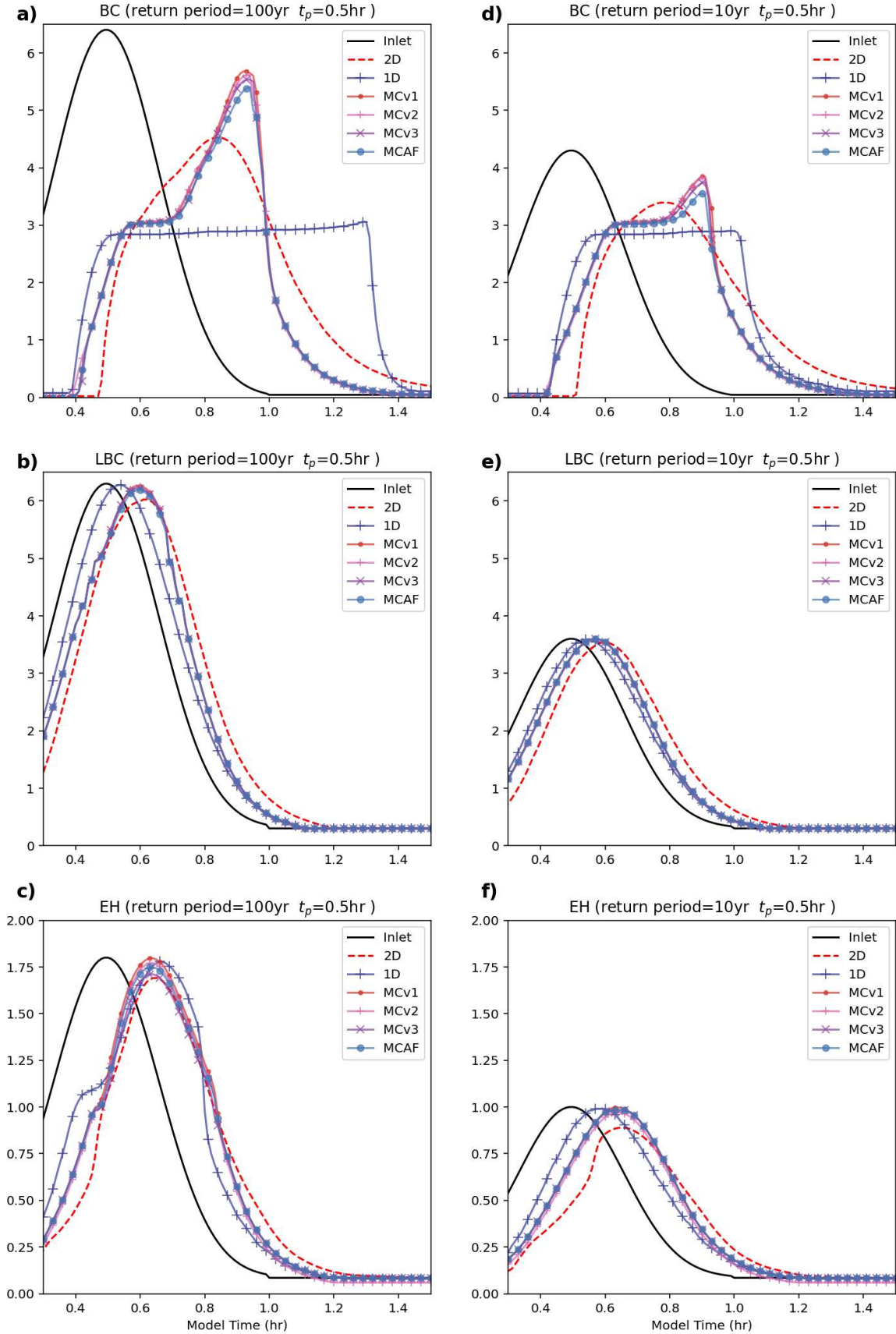


Figure 3.1 The outlet hydrographs for the 100-year (a-c), and 10-year return period (d-f) with a 0.5-hr time to peak (t_p) flood for each model show the impact of model structure on the different sections of the hydrograph for the three sites Beaver Creek (a, d), Little Beaver Creek (b, e), and Elkhorn (c, f). Differences are most pronounced for BC as it has the largest floodplain and longest reach length.

The models did not have uniform performance across the studied sites or flood magnitudes (Figure 3.2). The model runs with low performance were the runs with high attenuation (e.g., large magnitude events at the BC site). In scenarios with less attenuation (e.g., large magnitude events at LBC), results were amongst the best observed. Results of the 1D hydrodynamic model are not included in Figure 3.2 as their inclusion broadens the y-scale excessively, obscuring differences between the routing methods tested. Similar plots for the 1D hydrodynamic model can be found in the supplemental information plots A1-A4.

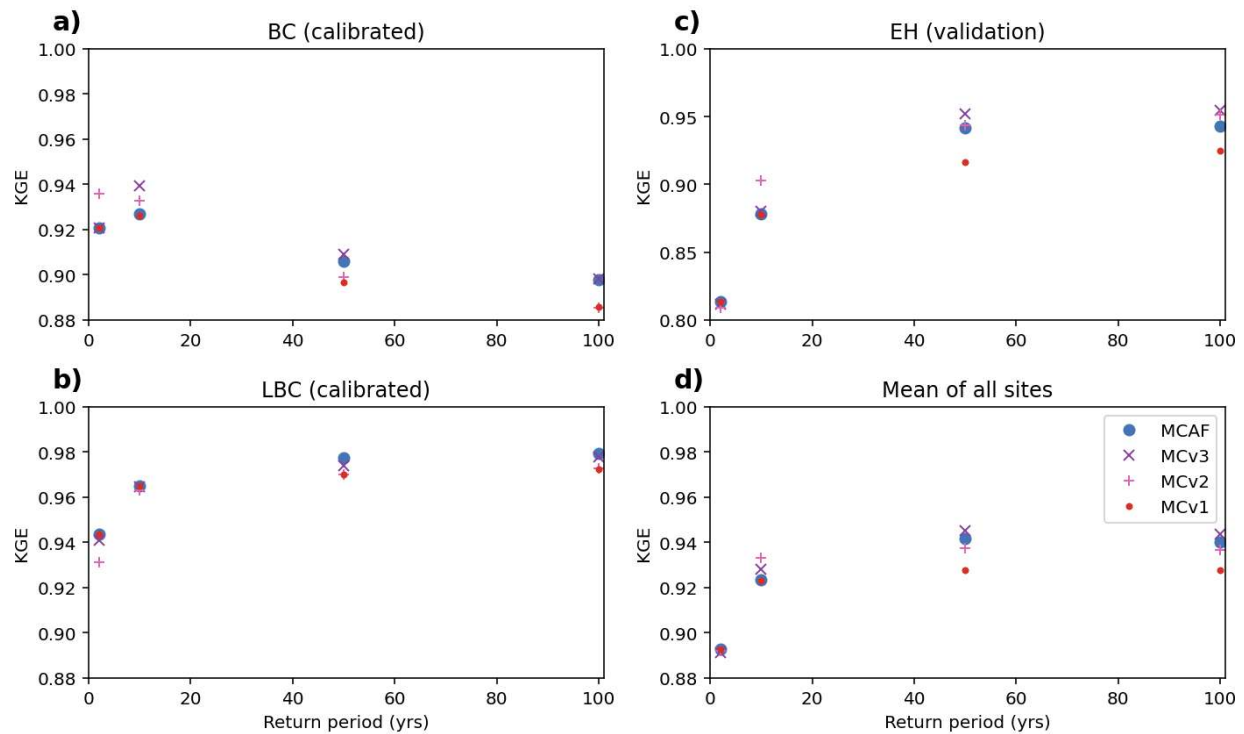


Figure 3.2 Kling Gupta Efficiency for each model at each site over the range of event magnitudes.

The addition of a lateral term in MCv2 improved the performance of the routing model, with a 0.005 increase in *KGE* from MCv1 (Table 3.3). Surprisingly, the largest increase in *KGE* was in the validation set during the 10-year recurrence interval flood. While *KGE* was improved for the validation dataset with this method, the validation *NSE* did not improve.

With the MCv3 method, the *KGE* and *NSE* improved marginally compared with MCv2 method, with an average *KGE* = 0.944 and *NSE* = 0.956. The MCv3 method improved the *NSE* at BC compared with MCv2 and had similar *NSE* for the LBC and EH model runs (Figure 3.2b). The performance at low recurrence intervals at EH suffered compared to the MCv2 method. During the largest magnitude flows at EH, performance was improved over the MCv2 method (Figure 3.2c). Performance at LBC changed little compared with MCv2, likely because the overbank flow occurred for fewer of the model runs compared with the other sites (Figure 3.2b).

Implementing a dynamic calculation of floodplain storage with MCAF resulted in similar *KGE* and *NSE* values to the MCv3 model (0.942 and 0.954, respectively) (Table 3.3). MCAF performed best for the high return period flows with significant portions of the flow moving on the floodplain during the peak flows. The increases in *NSE* were greatest for the smaller magnitude floods (return periods of 2-10 years) where small retention proportional to the amount of floodplain inundation was predicted. The increases in *NSE* for the validation dataset was greater than for the calibration set, with an *NSE* increase of 0.006 for the calibration set and 0.013 for the validation set. The improvements of *NSE* were an order of magnitude lower for LBC (0.0015) compared with the other two sites. Improvements in *KGE* were mainly observed in the calibration dataset, with the largest improvements for large floods in the large floodplain of the BC site (increase of 0.11). *KGE* improvements were smaller for sites with smaller

floodplains, including the validation dataset, where improvement using the MCAF model was similar to MCv3 and MCv2.

3.3.2 Flood Volume Retention

The 1D model underpredicted retention compared with the 2D hydrodynamic model at all study sites (Table 3.4, Figure 3.3). This is not unexpected since the 1D model has no mechanism for retaining water. All volume which has been input to the model will reach the outlet excepting calculation errors, which for these runs was on the order of 0.1% of the total water volume.

Table 3.4 Differences in water volume retained for each model compared with the 2D model $\Delta V_{fp,ret}$. Negative values indicate the model underpredicted the retained volume, while positive values indicate the model overpredicted the amount retained. The average change in absolute volume retention difference is also tabulated.

Model	$\Delta V_{fp,ret}$ (%)				$ \Delta V_{fp,ret} $ (%)			
	Calibrated		Validation		Calibrated		Validation	
	BC	LBC	EH	Avg.	BC	LBC	EH	Avg.
1D Uniform hydrodynamic	-8.2	-3.9	-11.1	-7.7	8.2	3.9	11.1	7.7
MCv1	-1.5	0.7	-5.2	-2	4.5	0.7	5.2	3.5
MCv2	-1.2	-1.7	-1.7	-1.5	4.6	1.7	2.0	2.8
MCv3	-1.9	-0.8	3.1	-0.1	3.1	0.8	3.6	2.5
MCAF	-1.2	-1.0	4.1	0.5	3.2	1.0	4.1	2.8

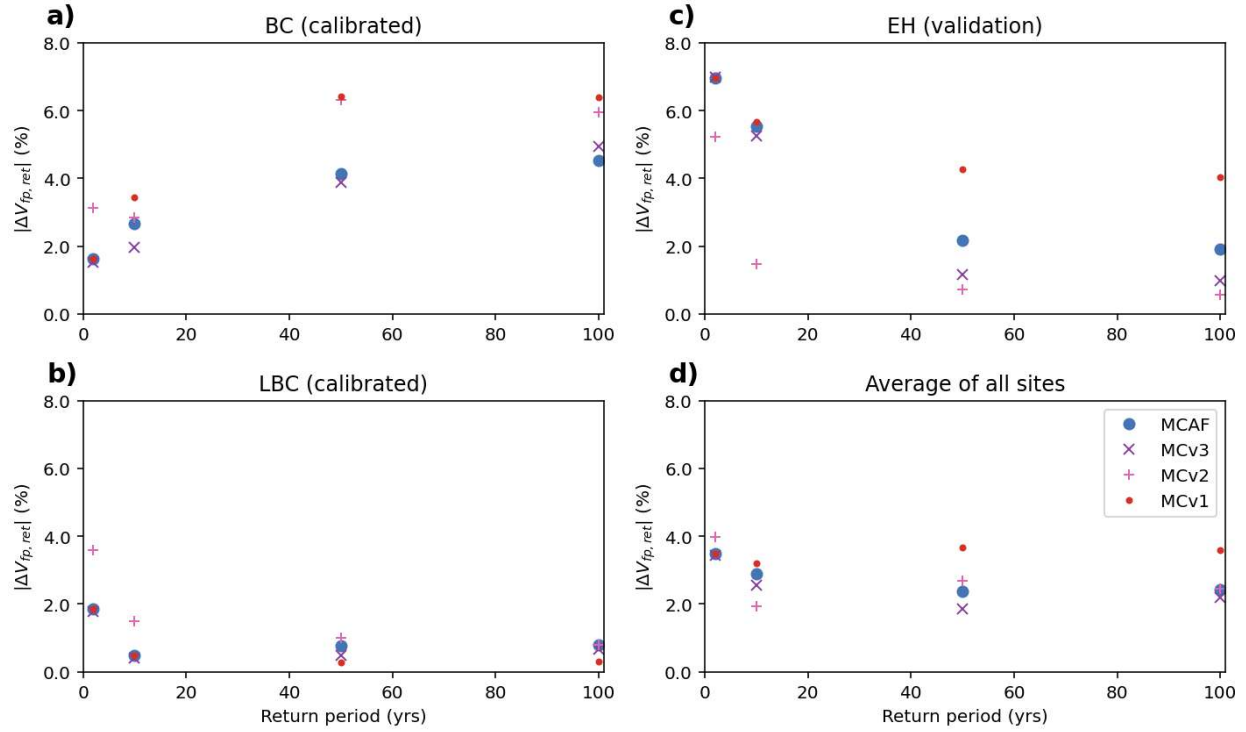


Figure 3.3 Absolute volume error varied between model types and with event magnitude. The MCAF method produced the lowest absolute volume error and performed best during the highest magnitude events.

The MCv1 routing model retained volume through numerical diffusion, which had the largest impact when there are rapid changes of flow rate in time or space, but it does not have an explicit method of determining the volume retention based on real floodplain processes. When comparing this method with the 2D model, which has many floodplain depressions to retain water, I see that the model nearly always underestimates the volume retained ($\Delta V_{fp,ret} = -2.2\%$). The MCv1 model did not universally underpredict the volume retained in the floodplain as the 1D hydrodynamic model did, with some model scenarios for MCv1 overpredicting volume retained (e.g., LBC large floods).

Adding a constant c_4 for MCv2 did not improve the absolute error in volume retention compared with MCv1. The MCv2 method consistently overpredicted the retained volume, especially for the EH (validation) dataset ($\Delta V_{fp,ret} = 8.4 \%$).

The MCv3 model improved volume retention, producing the lowest error in volume retention ($|\Delta V_{fp,ret}| = 2.5\%$). The model bias was low, with $\Delta V_{fp,ret} = -0.1\%$, indicating that the model nearly equally over and underpredicted volume retention. Prediction of volume retention was best in the MCv3 runs for BC and LBC but suffered for the EH runs. The MCv3 method generally overpredicted volume retention for the validation dataset, with the largest errors for the smaller floods.

Volume retention for the MCAF model was similar to retention in the MCv3 method, with low bias ($\Delta V_{fp,ret} = 0.5\%$) and low absolute error in volume retention ($|\Delta V_{fp,ret}| = 2.8\%$). This method had the same issue of underpredicting retention in low recurrence interval flows and overpredicting retention during the largest floods.

3.3.3 Peak Discharge Prediction

The 1D hydrodynamic model consistently underpredicted the peak discharge attenuation for the LBC and EH models (Table 3.5). The 1D hydrodynamic model overpredicted peak discharge attenuation for some scenarios at BC but otherwise underpredicted attenuation across all the flood scenarios.

MCv1 suffered the same issue as the 1D hydrodynamic model, consistently underpredicting attenuation due to the lack of explicit volume retention methods. The average absolute error was similar, with $|\Delta Q_{a/l}| = 11.7 \%/km$ and an even stronger tendency to underpredict attenuation with $\Delta Q_{a/l} = -12 \%/km$.

Table 3.5 Change in peak discharge attenuation between each model and the 2D fine mesh model ($\Delta Q_{a/l}$), and average absolute difference in peak discharge attenuation between a given model and the 2D fine mesh model ($|\Delta Q_{a/l}|$).

Model	$\Delta Q_{a/l}$ (%/km)				$\Delta Q_{a/l}$ (%/km)			
	Calibrated		Validation		Calibrated		Validation	
	BC	LBC	EH	Avg.	BC	LBC	EH	Avg.
1D Uniform hydrodynamic	2.4	-1.2	-6.6	-1.8	9.8	6.6	1.2	5.9
MCv1	-10	-2.4	-21	-11.4	10.1	2.4	21.4	8.7
MCv2	-9.3	-1.6	-14.0	-5.6	9.3	2.1	14.0	4.6
MCv3	-6.2	-1.6	-10.1	-6.7	6.2	1.9	17.6	7.4
MCAF	-6.4	-1.0	-15.5	-5.0	6.8	1.9	16.8	6.3

Of the Muskingum models, MCv2 performed the best in terms of absolute error in peak discharge prediction ($|\Delta Q_{a/l}| = 4.6$ %/km) but consistently underpredicted attenuation ($\Delta Q_{a/l} = -5.2$ %/km). The constant c_4 method employed for MCv2 reduced peak flows for the lower recurrence interval and larger floods at the same rate, leading to underpredictions of peak attenuation for the large floods (Figure 3.4). The MCv3 method showed higher absolute error in peak discharge reproduction ($|\Delta Q_{a/l}| = 7.4$ %/km), mainly due to an underprediction for the attenuation of the small floods (Figure 3.4). The MCAF method performed similarly to MCv3 ($|\Delta Q_{a/l}| = 6.3$ %/km) but with better prediction of attenuation for large magnitude events (Figure 3.4).

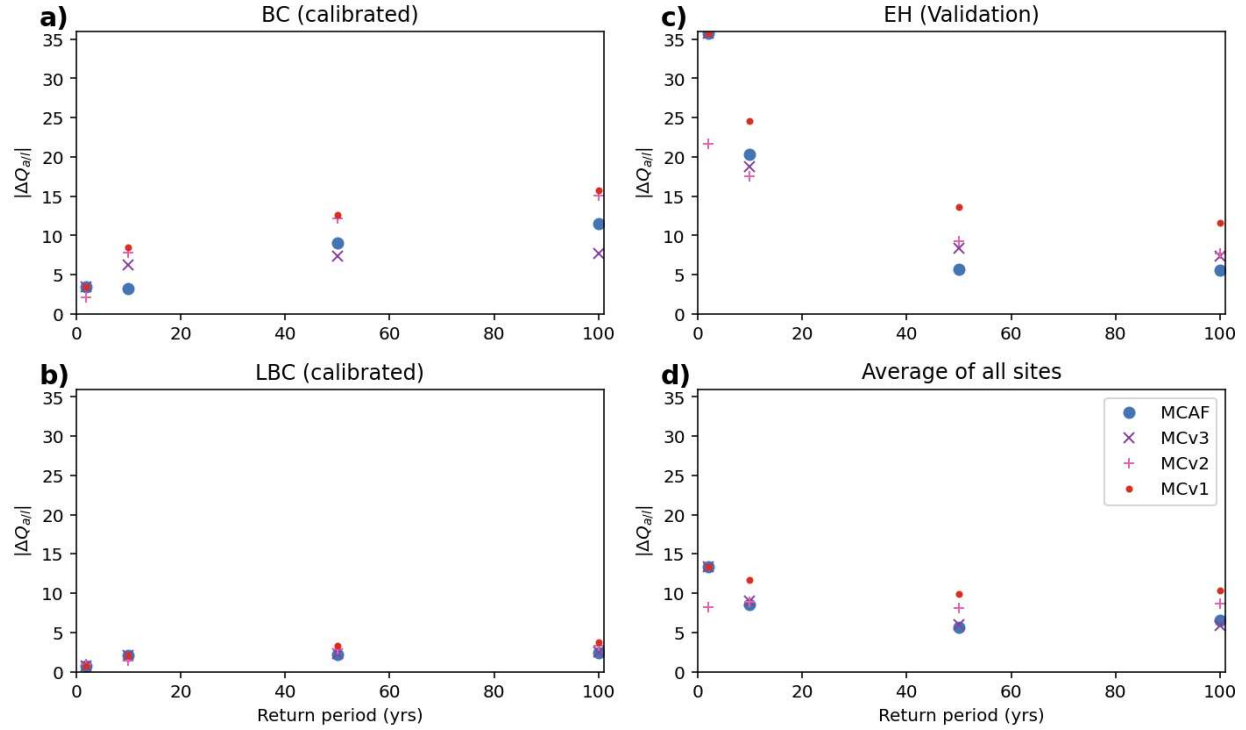


Figure 3.4 Model error in attenuation prediction decreased with increasing flood magnitude and was lowest for MCAF for the high magnitude events. The largest errors were in the small magnitude floods for the validation dataset (EH).

3.3.4 Uncertainty

The GLUE analysis produced many behavioral models for each model method; 23 for the MCv2, 2126 for the MCv3, and 38 for MCAF. The GLUE analysis for the 3 calibrated methods produced different ranges of uncertainty, with the MCv3 and MCAF methods producing larger prediction intervals during peak discharges (Figure 3.5). This larger prediction interval during higher discharges corresponded with the uncertainty in the prediction of c_4 during activated floodplain conditions. The highest uncertainty was for large events in the BC model, where the maximum range of the 95% GLUE interval was $1.9 \text{ m}^3/\text{s}$ predicted for the MCv3 model. Uncertainty was highest for these events in the MCv2 and MCAF models as well, but the maximum uncertainty was comparatively low, with prediction interval ranges of $1.4 \text{ m}^3/\text{s}$ for each model.

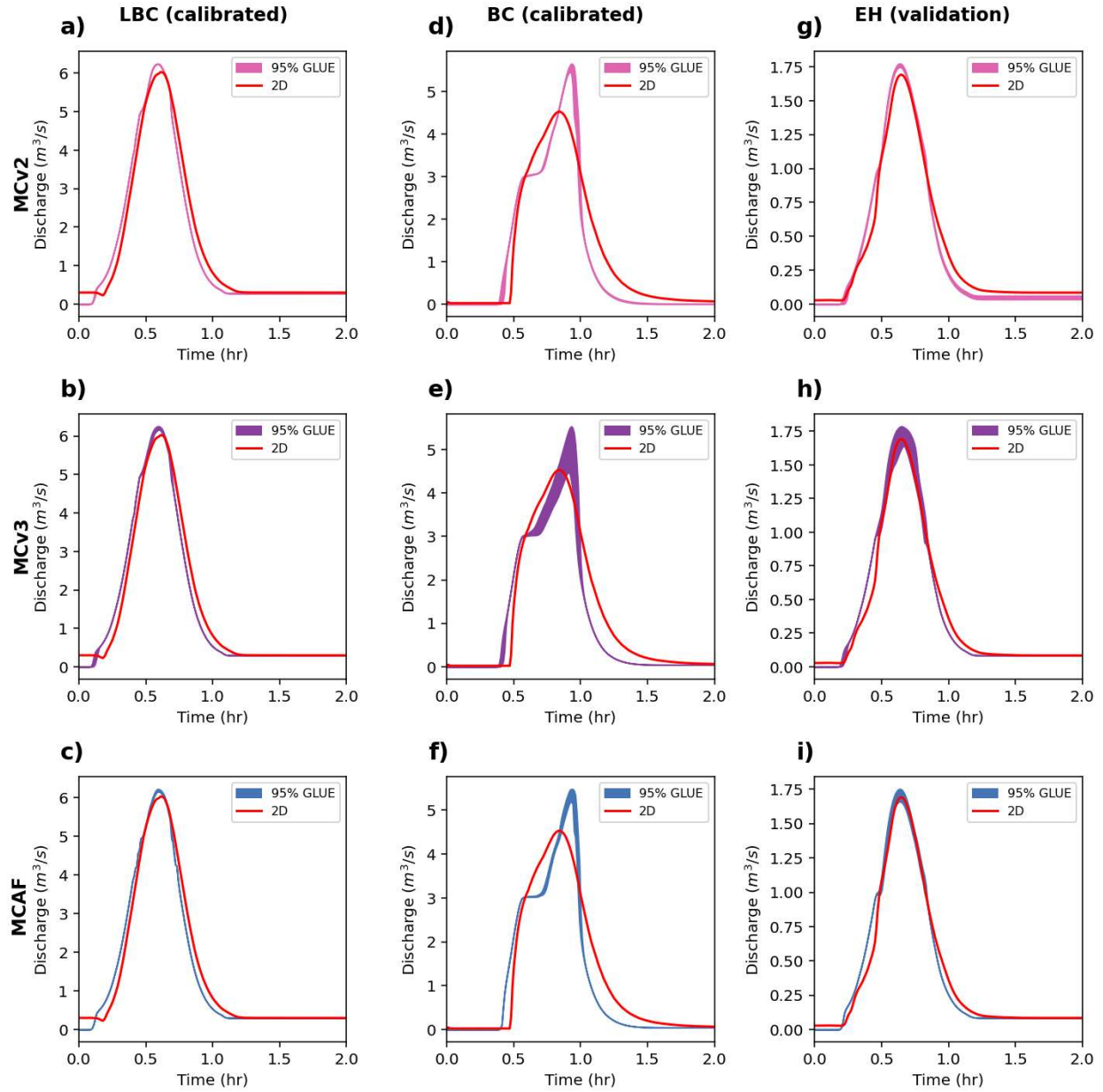


Figure 3.5 The GLUE prediction intervals were largest high flows in the MCv3 model. The MCAF and MCv2 models had similar uncertainty. Each site is constant through the columns (eg. a-c), while the model for which the GLUE interval is displayed is constant across rows (eg. a, d, g).

3.4 Discussion

I found that the two common methods for routing flows—Muskingum-Cunge without lateral inflow (MCv1) and 1D hydrodynamic models—had major shortcomings in predicting the

outlet discharge of flash floods in headwater streams. These methods often overpredicted the total outlet volume, which resulted in large absolute error in outlet volume prediction, particularly in the validation dataset (Table 4.4). The errors I observed were over relatively short reaches of stream (<1 km), which would likely compound over larger spatial scales (Read et al., 2023). Read et al. (2023) found that at large scales models using routing equivalent to MCv1 have even more severe errors in predicting peak discharge and timing, with the modeled peak lagging several hours behind the observed flood. These shortcomings demonstrated that alternative methods are necessary to sufficiently predict routing of flash floods in mountain streams.

Previous studies have also reported errors in outlet volume prediction using Muskingum-Cunge in a variety of environments (Elbashir, 2011; Todini, 2007). The solutions which have thus far been proposed involved non-physically based changes to the routing scheme including the use of variable parameter Muskingum instead of Muskingum-Cunge (Almaoudi & Saleh, 2021; Niazkar & Zakwan, 2022). While the results were improved by this method, its versatility for applications to ungauged basins is lacking given its lack of a physical basis. Additional studies have been conducted to address the shortcomings of Muskingum-Cunge routing by incorporating more floodplain physical characteristics for improved routing, but these studies focused on larger rivers with longer duration floods (O'Sullivan et al., 2012; Paiva & Lima, 2024). These approaches included changes to the calculation method of the C_1 , C_2 , and C_3 parameters and was sufficient for calculating routing for large rivers (O'Sullivan et al., 2012). This work utilized 1D hydrodynamic models to inform their routing changes, which I have found to have major errors in predicting outflow for my study sites (Table 3.3), likely due to the importance of floodplain depression storage in flash flood routing (Christensen & Morrison,

2026b). This work builds on this with a method that can be readily applied to steep, flashy systems with numerical methods that directly simulate the physical processes driving attenuation in mountain streams.

The development of MCAF provided a simply applied method that reduced the modeled error in outlet volume prediction and peak discharge prediction compared to the 1D hydrodynamic and standard application of the Muskingum-Cunge method. This method reduced the water volume retention error by 20% on average and improved prediction of the peak discharge at the outlet by 21% for the validation dataset (Table 3.5). The improvements were greatest in the shortest duration flows with the largest floodplains and high attenuation. This improvement in water volume storage and peak discharge can be achieved with no additional data collection and minimal increases in computational time. The improvements made in common dimensionless model performance metrics were comparatively small, with increases in *KGE* of 0.24 on average for the MCAF method compared to the MCv1 method. This difference is likely to grow for applications at larger scales rather than a single reach application (Johnson et al., 2023). Overall, the improvements to flash flood routing observed for MCAF merit larger scale testing in other environments and at the watershed scale.

Though there have been many modification to the Muskingum and Muskingum-Cunge methods, this is the first time to my knowledge that floodplain topographic storage has been implemented in a Muskingum-Cunge model (Salvati et al., 2024). The novel method of continually reevaluating the c_4 parameter based on characteristics of the flow provides flexibility in applying this model to reaches that have minimal data. This quality makes my approach uniquely applicable in large scale modeling scenarios where data are sparse (Yang et al., 2020). A potential application of this work is in the routing portion of the United States National Water

Model, where the current method of Muskingum-Cunge routing has been shown to have significant shortcomings (Johnson et al., 2023; Read et al., 2023). Any of the Muskingum iterations tested beyond MCv1 could be tested in large scale models, but the failure of MCv2 and MCv3 to scale the c_4 parameter with channel characteristics may lead to scaling issues. Applications of the MCAF method in such a large scenario would have to consider the system characteristics thoroughly to ensure that the method is only applied in scenarios with similar geomorphic and hydrological characteristics as the calibration data.

Although the MCAF model adequately routed events in untrained data (Figure 3.2c), special care is needed to apply the model in systems that have drastically different characteristics than the reaches on which it was trained. The calibration and validation datasets both have historically beaver-inhabited floodplains, similar valley slopes (1-3%), and similar hydrologic regimes. The scaling of the floodplain depression storage is dependent on floodplain size and accessibility, offering some flexibility, but this scaling needs to be tested at larger scales before being applied. The MCAF model may work well in other systems (e.g., more gradual slopes or systems without beaver) but will certainly require validation and will likely require recalibration. Manual calibration of these parameters is encouraged for future users to identify a suitable, narrow range of values before attempting to apply any automatic calibration techniques. Future work should test this method on more diverse reaches with more varied geometry.

A limitation of both the MCv3 and MCAF models is their binary decision for floodplain activation. The bankfull threshold has repeatedly been shown to be more of a spectrum than a true threshold (Christensen et al., 2024; Czuba et al., 2019), but the models do not begin to alter the c_4 parameter until the capacity of the reach-average channel is exceeded. This simplification manifested itself in lower NSE and higher errors in $Q_{a/l}$ for the small magnitude events (Figure

3.2c, Figure 3.5c). While this simplification did impact model performance near the bankfull threshold, larger events that are often of the most concern did not suffer from this binary decision structure as the floodplain was well inundated during most of the event. This may be addressed in future work through considerations of variation in cross section capacity throughout the reach. Using varied cross sections at each spatial step in the model could incorporate this variability but would need a scheme to ensure the reach is accurately represented.

Another limitation of this work is that it relied on simulations from a calibrated 2D hydrodynamic model to calibrate and evaluate model outputs. While this strategy is valid and has been applied before (Ghavasieh et al., 2006), future efforts should be made to record flash flood propagation data in similar reaches to those studied here to ensure accuracy. This work also ignores the network-scale implications of the novel routing schemes developed. Changes in reach-scale routing can have a compounding effect on downstream hydrographs in river networks (Dixon et al., 2016; Rinaldo et al., 1991). Future work needs to address this by applying the model in a network scenario with sufficient calibration data throughout the network.

3.5. Conclusions

I identified shortcomings of several simplification strategies in flash flood routing for mountain streams and developed and tested a model scheme that approximates physical processes to address these shortcomings without requiring significantly more computational power. The two novel routing methods I developed built on the Muskingum-Cunge method with a staged c_4 (MCv3) and dynamically calculated c_4 (Muskingum-Cunge Augmented Floodplain, MCAF) that are based on physical processes in flash flood routing. The best performing model created was the MCAF method, which accurately reproduced outlet hydrographs on trained and untrained reaches (average $KGE = 0.928$). This method also had the smallest volume retention

error and the highest accuracy in reproducing outlet peak flow for large events (return period ≥ 50 years). The traditional routing schemes I tested for reproduction of flash floods did not sufficiently represent the processes which drive attenuation of flash floods in mountain streams, resulting in lower performance. The uniform 1D hydrodynamic model had the worst overall performance because it did not have a mechanism to retain flood waters within the floodplain. The Muskingum-Cunge method without a lateral term (MCv1) had similar shortcomings to the 1D hydrodynamic model. The introduction of a constant c_4 term in MCv2 improved performance over MCv1 slightly but failed to separate floodplain and channel processes, leading to errors in volume retention. The MCAF method can be readily applied to reaches with similar morphology and hydrology to those it was developed for but requires additional testing and calibration before it is applied in significantly different settings.

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Chapter 4 : Flash floods are dampened and slowed at the network scale by in-channel wood

4.2 Introduction

Flooding remains one of the most concerning extreme events, costing >500 million USD in infrastructure damage and the loss of >100,000 lives globally every year (Pielke & Downton, 2000). Flash flooding raises additional safety concerns as, by definition, there is less time to evacuate than during other floods (NOAA, 2024; Saharia et al., 2017). Flash flooding is being exacerbated by the warming of the climate through increases in precipitation intensity and intensifying widespread wildfires (Saharia et al., 2017; Triantafillou & Wohl, 2024). Despite extensive and expensive flood control infrastructure projects, flash floods continue to take lives and ravage communities across the world and especially those in steep regions where water moves fastest (NOAA, 2024). The current standards for flood control in the United States are to increase conveyance through channels near populated areas and contain floodwaters behind flood control dams where there is sufficient funding and opportunity (USACE, 2026; USDA, 2022).

Flood conveyance is generally increased using two methods: snagging and channelization (USDA, 2022). Snagging is done by removing obstructions to flow including wood, riparian vegetation, and boulders. Channelization involves major earthwork efforts to deepen and widen the river channels, or dig a new channel where water was previously conveyed slowly through a nexus. There are major costs associated with increasing the conveyance of stream channels, monetarily, economically, and to downstream users. With floodwaters confined and accelerated in channels locally, the floodplains which used to store flood waters remain dry, preventing them

from providing their many economic and ecosystem services (Knox, Wohl, et al., 2022; Opperman et al., 2010). The removal of wood from the channel during snagging has long been understood by the scientific community to disrupt many of the natural cycles within streams, leading to imbalances in sediment and energy balances and degrading the ecosystems of rivers and streams (Hohensinner et al., 2018). Channelization often has cascading morphological effects throughout the watershed as the local changes to the channel cause an imbalance in energy for the stream system, destabilizing streams within the system, which adjust to their new constraints (Hohensinner et al., 2018). The destabilization of connected reaches causes large exports of sediment and threatens the infrastructure built in the river corridor. Beyond these costs, increased conveyance has been a double-edged sword, with the acceleration of floodwaters compounding throughout the system and causing magnified flooding downstream. Recent works have shown that increases in the conveyance of channels has an accelerating affect which can cause net increases in flood damages (Knox, Wohl, et al., 2022).

Given the associated costs of traditional flood control measures and their failure to protect communities from flooding, a growing interest in alternative strategies for flood control have been gaining traction in recent decades (Follett et al., 2024; Lane, 2017; Puttock et al., 2021). These alternative approaches to flood control include leveraging the natural ability of functional floodplains and wetlands to absorb floods, termed “Natural Flood Management” and popularized in a landmark paper (Lane, 2017). Floodplains have a remarkable ability to absorb flood waters when they are readily accessed by their associated rivers and can provide numerous other services while contributing to flood control (Dadson et al., 2017; Puttock et al., 2021; USGS, 1986). Floodplains facilitate exchange of water and nutrients between the aquatic and terrestrial worlds, making them some of the most productive areas on Earth, and have been used

to grow crops through adaptive techniques, serve as nurseries for fish, and create highly biodiverse ecosystems (Opperman et al., 2010; Sommer et al., 2001). These services have been appreciated for thousands of years but have recently been sacrificed to enable less adaptive, short-sighted land use strategies (Chevalier et al., 2023; Wang et al., 2011).

Previous works on restoration of in-channel wood and floodplain reconnection have found reductions in peak flow at the reach and watershed scales. Most of the literature on reach-scale attenuation has utilized calibrated hydrodynamic simulations, which indicate that a reach may reduce the peak discharge in a variety of settings, with the most effective attenuation occurring for flash floods in mountain streams (Christensen & Morrison, 2026b; Federman et al., 2023; Neumayer et al., 2020). These models have a strong physical basis but are generally not applicable at the watershed scale. Some reach-scale studies have indicated that beaver meadows, some of the most connected channel-floodplain systems, offer major reductions in peak discharge through direct observations of floods (Puttock et al., 2017, 2021). Increasing roughness at the reach scale has been linked to increased attenuation for decades, with recent studies indicating that during flash floods, increases in roughness can be especially effective at reducing peak flows (Christensen & Morrison, 2026b; Sholtes, 2009; Woltemade & Potter, 1994).

Healthy, rough riverscapes reduce outlet discharges through storage of flood water and dispersion of the flood wave and studies that aim to discern the impacts of floodplain restoration on flood attenuation must consider both mechanics (Barry & Bajracharya, 1995; Chow, 1959; Lininger & Latrubesse, 2016). As floods spread over the floodplain, some water is trapped within the depressions of the floodplain (“dead storage”). This is of particular importance in flash floods where the lower total flood volume makes this dead storage more significant in reducing overall exiting volume and outlet peak flow (Christensen & Morrison, 2026b). Many

previous studies of the impact of floodplain restoration on flood wave propagation have utilized methods that do not explicitly account for this dead storage (Dixon et al., 2016; Ghavasieh et al., 2006). Recently developed models for flood routing have explicit considerations for these processes and can be readily applied at the watershed scale (Christensen & Morrison, 2026a).

The existing studies that have investigated the watershed-scale impact of channel and floodplain restoration have largely focused on longer duration floods with lower intensity rainfall (Dadson et al., 2017; Dixon et al., 2016; Ghavasieh et al., 2006). There is a lack of investigations on the impact of roughness additions in the channel and floodplains for flashy systems in mountainous areas, where reach-scale attenuation has been found to be high and highly sensitive to roughness (Christensen & Morrison, 2026b; USGS, 1986). Studies are also needed that test novel routing methods, which account for more riverscape flood attenuation processes at the watershed scale, to determine their applicability in this setting. The potential for synchronization of tributary flows is also poorly studied in steep mountainous settings, further necessitating investigations of watershed-scale interactions under different management regimes in flashy mountainous watersheds.

4.3 Methods

4.3.1 Site description

The Elkhorn Creek Watershed is a tributary of the Cache la Poudre River in northern Colorado, USA (Figure 1). The watershed spans from 3,350 m in its headwaters to 2,000 m at its confluence with the Cache la Poudre River. The stream reaches of the watershed are numbered in Figure 1 as r1-r13. The high peaks in the watershed build up snow stores in the winter months, leading to elevated flows in the spring melt-off. Summer convective storms between June and September are a major driver of floods in the watershed, with concentrated precipitation on steep

slopes leading to flash floods. Vegetation type and density throughout the watershed vary with elevation, water access, and aspect. Generally, northern aspects are characterized by medium density pinyon pine (*Pinus edulis*) forest, while southern aspect slopes support more sparse xeric species of vegetation such as sage (*Salvia sp.*), juniper (*Juniperus sp.*), and prickly pear cactus (*Opuntia sp.*). The valley bottoms are comparatively wet and contain introduced grasses and stands of riparian shrubs including willow (*Salix sp.*) and alder (*Populus sp.*). The thickness of these shrub stands varies between reaches due to differences in management practices, with dense stands in minimally grazed areas (e.g., r10) and sparse to non-existent riparian woody vegetation on reaches with heavy cattle grazing (e.g., r9). The steep glaciated hillslopes of the watershed often include rocky outcroppings and poorly developed soils with coarse gruss material from the underlying granitic rock.

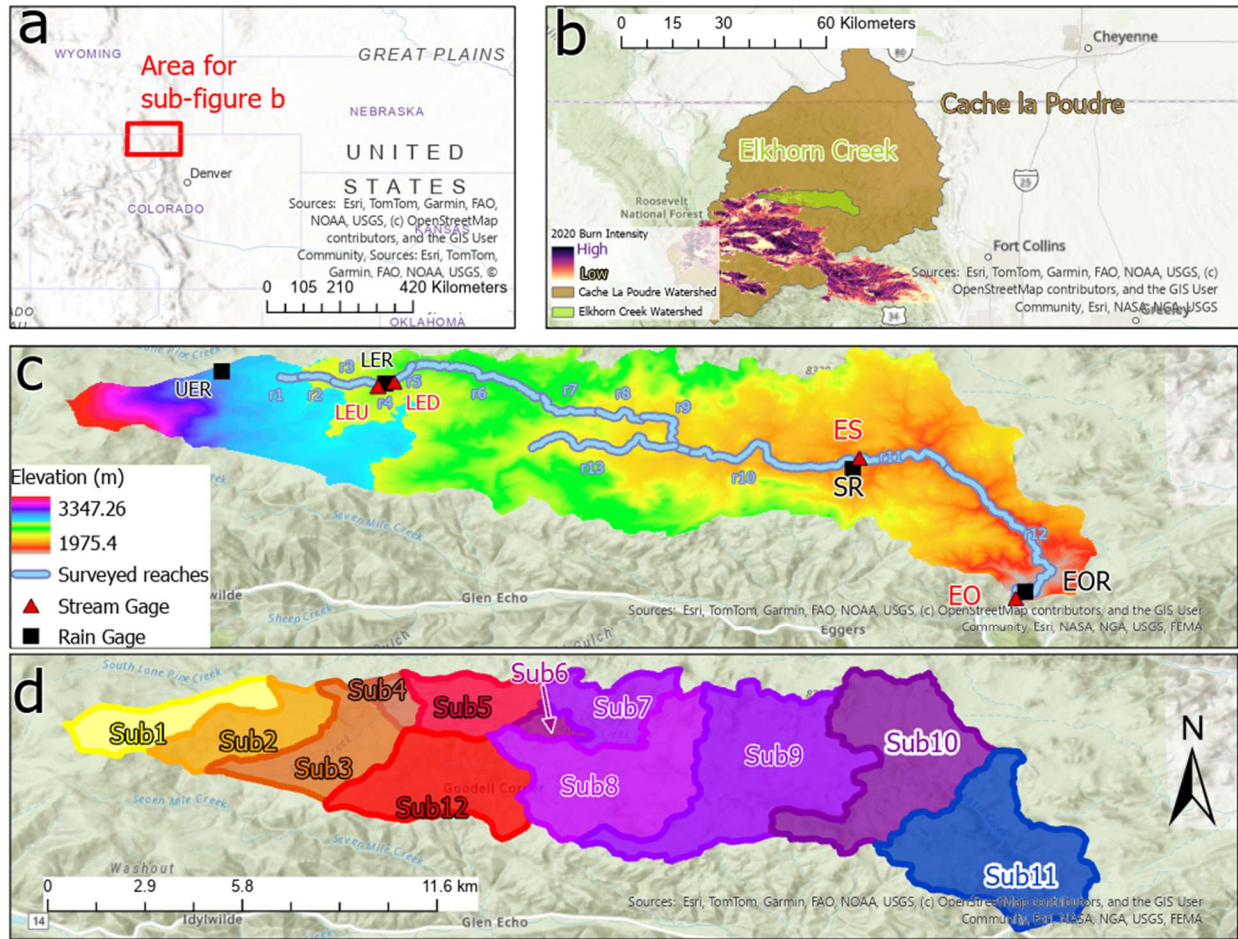


Figure 4.1 The Elkhorn Creek watershed drains the Southern Rocky Mountains in northern Colorado and enters the Cache la Poudre River at its terminus (a,b). The upper watershed was severely burned in the 2020 wildfire (b). The hydrologic monitoring equipment throughout the watershed and the discretization used for the hydrologic model are shown in subfigures c and d respectively. All subfigures share a north arrow. Subfigures c and d share a scale bar.

The historical management of the stream channel in the study area has been removal of instream wood (“snagging”) and of North American beaver (*Castor canadensis*) (USDA, 2022; Wohl, 2021). Many of the reaches have periodically hosted valley-spanning beaver structures, but due to the continual removal of beaver most of the historically beaver-dominated reaches have no beaver as of this writing, resulting in a dried valley bottom and incised streams (r1-6, and r11) (Seton, 1928; Wohl, 2021). Although official documentation is lacking, reports from local landowners indicate that beaver extirpation was carried out in the early 2010’s, with one

account noting another removal in 2025 (personal communications with Bob Sturtevant of Ben Delatour Scout Ranch, June 11, 2025). Despite removal efforts, three of the reaches, r8, r10, and r13, are home to active beaver lodges with large ponds. Several of the more remote reaches of stream have also maintained significant in-channel wood as snagging is impractical due to steep canyon walls and lack of road access (e.g., r7 and r12).

The upper reaches of the watershed were burned at moderate to high intensity during the 2020 Cameron peak fire (figure 1b). The fire severely impacted the hydrology of the system both on the hillslopes and in the riparian zone, leading to flashy flows and elevated sediment loads (Hahn et al., 2025). The fire brought attention to this watershed, leading to major changes to the management of several reaches (Triantafillou & Wohl, 2024). Since 2020 there have been 4 reaches (r1, r2, r4 and r6) in which the large wood was replenished in the stream. In r1, r4, and r6 logs were brought from nearby hillslopes along with driven wooden posts to create stabilized jams, described as “Post Assisted Log Structures” (Wheaton et al., 2019). These structures aim to slow water velocities, retain sediment, increase pool depths, and to kickstart beaver recolonization but, as of this writing, these reaches remain beaver-less. In r2, the in-channel wood was supplemented with nearby logs and branches, but no stabilized log structures were created. Willow stakes were planted in each of the restoration reaches, bolstering the density of riparian vegetation to increase hydraulic roughness and food stock for recolonizing beaver.

Diversion structures are present on reaches r1, r6, r10, r11 and r13. The amount of water diverted by these structures is not publicly documented but ranged between 0.03-0.06 m³/s in August and September 2025 from field observations. These diversions, along with natural loss to groundwater and evapotranspiration, result in a loss of more than half the baseflow but their impact during higher flows is unclear.

4.3.2 Data collection

I collected hydrologic data throughout the watershed over two years (2024 and 2025). In 2024, I began installing precipitation and discharge gages but did not fully complete the network of sensors due to time constraints. I installed the LER, LEU and LED gages on July 17, 2024, with a 15-minute interval of record for the discharge gages. In 2025, I was able to expand the network of discharge collection to 4 locations throughout the watershed from March to October 2025 using pressure transducers U20L loggers (LEU, LED, ES, and EO denoted “stream gage” in Figure 1c). In 2025, I increased the sample frequency of the transducers to 5-minute intervals for a higher temporal resolution of discharge throughout the watershed. I stabilized the cross-sectional geometry around each discharge gage with boulder weirs to maintain the depth-discharge relationship over the study period. I routinely inspected each discharge gage for shifts in the channel to ensure there was consistent channel geometry. I installed one additional discharge gage (not indicated in Figure 1). This gage had a major shift in channel geometry during a high flow, and so the data collected at that gage were excluded from this analysis.

The recorded pressure at each gage was converted to flow depth by subtracting the atmospheric pressure and converting hydrostatic pressure to depth. I then related this to a static in stream staff gage to ensure consistency between the transducer depth and water surface elevation. I developed a rating curve relating flow depth and discharge for the gage by measuring discharge at each sensor over the largest range of discharge conditions possible utilizing the snowmelt driven high flows in spring in 2025. For depths higher than the flows I was able to measure for the rating curve, I estimated the discharge with a 1-dimensional hydrodynamic model. I created this model by surveying a short stream reach for each gage, with cross-sections several decimeters upstream and downstream of the gage. I used the highest recorded discharge-

depth pair to calibrate the Mannings roughness for each model and validated the calibration with the next highest recorded discharge-depth pair. The resultant rating curves for each site are tabulated in Appendix A, Table A1.

I recorded precipitation intensity continuously throughout the watershed with four tipping bucket rain gages in the 2025 season (Figure 1c). The precipitation gage names are abbreviated on figure 1c with 2-3 letter names ending in “R” for rain. I designed the precipitation gaging locations to cover the watershed as evenly as possible with the added constraint of the limited access to private lands in the watershed. Each bucket tips and records an “event” after 0.254 mm of precipitation. I post-processed these data by counting events in each 5-minute window to obtain the 5-minute precipitation intensity. In 2024, only the LER rain gage was established. To supplement the precipitation data for simulations in the 2024 period, I utilized nearby rain gage data provided by Larimer County (County, 2024, 2024).

In addition to the hydrologic data, I collected morphological data for the streams to conduct routing of flows throughout the watershed in 2025. I conducted laser level surveys of 13 reaches of stream with 10 cross sections for each reach (Figure 1). The cross sections extended from the surface of the floodplain on the left bank to the surface of the floodplain on the right bank. For each cross-section, I calculated the bankfull area and hydraulic radius at bankfull. The cross sections were evenly distributed throughout each reach and were randomly chosen to reduce the bias for cross sections based on accessibility. At each reach I walked in the channel for the full length and performed a field estimate of the Mannings roughness following the visual roughness estimation method (Arcement & Schneider, 1989) for the channel and the floodplain.

4.3.3 Model Structure and workflow

I developed a semi-lumped event-based model to investigate the propagation of floods throughout the Elkhorn Creek watershed using the above-described field data and remotely sensed data. The discretization of the watershed is highlighted in Figure 1d. I implemented runoff generation for each subbasin using the NRCS guidelines (Moore et al., 2016) for modeling watersheds after wildfire. This method of runoff generation was developed specifically for studying intense rain events in burnt environments where Hortonian runoff is elevated by reduced soil infiltration rates. The method utilizes Green-Ampt loss with elevated impervious surface area based on the burn severity along with the SCS curve number transform method to transform runoff into discharge at the watershed outlet. In this analysis, I lumped transmission losses due to groundwater and diversions as a constant loss (Ebel et al., 2023; Rengers et al., 2019). I applied a constant baseflow assigned to each reach using the average gaged baseflow during the late summer and interpolating values for baseflow at the intermediate reaches that are not gaged. I routed flows through each reach using the Muskingum Cunge Augmented Floodplain method (MCAF) developed in Christensen & Morrison (2026a). My general model workflow is depicted in the flowchart in Figure 4.2.

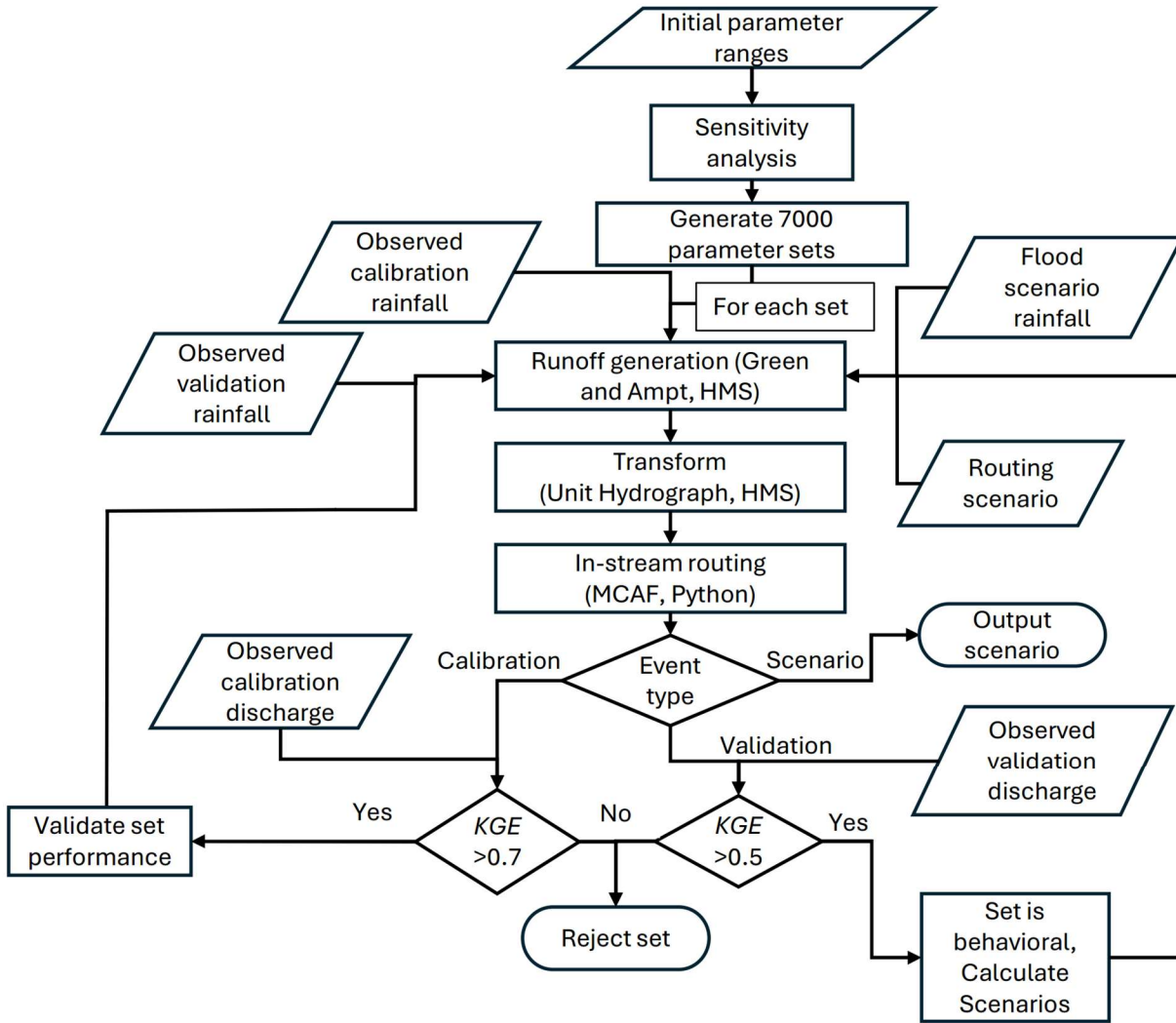


Figure 4.2 Flow of model development and application to reach desired scenario hydrographs. More details on each process are available in the following methods subsections. Runoff generation and transform were completed in the United States Army Corps of Engineer's Hydrologic Modeling Software (HMS). In-stream routing was completed using the Muskingum Cunge Augmented Floodplain method in python (Christensen & Morrison, 2026a).

The assumed dominance of overland flow for runoff generation is a simplification that excludes saturation excess runoff and the contribution of shallow groundwater. This exclusion is most valid for short-duration storms and watersheds with low infiltration rates (Moody, 2012). These assumptions have been tested and applied to model post-fire systems in many studies with similar geologic, hydrologic, and vegetative settings (McGuire et al., 2018; Moody, 2012;

Rengers et al., 2019). This method also assumes that runoff translation to streamflow occurs uniformly throughout the event by applying the unit hydrograph method. Again, this assumption holds best for short duration storms and is applicable to this environment (Rengers et al., 2019).

4.3.4 Model parameterization

I determined initial parameters for the runoff generation method using the web soil survey data (USDA, 2025). Web soil survey provided us with estimates of soil texture, porosity, and saturated hydrologic conductivity (K_s). I set the initial soil moisture (D_i) to half the porosity, set the suction head (ψ_f) based on the soil texture, and set the total deficit as the soil porosity. For the routing method, I measured each reach length and reach slope in ArcGIS Pro using a digital elevation model collected in 2020 by the United States Geological Survey (USGS, 2021). I set the reach channel cross section dimensions (bankfull area and bankfull hydraulic radius) as the average of the 10 surveyed cross sections within a compound reach. I set the floodplain width of each reach by mapping the geomorphic floodplain as determined using the fluvial hazards mapping protocol v. 1.0 (Blazewicz et al., 2020). For the channel and floodplain hydraulic roughness, I followed the methodology of Acreman et al. (2003) for visually assessing each reach.

4.3.4 Model calibration

I performed the watershed model calibration through maximizing the average Kling Gupta Efficiency (KGE) of the model predictions for the hydrographs at all gages during the flood event observed in 2025. I determined the calibration parameters and calibration range by conducting a localized sensitivity analysis with a “One factor At a Time” (OAT) approach (Morris, 1991). In this OAT sensitivity analysis and subsequent model calibration, I varied runoff characteristics of each subbasin and routing parameters. After the sensitivity analysis I

found that the essential calibration variables for each sub-basin were the impervious fraction (f_{imp}), the lag time (t_l), infiltration rate (I), and the peak rate factor (PRF) for the runoff generation and transform components of the model. For the f_{imp} of each subbasin, I limited the calibration value range from 0-5% imperviousness from the estimates from web soil survey (USDA, 2025). For the transform method, I limited values for PRF from 484 (the standard) to 600 (the largest value in the base HMS program) and varied the lag time t_l +/- 20% of the estimate provided by the flow path method (Moody, 2012; USDA, 2010). For the routing component of the model, I calibrated the 4 floodplain routing variables a , b , c , and d . The range of calibration values tested are detailed in Table 4.1 (Christensen & Morrison, 2026a).

Table 4.1 Range for tested values for each of the calibration variables: Impervious fraction (f_{imp}), lag time (t_l), Peak Rate factor (PRF), Infiltration rate (I), and floodplain routing variables a , b , c , and d .

Variable (units)	Calibration range
f_{imp} (%)	0-5
PRF (unitless)	484-600
I (cm/hr)	0-7
t_l (hours)	+/- 20%
a (unitless)	0-0.1
b (unitless)	0-0.5
c (unitless)	0-0.01
d (unitless)	0-0.05

4.3.5 Model validation

To validate model performance and determine behavioral models, I simulated the flood event which was observed in 2024. This flood occurred before the full network of gages was complete, so fewer data were available to compare performance. For this event, discharge data were captured at two gages on a 15-minute interval. I assessed the model KGE at the two recording gages along with the error of peak discharge and peak discharge timing. I set a performance threshold of $KGE > 0.5$ for the validation event, yielding a set of behavioral models that fit both the calibration and validation sets (Döll et al., 2024; Hossain et al., 2019; Wu et al., 2021). I used the same initial conditions for the validation event as the calibration and simulation events. Though conditions were similar at the start of this event (hot and dry conditions in late summer punctuated with intense rains), the likelihood that soil moisture conditions were identical is low. This is a source of error for the validation event. The validation event occurred before the restoration structures were built in r4, so I used the channel roughness assessment from before restoration in the routing.

4.3.6 Uncertainty Analysis

I conducted a Generalized Likelihood Uncertainty Estimation (GLUE) analysis, using a Monte-Carlo structure to generate 7,000 simulations across the parameter calibration range (Beven & Binley, 1992). Each parameter value for a given simulation was selected from a uniform distribution across the given parameters' calibration range. I defined the behavioral models as having $KGE > 0.70$ on the calibration event and $KGE > 0.50$ on the validation event (Hossain et al., 2019; Wu et al., 2021). I calculated the “likelihood” of each model L_j using the residuals of the model at each gage for the calibration event, detailed in equation 1 (Beven & Binley, 1992).

$$L_j = \sum_{j=1}^j \sum_{i=1}^i (Q_{obs,i} - Q_{mod,i,j})^2^{-1}$$

(1)

Where i is the number of gages in the model $Q_{obs,i}$ is the set of observed discharges at gage i , j is the number of behavioral parameter sets, $Q_{mod,i,j}$ is the discharge modeled at gage i in parameter set j . I recorded the predictions from the full set of calibrated models and the 95% prediction interval of the behavioral models for both the calibration event and all simulation events.

4.3.7 Simulation events

I simulated 288 scenarios with the calibrated model, which predicted hydrographs across the watershed with each of the 6 behavioral models, yielding 1,728 total scenario runs. The set of simulated events is detailed in Table 4.2. I assigned the simulated precipitation intensity using the NOAA Atlas tool (NOAA, 2025), with the recurrence interval ranging from 2 and 200 years and duration ranging from 15 minutes to 1 hour based on the observation by Moody (2012). I simulated events with varying spatial distribution of rainfall with 3 spatial rainfall cases; uniform across the watershed, concentrated within the upper watershed subbasins, and concentrated in the lower subbasin. For the simulations where precipitation was non-uniform throughout the basin, I used inverse distance weighting between the rain gages. I assigned the full intensity set at UER and LER for the headwaters concentrated simulations and no rainfall at the lower rain gages (EBR and EOR). For the lower watershed concentrated rainfall scenarios, I used the full intensity at EBR and EOR and no rainfall at UER and LER. I simulated these events with all behavioral models and reported the results of all models to determine the uncertainty in the model outputs.

Table 4.2 simulation events

Rainfall scenarios	Rainfall distribution	Uniform
		Concentrated in headwaters
		Concentrated in Lower watershed
	Intensity return period	2 year
		10 year
		100 year
		200 year
	Storm duration	15 minute
		30 minute
		1 hour
Routing scenarios	Roughness scenarios	Current conditions
		Rough headwaters
		Rough throughout
		Rough outlet reaches
		Snagged headwaters
		Snagged outlet
		Snagged throughout
		Pre-restoration

For the routing scenarios, the only parameter that I altered between scenarios was the channel hydraulic roughness. I changed the contributions from vegetation and obstructions in the Acreman et al. (2003) method based on the scenario. For the pre-restoration scenario, I used observations for the sites from before the installation of in-stream structures. The reaches that have received restoration treatment are r1, r2, r4, and r6. For the snagged scenarios I set the vegetation and obstruction contributions to “minor” (0.005) and “medium” (0.01), respectively. For the rough scenarios I set the vegetation and obstruction to “severe” (0.05) and “very large” (0.1). The resulting channel roughness for each of these scenarios is detailed in table A1. For the scenarios where I altered only “headwaters” or “outlet”, I changed roughness values for r1-8 and r13 or r9-12, respectively.

4.3.8 Key outputs

To determine the impact of the different channel management scenarios, I compared hydrograph outputs at the four gage locations between the existing conditions scenario and each altered management scenario (inspired by Dixon et al., 2016). For each realization of each rainfall scenario, I assessed the changes in watershed-scale flood attenuation using the changes in peak discharge ($\Delta Q_{p,out}$), total flood volume (ΔV), and time to peak (Δt_p). These metrics were chosen to represent the key issues for flash floods. Peak discharges are of regulatory importance for the sizing of infrastructure; total flood volume has implications for the efficacy of flood infrastructure such as reservoirs; and the time to peak determines who can climb to safety out of the floodway (Federal Highway Administration, 2012; Saharia et al., 2017).

4.4 Results

4.4.1 Calibration

After running 7,000 parameter sets, I produced 23 models with an average $KGE > 0.70$ for the calibration event. The highest performing parameter set had an average $KGE = 0.73$ across the 4 gages. The model performance metrics are summarized in Figure 4.3 with additional metrics in Table 4.3. The highest KGE was at the uppermost gage in the watershed (LEU), with a $KGE=0.87$ (Figure 4.3). Performance at the next two gages downstream degraded slightly, with $KGE=0.74$ at LED and $KGE=0.80$ EBS gages. Performance was worst at the outlet gage (EO) with $KGE=0.50$. The modeled falling limb of the hydrograph was shorter for the two upstream gages (LEU and LED) than the observed falling limb, but the falling limb on the two downstream gages were followed closely by the model results. The prediction of flood timing by the model indicates close agreement with calibration flood, more so at the upstream gages than the downstream gages. The bias in predicting peak discharge timing across all gages was low,

with the model predicting the peak 0.26 hr early across all behavioral models at all gages. The error in peak discharge prediction was highest at the outlet gage (EO), with an average 29% overestimation of peak discharge. The overall bias for peak discharge was low, with no bias for overestimation or underestimation when averaged across all gages and behavioral models.

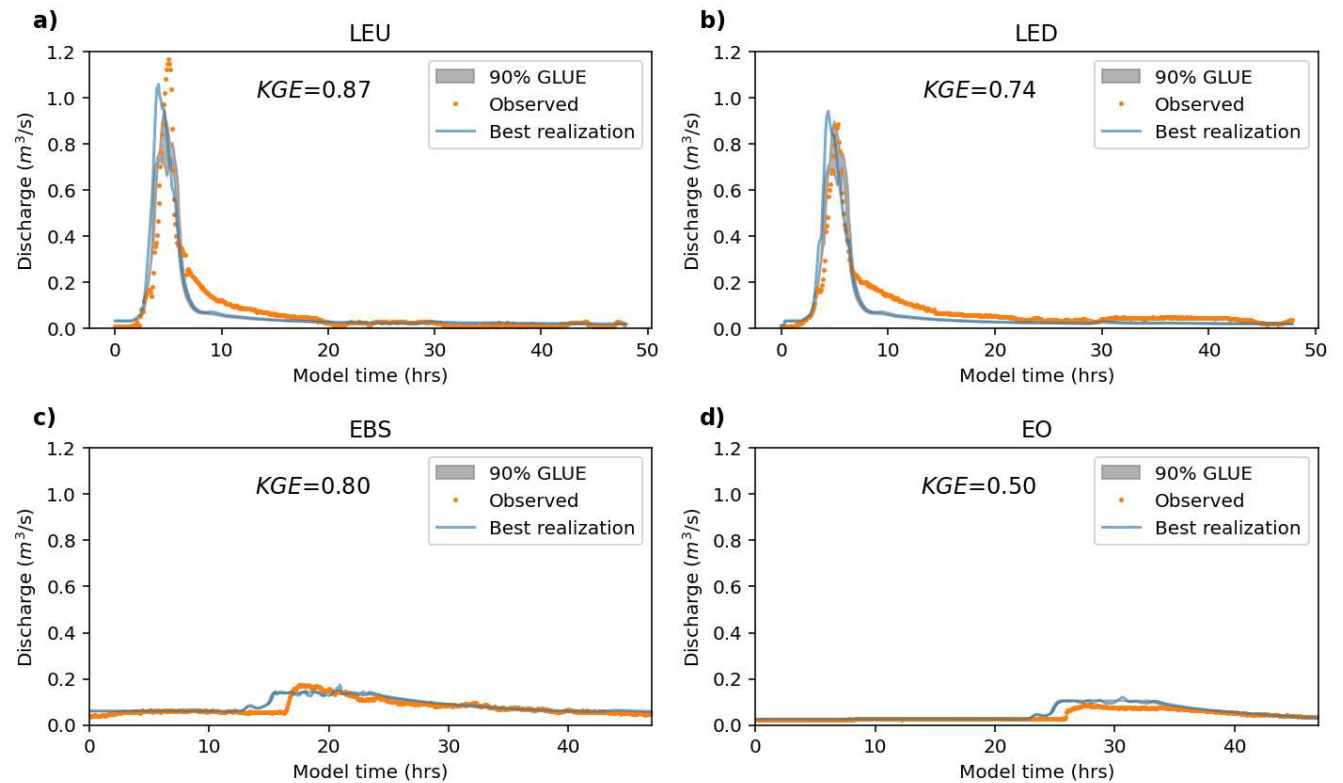


Figure 4.3 Observed hydrographs at each gage for the calibration event with the highest Kling Gupta Efficiency (KGE) realization plotted along with the 90% GLUE prediction interval. Modeled results adequately reproduced the observed flood, with the worst performance at the outlet.

Table 4.3 Calibration performance metrics averaged across the behavioral models.

	KGE	NSE	Delta Qp (%)	Delta V (m^3)	Delta tp (hrs)	RMSE (m^3/s)
LEU:	0.88	0.83	-0.19	-0.07	-0.35	0.07
LED:	0.74	0.80	-0.00	-0.18	-0.36	0.06
EBS:	0.82	0.65	-0.08	0.08	1.63	0.02

EOUT:	0.44	0.26	0.29	0.20	0.60	0.02
Mean:	0.72	0.623	0.00	0.01	0.26	0.04

4.4.2 Validation

The validation event showed lower *KGE* values than the calibration event, with the best performing set producing an average *KGE* of 0.61 across the two recording gages, and a mean *KGE* 0.57 across all behavioral models (Figure 4.4). Of the 23 calibrated models, only 6 met the threshold for satisfactory *KGE* in the validation event. The model prediction had small errors in baseflow discharge, with an average RMSE of 0.02 m³/s at both LEU and LED during baseflow across all behavioral models. Prediction of the peak discharge suffered, with an average 31% underprediction of peak discharge prediction. The modeled validation event had a shorter recession curve than the observed flood, a pattern which has continued from the models of the calibration event. The timing of this peak discharge was similar to the calibration event, with a 0.31 hr discrepancy on average. The behavioral models predicted 19% less discharge volume than the observed discharge on average, again considerably more than the calibration event.

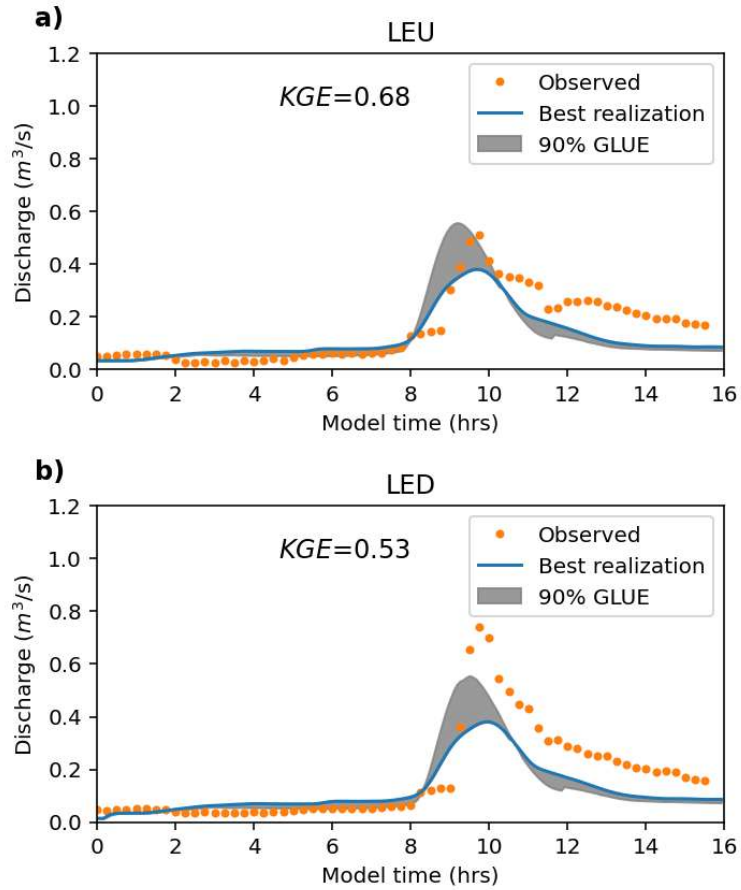


Figure 4.4 The model performed adequately for the validation event, with the best model realization yielding an average $KGE=0.61$. The recession curve for the observed data was longer than the modeled recession, contributing to the lower KGE for this event.

Table 4.4 Normalized and absolute performance metrics for the validation flow across all behavioral models.

	KGE	NSE	Delta Qp (%)	Delta V (m^3)	Delta tp (hrs)	RMSE (m^3/s)
LEU:	0.60	0.33	0.00	-0.14	-0.46	0.10
LED:	0.54	0.51	-0.32	-0.23	-0.17	0.12
Mean:	0.57	0.42	-0.16	0.19	-0.31	0.11

4.4.3 Snagging

The model simulations indicated that snagging increased the peak discharge and accelerated the flood wave, an example of which is shown as a weighted GLUE interval of all simulations of the uniformly distributed 10-year 15-minute precipitation intensity event (Figure 4.5). For this event, there was some overlap between predictions with and without snagging at the uppermost gages (Figure 4.5 a), with the snagged simulations generally producing a higher peak discharge. The next downstream gage (Figure 4.5 b) had no overlap in the 90% GLUE interval between the existing conditions and snagged simulations, with an average increase in peak discharge of 25% due to snagging. The impact of snagging was greater for reaches farther downstream, with the two downstream gages showing large increases in flood magnitude and much earlier times of peak discharge (Figure 4.5 c and d). This event was a drastic example of snagging accelerating and magnifying flooding, but I observed this pattern to varying degrees across the simulated precipitation scenarios. Snagging changed the response for this short, moderate rain event from a small increase in flow (still well below the channel capacity) at the outlet, into a moderate size flood event (just above the channel capacity for many of the reaches).

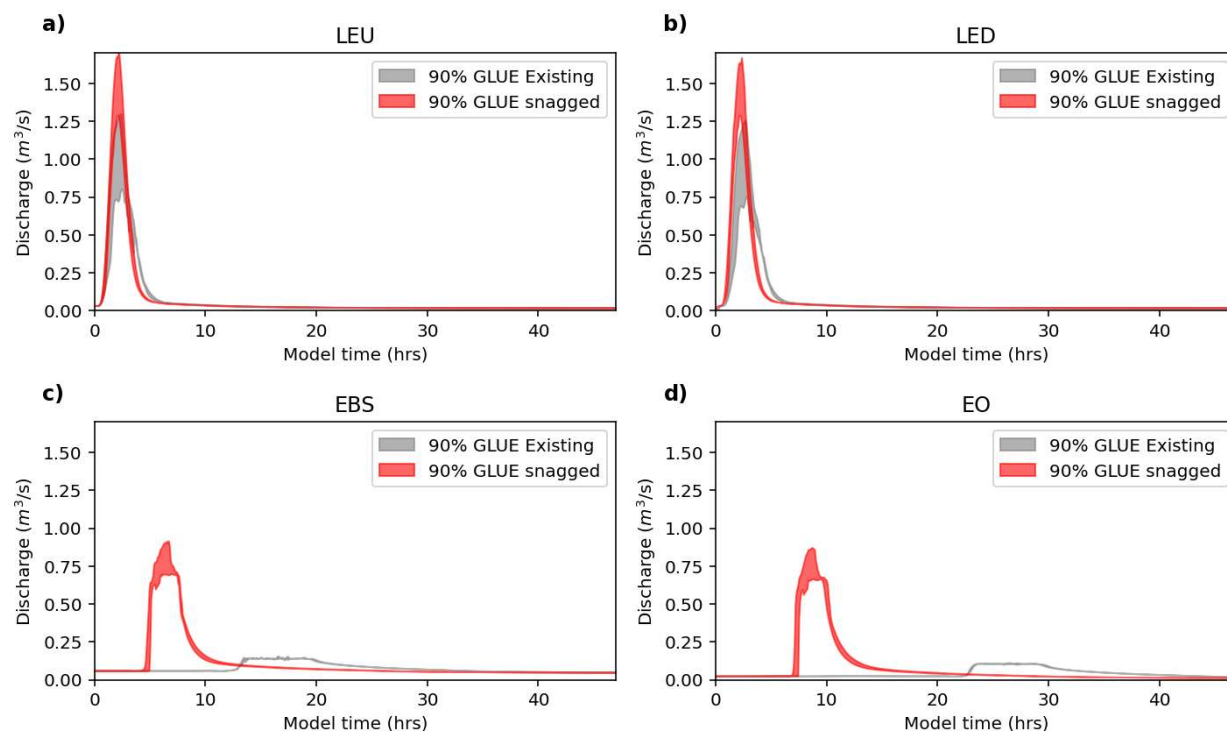


Figure 4.5 The output for the uniformly distributed 10-year recurrence interval 15-minute precipitation event realized with all the behavioral models for the existing conditions routing scenario and the snagged throughout routing scenario at each gage. This event was the most impacted by snagging of all the simulated events, with a minor increase in the peak discharge at the headwater reaches, and a major magnification and acceleration of flooding at the outlet reaches.

Simulated snagging scenarios reduced the time for water to travel the watershed and reach the outlet, often resulting in increased peak discharges (Figure 4.6). This snagging increased peak discharges markedly at both the LEU and LED locations, with a median increase in flow of 14.9% and 17.5% at each location, respectively (Figure 4.6 a and b). The mean increase in peak discharge was similar to the median increase, with only a few extreme examples. The maximum modeled impact for the peak discharge at the upper two gages was an increase of 63.5% and 72.3% at LEU and LED, respectively. There were some scenarios where no runoff was generated in the upper watershed; for example, in the scenarios where the spatial distribution of precipitation was focused on the lower section of the watershed. In these scenarios

with no runoff in the upper watershed, there was, of course, no difference created by snagging. Predictably, snagging the outlet streams had no impact on discharges for the headwater streams (Figure 4.6 a and b). The examples of extreme magnification of peak flows were characterized by moderate flooding events (10-year return period precipitation events), which were absorbed by the floodplain in the existing conditions, but accelerated throughout the watershed by snagging conditions, hampering the floodplain's ability to absorb flow and synchronizing peaks into larger events near the outlet (Figure 4.5).

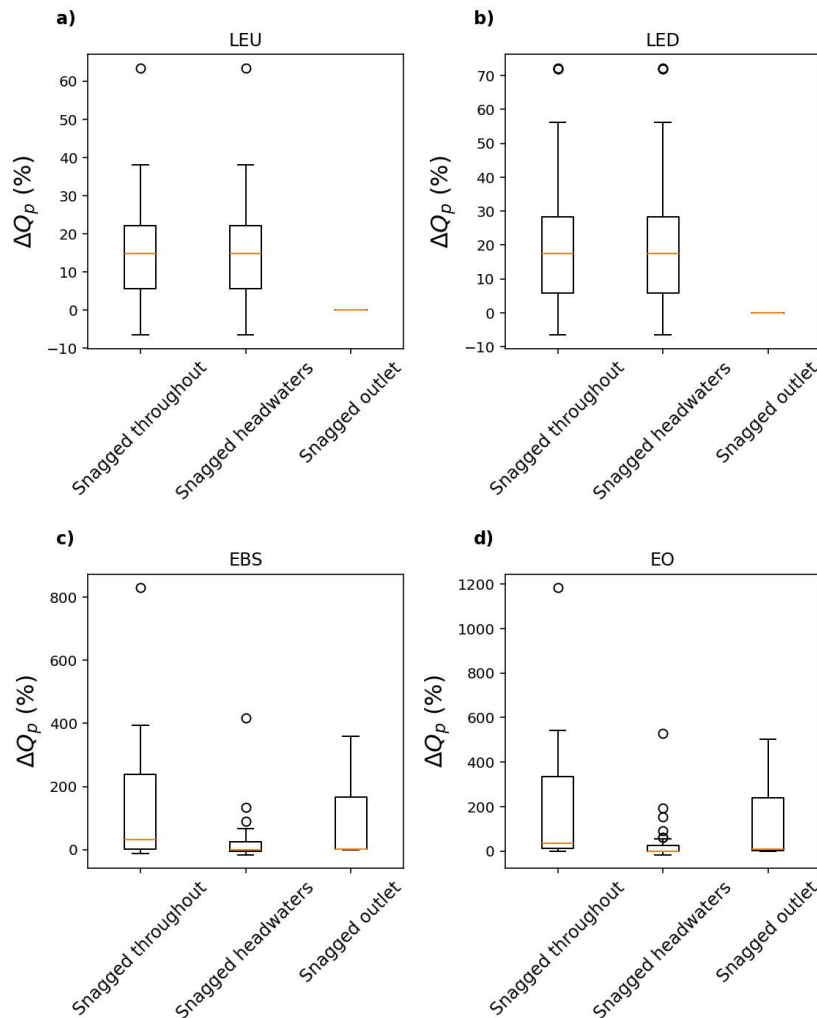


Figure 4.6 Snagging scenarios simulations indicated increases in simulated peak discharges (positive ΔQ_p) at all measured locations, especially for the outlet reaches.

Snagging only the headwaters did not impact peak flows at the outlet streams in most scenarios, with the median change on peak discharge at EBS and EO changing $<0.1\%$. Despite the small median impact of snagging the headwaters on the outlet, certain flood scenarios saw extreme increases in peak discharge at EBS and EO. These events with extreme differences lead to a greater mean difference than the median change, with a mean increase in peak discharge of 11.4% and 13.7% for EBS and EO, respectively. Snagging the downstream reaches caused more substantial increases in the downstream peak flows than snagging the upstream reaches did, with a median increase of 1.8% and 8.5% increases at EBS and EO, respectively. There was a compounding effect for the outlet gage discharges by snagging both the outlet and headwater reaches, with a median increase of 32.7% and 34.9% at EBS and EO, respectively (Figure 4.6 c and d).

Snagging resulted in a near-universal acceleration of the flood wave, with the peak discharge occurring 1.44 hours earlier for the equivalent precipitation event in the base scenario (Figure 4.7). The impact was larger on the outlet gages, with median $\Delta t_p = -8.75$ and -2.54 at EBS and EO, respectively. There were some cases where the time to peak was earlier in the base scenario than in a snagged scenario ($\Delta t_p > 0$). This occurred more often for the upper gages than the lower gages and was due to synchronization of tributaries, which created a second, larger peak in the hydrograph in the snagged scenario. An example of this acceleration is shown clearly in Figure 4.5c and d, where the peak discharge occurred >10 hours earlier in the snagged scenario than in the base scenario. In this simulation, snagging led to synchronization of tributaries in the lower subbasins, leading to a much earlier peak discharge.

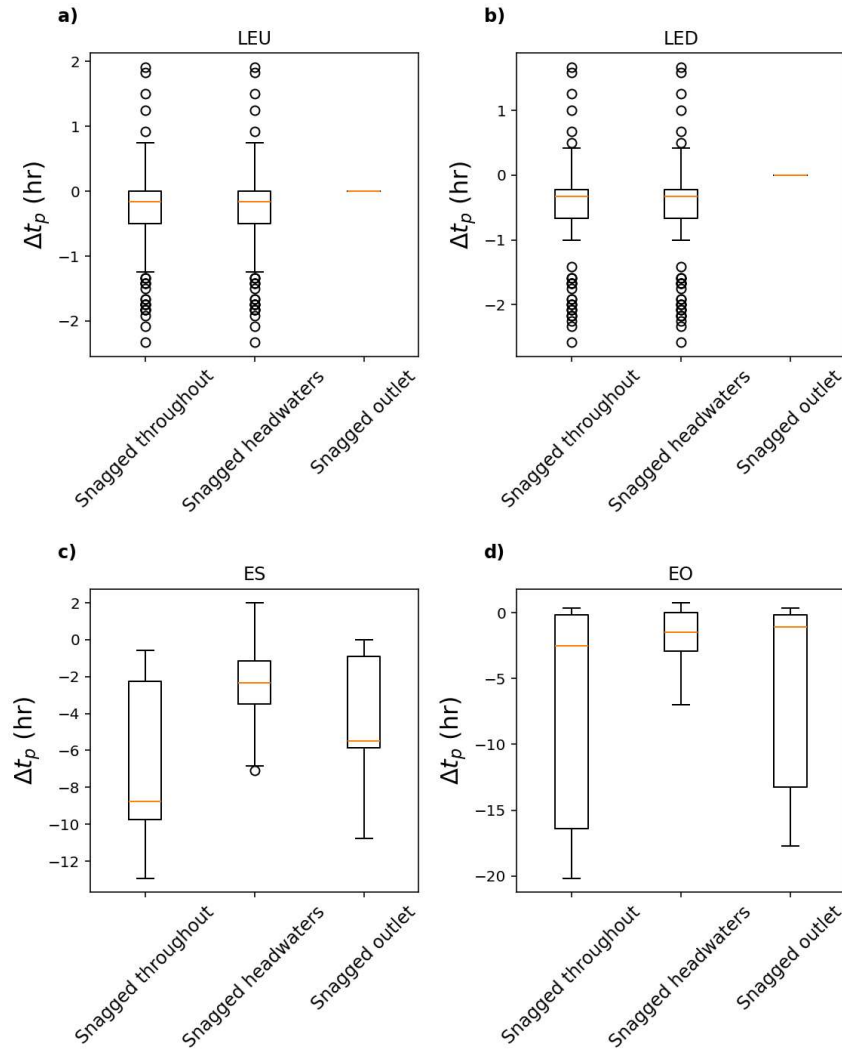


Figure 4.7 The difference between the time of peak discharge (Δt_p) in the snagged scenarios and the base scenarios displayed for each gage and each model realization. The time of peak discharge in nearly all snagged scenarios was earlier than the base scenario. Some scenarios had small delays in time of peak discharge due to synchronization of tributaries later in the simulation than the base conditions scenarios.

Most snagged scenarios yielded a higher flood volume than the base conditions for the lower reaches but had little impact on the total flood volume in the headwater reaches (Figure 2.8). The median changes in flood volume were nearly zero at both upper watershed stream gages with median change in flood volume $\Delta V = -0.6\%$ and 0.72% at LEU and LED, respectively. At the lower gages there were considerable increases in flood discharge, with median increases

in flood volume of 5.7% and 7.0% at EBS and EO, respectively. Similar to the changes in peak discharges driven by snagging, certain rainfall scenarios produced drastic increases due to snagging while many scenarios had no increase or only a minor increase in volume. One of these cases of extreme increase for flood volume is depicted in Figure 4.5, where there was a drastic increase (71%) in flood volume, with a much earlier and higher peak.

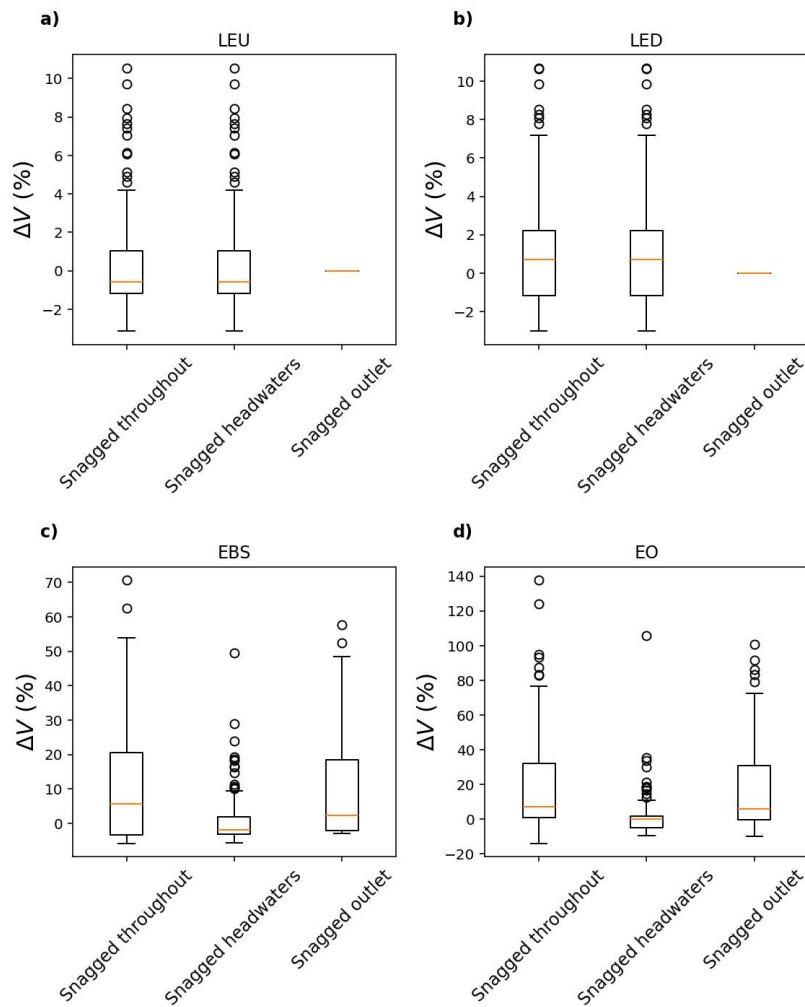


Figure 4.8 The difference between the total hydrograph volume (ΔV) in the snagged scenarios and the base scenarios displayed for each gage and each model realization.

4.4.4 Roughened channels

Adding roughness to the channel across the watershed had a relatively small impact when compared with removing the existing roughness elements; with the 90% GLUE interval, most simulated events overlapped nearly entirely with the simulations of existing conditions (Figure 9). For many of the events, there was no measurable difference between the existing conditions and adding more roughness to the system (Figure 9 a and b). There was a short delay in the peak discharge for the downstream gages, but no change in peak discharge magnitude (Figure 9 c and d). The median change in peak discharge was <1% across all gages for simulations roughening the headwaters, outlet reaches, or throughout the catchment (Figure 10). There were some fringe cases where roughening the headwaters impacted peak flows by desynchronizing or synchronizing different tributaries, with a maximum increase of 98% (Figure 10 c and d, see outlier points) and a maximum decrease of 30%. The impacted events tended to have small discharges near the channel bankfull capacity, meaning the changes in discharge would likely be inconsequential to the level of danger or destructive power of the flood.

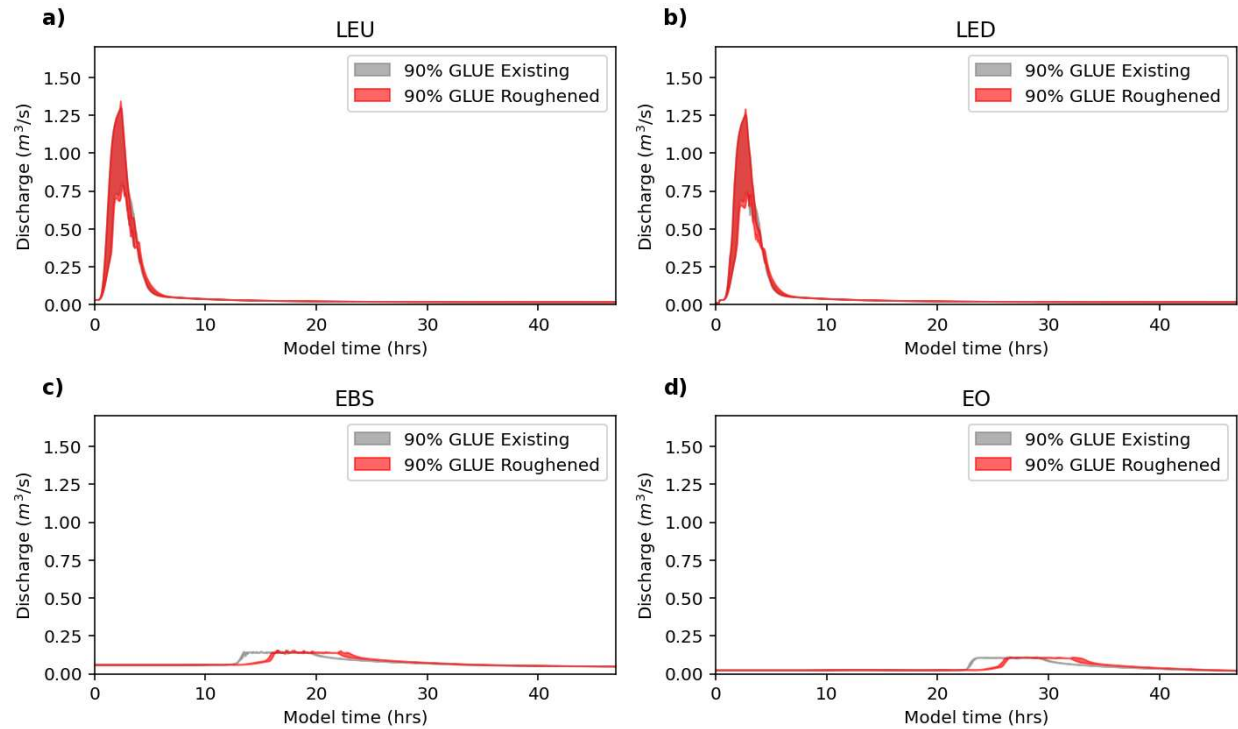


Figure 4.9 The output for the uniformly distributed 10-year recurrence interval 15-minute precipitation event realized with all the behavioral models for the existing conditions routing scenario and the roughness added throughout routing scenario at each gage. This event is representative of the majority of events in the added roughness scenarios, with no change in peak discharge and a slight delay in peak timing at the outlet reaches.

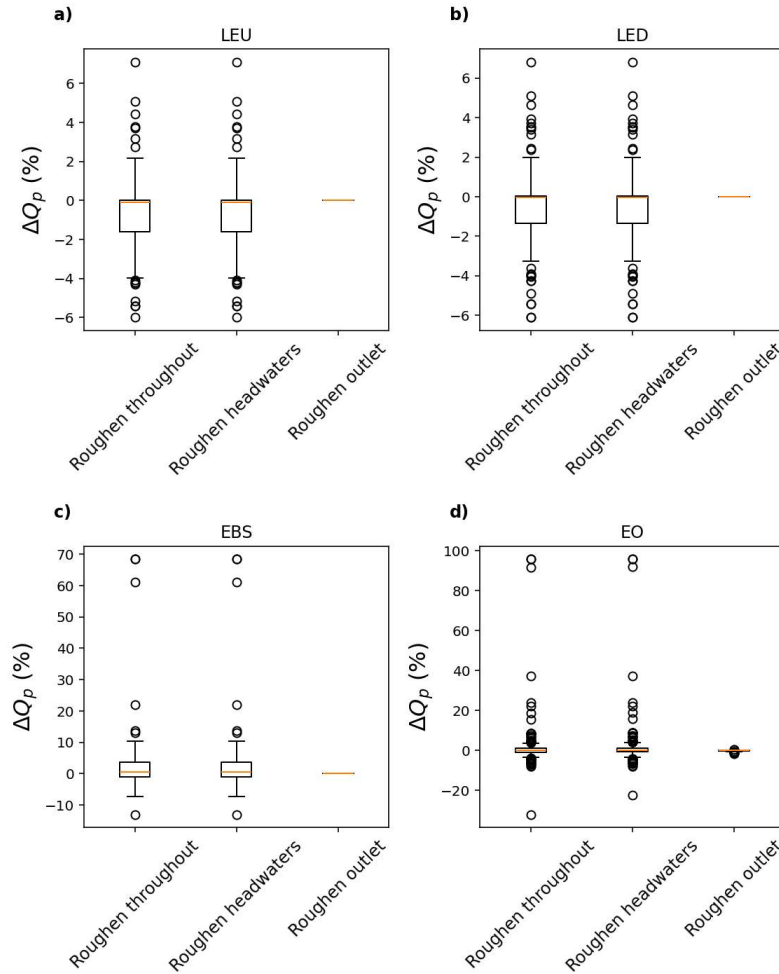


Figure 4.10 The simulated increases in roughness yielded negligible changes in the peak discharge (ΔQ_p) across the watershed.

The simulated increase in roughness brought a minor shift in peak timing at the EBS gage, with a median delay of 1 hr in the roughened throughout and roughened headwaters scenario, but a negligible change for the other gages (figure 11). Certain outlier events did bring notable delays or accelerations in peak timing through synchronizing or desynchronizing tributaries, but the average of the tested precipitation scenarios yielded minor changes in peak flow timing for the majority of the watershed; the 75th percentile of peak flow timing changed ~2 hr. Comparing this impact to the 6+ hour acceleration brought by snagging, these further additions of wood were relatively insignificant.

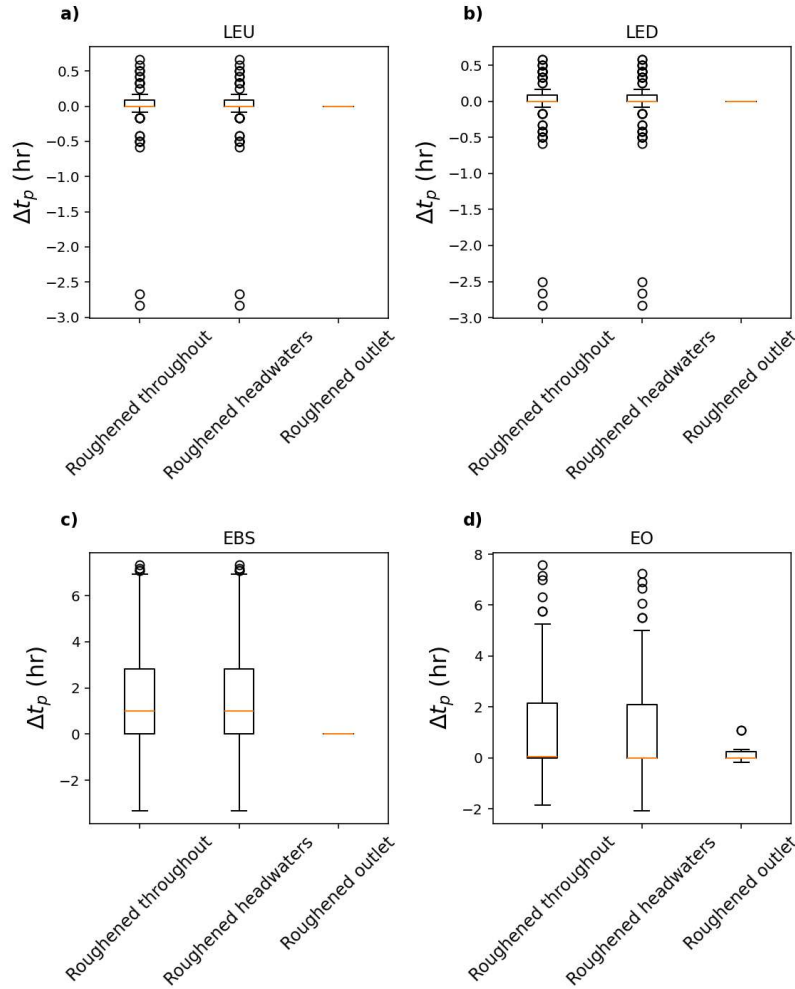


Figure 4.11 The difference between the time to peak (Δt_p) in the added roughness scenarios and the base scenarios displayed for each gage and each model realization. Additional roughness caused a slight delay in peak discharge timing at the downstream gages (c and d) and had a negligible impact on the peak timing for the upstream gages (a and b).

The changes in total flood volume brought by simulating increases in roughness were similarly small, with mean changes of 1% or less across watershed for the full set of simulations (Figure 12). Most of the simulations showed very little volumetric impact of increasing roughness with the inner quartile range (IQR) for the simulations between $\sim 2\%$ and -2% . Outlier simulations did have notable impacts on the volume of small floods, with maximum reductions of 12% in headwater reaches and 10-20% in the downstream reaches (Figure 12 c and d). These events with larger reductions in total flood volume tended to be small rain events (return period

≤ 10 years) where floodplain access was increased by the elevated roughness in the headwater reaches, leading to volume transfer from the flood wave to the floodplain depression storage.

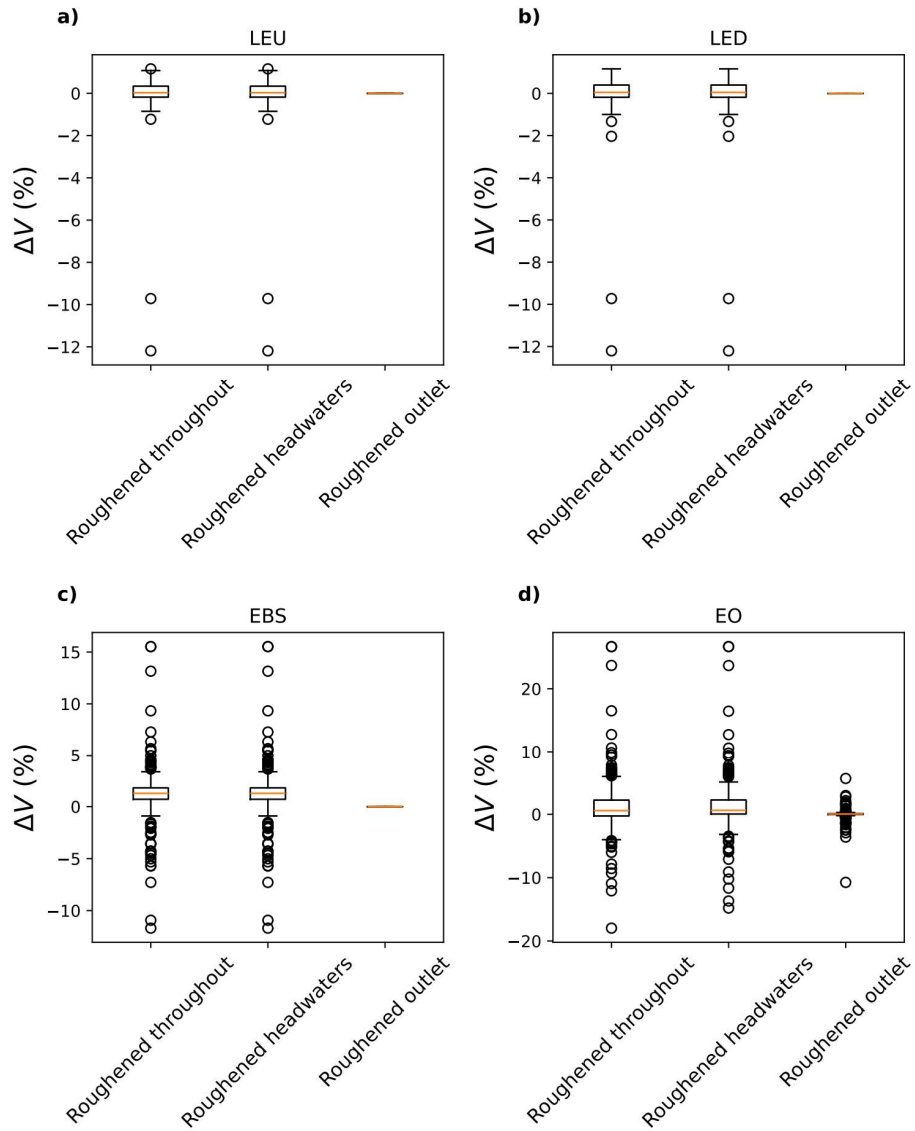


Figure 4.12 The difference between the total hydrograph volume (ΔV) in the added roughness scenarios and the base scenarios displayed for each gauge and each model realization.

4.4.5 Restoration efforts

The simulations indicated that the restoration efforts of the past 4 years have reduced the peak discharges throughout the watershed, with the IQR of ΔQ_p all positive for each gage, with the most peak flow reduction at the upstream gage (LEU) and lower reductions at the other gages (Figure 13a). The largest reductions in peak flow were for the larger floods in the headwater reaches that were created by precipitation events of >10-year return period (Figure 14). These events had increased floodplain access during peak flow, leading to storage of flood water within floodplain depressions and reducing the peak discharge and total flood volume exiting the reach (Figure 13 a and b). Many of the large floods were reduced in magnitude by the restoration, including the flood generated by the 200-year recurrence interval 15-minute rainfall, where the model indicated that the peak discharge was decreased by 13% at both headwater gages compared with the pre-restoration conditions. The response was generally greatest in the headwaters, which is where all the restoration efforts have been implemented. The restoration also delayed peak timing in most scenarios, with a median increase of 0.41 hours at EBS and a maximum increase of 6 hours at EBS. Again, there were some cases where tributary inputs were synchronized by the added roughness of the restoration treatments, but these were rare, falling outside the IQR.

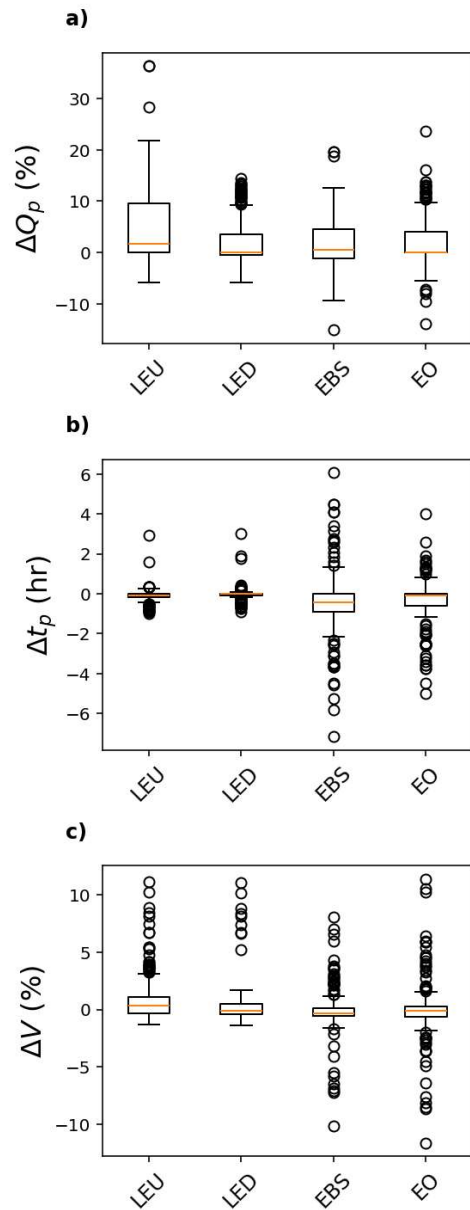


Figure 4.13 Change in peak flow magnitude, timing and total flood volume between the current conditions and conditions of the watershed before the four existing reach restoration projects were implemented.

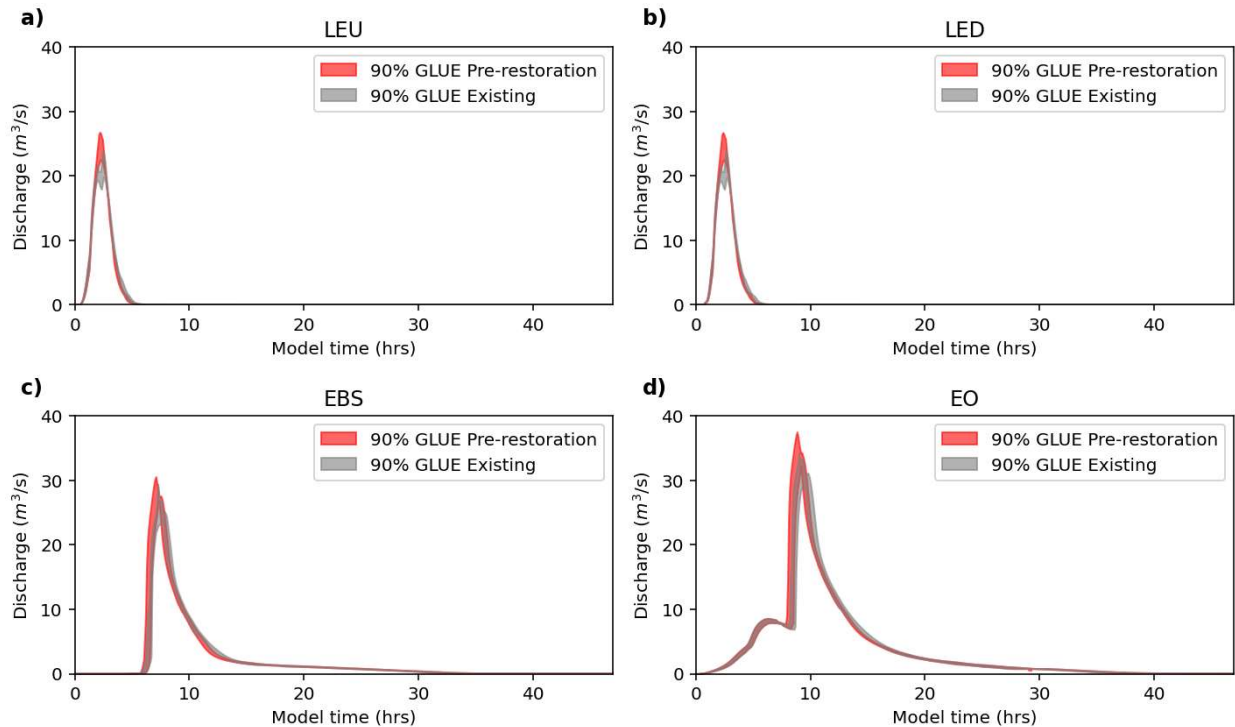


Figure 4.14 The output for the uniformly distributed 100-year recurrence interval 15-minute precipitation event realized with all the behavioral models for the existing conditions routing scenario and the pre-restoration routing scenario at each gage. There was a small decrease in peak discharge for the existing conditions compared to the pre-restoration conditions for this event throughout (a-d). The downstream gages (c and d) also experienced a delayed time to peak, along with the small change in magnitude.

4.5 Discussion

Over the course of the study, I was able to observe two floods in this watershed, the results of which were valuable in and of themselves (Figure 4.3 and 4.4). The larger flood (observed in 2025) was attenuated extremely effectively as it propagated downstream. The 2025 flood was roughly a five-year recurrence interval flood at the farthest upstream gage (Capesius & Stephens, 2009) and inundated large portions of the floodplain in the lower gradient reaches of the watershed. The 2025 larger flood had the power to move some of the wood within r4, although no wood was transported more than a few meters. The 2025 flood was reduced in size between LEU and LED and was drastically reduced between LED and EBS (Figure 4.3). This

observed reduction indicates the value of healthy floodplains as there are several reaches with large, well connected, floodplains between LED and EBS. This field observation alone is not enough to determine the role of these floodplains in attenuation, but it does indicate that these reaches are valuable for attenuation in their current state.

The lack of attenuation in r4 during the 2024 flood indicates that the attenuation is not static and is dependent on the conditions of the river corridor before the flood. This flood occurred before the addition of wood to the system in summer 2025, likely reducing floodplain inundation and therefore attenuation (Christensen & Morrison, 2026b) but, given the difference in flood size between 2024 and 2025 and the other uncontrolled variables between the floods, I cannot draw conclusions as to the impacts of the restoration based on these field data alone. The 2024 flood was smaller in magnitude than the 2025 flood and so gained less floodplain access regardless of restoration status, likely contributing to the lack of attenuation. The 2024 flood was in the same season as the 2024 flood, but there was more low-intensity rainfall in the days leading up to the flood. This may have filled both hillslope soil pores and floodplain depressions before the flood, leaving less space for storage of water from the channel into the floodplain and contributing additional runoff from the nearby hillslopes.

The performance of the model on the calibration data was within the range of other recent works recreating flood events in similar settings. Ebel et al. (2023) compiled 206 hydrologic models for burned watersheds published in peer-reviewed journals and found that model performance was commonly reported using Nash Sutcliffe Efficiency (*NSE*). They found that *NSE* was generally lower for models with smaller time steps, stating that the highest *NSE* values were for models with a daily timestep. Overall, this review found that the inner quartile range of calibrated *NSE* values of -0.13 to 0.87, with a median *NSE*=0.62. My calibration used higher

frequency data than any of the papers in the review and I achieved an average $NSE=0.62$ for the calibration dataset, the same as the median of the 206 hydrologic models within the review (Ebel et al., 2023). Studies have achieved higher NSE than I did for the calibration event, for example in Dixon et al. (2016), which a single gauge was used to calibrate the watershed model an extremely high NSE of 0.98. Using multiple gages to calibrate and validate the model as I have done tends to decrease average performance as there are more targets for the model to hit. The window used in the model also included more of the pre and post flood data for each gage than the Dixon et al. (2016) study so that the total time periods of flooding at all gages were captured. A reduction in the time window over which the dimensionless performance metrics were calculated may increase reported performance. With this context of model performance, I am satisfied with the calibration.

The validation event exhibited reduced performance metrics compared to the model calibration (Figures 3 and 4). Reduced performance metrics in validation are likely to be due to using the same initial conditions when initial conditions certainly differed to some degree for the two observed floods. Both floods occurred in relatively dry seasons, but the chances of identical soil moisture conditions are low and the model was sensitive to changes in initial soil moisture. This issue is less pressing for the scenario simulations as I conduct a comparative analysis (Dixon et al., 2016). In 2024 there was less recovery time post-fire, likely causing lower infiltration rates, which would have been overpredicted by calibrating to 2025 data (McGuire et al., 2018; Moody et al., 2013). Using uniform initial conditions is an effective way to evaluate how routing changes impact peak discharges, although the prediction of the discharge given a single rain event may not reflect real-world outflows, depending on the initial conditions of the watershed. Comparative analysis of this nature has been conducted in the past (Acreman et al.,

2003; Birkinshaw & Kristov, 2022b; Dixon et al., 2016; Ghavasieh et al., 2006). Understanding these limitations, I accepted the model validation results and can use the model scenario simulations to glean insights on watershed management practices.

Snagging the reaches within the watershed had the largest impact of any simulated management strategy, reducing the time to peak and increasing the observed peak discharges (Figures 5-8). Previous works have repeatedly likened reductions in river corridor roughness to increases in peak discharge for decades (Christensen & Morrison, 2026b; Dixon et al., 2016; J. S. Sholtes & Doyle, 2011; Woltemade & Potter, 1994). Woltemade & Potter (1994) found that peak flows may be up to 20% higher with lower roughness in a humid, low slope region. (J. S. Sholtes & Doyle, 2011) found similar differences between modeled attenuation for a low roughness and high roughness simulation at similarly gradual slopes. This work builds on this knowledge base indicating the same trend, but shows that in this setting, the roughness of the river corridor exerts an even stronger control on peak flows compared to the longer duration storms of those previous studies. The model showed that the mean impact of snagging on outlet gages was a 34.9% increase of peak flow, with extreme cases indicating an up to 8-fold increase in the peak discharge. I also built on the existing body of knowledge by demonstrating that snagging accelerated the flood wave propagation drastically for small and large magnitude floods, reducing the amount of time potential victims have for evacuation (Figure 4.7). This reduction in time could prove fatal in a large magnitude flood. Reducing snagging throughout watersheds such as this one has the advantage of costing nothing. Despite previous studies, snagging remains a common management strategy for reducing flooding without consideration for the downstream or network-scale impacts (USDA, 2022).

The simulations indicated that the current restoration actions reduced peak flow magnitude and delayed the peak flow time, but adding more roughness to the system did not make a large difference in the simulated flood propagation of this system (Figures 9-13). Adding more roughness did delay the time to peak but did not meaningfully influence the peak discharge at any of the gages (Figures 10 and 11). This indicates that there are diminishing returns to increasing channel roughness. Despite the efforts to snag the watershed and remove beaver, the system still had a robust supply of wood, especially after the resupply of wood to reaches r1, r2, r4, and r6. Along with these restoration efforts, several reaches including r5 and r10 had a high density of large wood within their channels. This may be because large portions of these reaches are difficult to access and do not have nearby infrastructure, disincentivizing snagging from a monetary and logistical standpoint. Many of the reaches which have had historical snagging and heavy grazing had their wood supply restored in the past 4 years, meaning that the simulated further additions of wood to achieve maximum obstruction were small. I identified one reach, r9, where grazing and wood removal have drastically reduced roughness. Other systems where the wood supply is still low in most reaches would likely see more impact through restoration of in-channel wood than the simulated additions to this currently wood-rich system.

This is the first application of the MCAF routing method at the watershed scale, and the results indicate that the modeling method is effective for simulating flash floods in mountain streams, with good performance metrics replicating two observed floods. There are two use-cases in which the model performs the same as a standard Muskingum-Cunge routing system: an a value of zero indicates that floodplain volume flux to depression storage is zero, and a b value of zero indicates that the floodplain volume flux to depression storage is constant. Neither of these use-cases produced any behavioral models, indicating that using dynamic floodplain

depression storage was necessary to adequately represent these floods. In the simulations where there was no floodplain depression storage, the attenuation was far too low throughout the watershed, producing a drastic overestimation of discharge at the lower gages. Given this, I recommend the use of MCAF in future modeling efforts in this setting.

Although I was able to elucidate the impacts of several management changes to this system through this modeling effort, several questions remain. This study focused on changes which can be made to the system through changes in wood management only, instead of considering changes that are commonly applied to streams in this setting. Several studies exist looking at the impacts of common regrading strategies, but there is little information available on how these channel geometry changes would impact flash flooding at the network scale (Goodman et al., 2026). Existing studies have pointed to roughness as the major driver of increased attenuation where roughness changes and channel geometry are explored in tandem, but more information could certainly be gleaned from additional studies at the scale and setting I focus on here (Federman et al., 2023; J. S. Sholtes & Doyle, 2011). In this study I used the peak magnitude and timing as the key outputs for flooding danger at the points of interest. While this is a common method for looking at flood danger at this scale, this assumes that the damage caused by a flood is directly proportional to the discharge within the corridor (Dixon et al., 2016; Goodman et al., 2026). Factors outside of peak discharge, including local infrastructure design and population dynamics through the flood corridor, certainly impact the damage caused by a flood. Future studies may incorporate these factors within their analysis, but I found it infeasible given the scale of this work.

4.6 Conclusions

I was able to observe and adequately model flash floods in a burned, mountainous, semiarid, watershed and simulate changes to the wood management to inform future wood management in the system. The best realization of the model reproduced the calibration and validation events with a *KGE* of 0.73 and 0.63, respectively. The model indicated that the current restoration actions that have been applied to the system reduced flood severity and decelerated the flood wave throughout the watershed (Figure 13). The simulations of further additions of wood to the system had smaller impacts than the currently applied restoration, with a slight delay in peak timing for the outlet reaches and negligible changes in peak magnitude (Figures 10 and 11). The simulations with wood removed from the system (“snagged”) showed a drastic increase in peak discharge across the watershed, with a maximum 8-fold increase in peak discharge occurring near the watershed outlet (Figure 4.6). The simulated snagging also accelerated the flood wave, reducing the time to peak by up to 20 hours, with a mean reduction in time to peak of 2.4 hours across the watershed. This analysis indicates that snagging could lead to more dangerous flooding conditions within the watershed and indicates that snagging is not a favorable flood reduction option in the headwaters of streams prone to flash floods. These findings indicate that maintaining the wood supply for forested headwaters is a key practice for managing flash floods but also shows there are diminishing returns to wood reintroduction when taken to its extreme.

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4.8 Appendix

Table a1: rating curves for each gage.

EOUT			LEU			LED			EBS		
Flow (cms)	Stage (m)	Sensor depth (m)	Flow (cms)	Stage (m)	Sensor depth (m)	Flow (cms)	Stage (m)	Sensor depth (m)	Flow (cms)	Stage (m)	Sensor depth (m)
0.000	0.042	0.000	0.000	0.046	0.000	0.000	0.028	0.000	0.000	0.031	0.000
0.029	0.176	0.134	0.006	0.147	0.086	0.011	0.191	0.106	0.007	0.129	0.098
0.059	0.204	0.162	0.010	0.120	0.059	0.021	0.198	0.113	0.015	0.149	0.119
0.088	0.233	0.191	0.023	0.125	0.064	0.022	0.201	0.116	0.022	0.163	0.132
0.118	0.257	0.215	0.026	0.140	0.080	0.031	0.213	0.128	0.029	0.174	0.144
0.147	0.278	0.236	0.030	0.133	0.072	0.049	0.231	0.147	0.059	0.209	0.178
0.176	0.296	0.255	0.030	0.127	0.066	0.063	0.256	0.171	0.088	0.234	0.203
0.206	0.312	0.271	0.039	0.156	0.095	0.072	0.275	0.190	0.118	0.256	0.225
0.235	0.326	0.285	0.051	0.160	0.100	0.087	0.278	0.193	0.147	0.274	0.244
0.265	0.339	0.297	0.067	0.173	0.112	0.211	0.353	0.268	0.221	0.314	0.283
0.294	0.351	0.309	0.188	0.231	0.171	0.277	0.380	0.295	0.294	0.346	0.315
0.323	0.361	0.319	0.238	0.273	0.212	0.303	0.384	0.299	0.323	0.356	0.326
0.353	0.370	0.329	0.273	0.267	0.206	0.335	0.390	0.305	0.353	0.368	0.337
0.382	0.379	0.338	0.326	0.275	0.214	0.435	0.404	0.319	0.382	0.377	0.347
0.412	0.388	0.346	0.363	0.301	0.240	0.441	0.408	0.323	0.412	0.387	0.356
0.441	0.395	0.353	0.382	0.330	0.269	0.515	0.428	0.344	0.441	0.395	0.364
0.470	0.403	0.361	0.412	0.340	0.279	0.588	0.447	0.362	0.468	0.402	0.372
0.500	0.410	0.368	0.441	0.349	0.288	0.662	0.465	0.380	0.470	0.403	0.372
0.529	0.417	0.375	0.515	0.370	0.309	0.735	0.481	0.396	0.500	0.411	0.380
0.559	0.423	0.381	0.588	0.390	0.329	0.809	0.497	0.412	0.529	0.419	0.388
0.588	0.429	0.387	0.662	0.408	0.347	0.882	0.512	0.427	0.559	0.427	0.396
0.617	0.435	0.393	0.735	0.425	0.364	0.956	0.526	0.441	0.588	0.434	0.404
0.647	0.440	0.399	0.809	0.441	0.380	1.029	0.539	0.454	0.617	0.442	0.411
0.676	0.446	0.404	0.882	0.456	0.395	1.103	0.552	0.467	0.647	0.449	0.418
0.706	0.451	0.410	0.956	0.469	0.408	1.176	0.564	0.479	0.676	0.456	0.425
0.735	0.456	0.415	1.029	0.482	0.421	1.250	0.576	0.491	0.706	0.464	0.433
0.764	0.461	0.420	1.103	0.493	0.432	1.323	0.588	0.503	0.735	0.471	0.440
0.794	0.466	0.425	1.176	0.504	0.443	1.397	0.599	0.514	0.764	0.477	0.447

0.823	0.471	0.430	1.250	0.514	0.453	1.470	0.610	0.525	0.794	0.484	0.453
0.853	0.476	0.434	1.323	0.524	0.463	1.544	0.621	0.536	0.823	0.491	0.460
0.882	0.481	0.439	1.397	0.533	0.472	1.617	0.631	0.546	0.853	0.497	0.466
			1.470	0.542	0.481	1.764	0.650	0.565	0.882	0.503	0.472
			1.544	0.550	0.489				0.956	0.519	0.488
			1.617	0.558	0.497				1.029	0.534	0.503
			1.691	0.565	0.504				1.103	0.548	0.517
			1.764	0.572	0.511				1.176	0.562	0.531
			1.838	0.580	0.519				1.250	0.576	0.545
			1.911	0.587	0.526				1.323	0.589	0.558
			1.985	0.594	0.533				1.397	0.602	0.571
			2.058	0.600	0.539				1.470	0.615	0.584
			2.132	0.607	0.546				1.544	0.627	0.596
			2.205	0.610	0.549				1.617	0.640	0.609
			2.279	0.616	0.555				1.691	0.651	0.621
			2.352	0.622	0.561				1.764	0.663	0.632
									1.838	0.675	0.644
									1.911	0.686	0.655
									1.985	0.697	0.666
									2.058	0.707	0.677
									2.132	0.718	0.687
									2.205	0.728	0.698
									2.279	0.739	0.708

Chapter 5 : Conclusions

5.1 Summary of work

Through this work I explored the ability of mountain streams to attenuate flash floods at multiple scales and elucidated the underlying drivers of this attenuation. I began looking at the reach scale, where I used an intensive field campaign on 3 small reaches of stream along with high resolution physics-based models to explore flash flooding and its drivers over short lengths of streams (1 km or less). This analysis revealed unprecedented levels of attenuation, indicating that mountain streams have a high capacity to attenuate floods, given that the flood is rapid and of relatively low volume. I determined that the most major driving forces for a mountain stream's ability to attenuate these floods was the duration of the flood, the roughness of the stream, the size of the floodplain, the diversity of flow paths within the floodplain, and the volume of floodplain depressions. I used this knowledge to develop simplified routing models with novel features that could approximate the complex floodplain dynamics which influence flash flood attenuation at the reach scale. These novel features were able to improve several performance metrics over traditional routing methods including volume accounting and Kling Gupta Efficiency for large flash floods. I made this novel method of routing available to the public with an open-source code, allowing researchers and practitioners to apply the model for their own settings. I then applied this model as one aspect of a larger watershed hydrologic model to explore the watershed-scale implications of different management strategies. I monitored the watershed for two field seasons and captured data for two flash flood events to train and validate the watershed model. I applied this model to simulate 288 floods for 8 wood management scenarios to determine the impact of these management strategies. The model

indicated that removal of wood from the watershed had a strong accelerating and magnifying effect on flash floods across the watershed. Existing additions of wood to the watershed had the opposite effect, dampening the peaks and delaying their propagation throughout the system. Further additions of wood to the system did not create further dampening of peak flows but did continue to delay the peak discharges.

5.2 Key findings for each objective

1) Investigate reach-scale attenuation for flash floods in mountain streams.

a) Quantify the range of attenuation of flash floods attainable.

The flash floods were extremely well attenuated in this study; more so than previous studies of longer duration floods. Reaches attenuated 13.8%/km on average, with the maximum reduction in peak flow over the course of one site of 40%, which occurred on the largest floodplain for a rapid 100 yr recurrence interval flood.

b) Identify the relative importance of the underlying floodplain mechanics that drive attenuation in these systems (storage and dispersion of flood waves).

The major driving forces for a mountain stream's ability to attenuate these floods was the duration of the flood, the roughness of the stream, the size of the floodplain, the diversity of flow paths within the floodplain, and the volume of floodplain depressions.

2) Adequately simulate reach-scale attenuation with methods that can be readily upscaled to watershed models.

I developed a method that has a novel feature to account for depression storage. This method, named the "Muskingum Cunge Augmented Floodplain," is publicly available in the form of an open-source python code. The method was able to improve prediction of reach-scale

attenuation, with major improvements in volume accounting and smaller improvements on average Kling Gupta Efficiency.

3) Determine the watershed-scale impact of management changes.

a. Determine whether attenuation of flash floods can be significantly influenced at the watershed scale through roughness additions.

Further restoration of the wood supply did not produce further reductions in the peak discharge. The currently implemented wood restoration projects were effective in reducing peak flows and delaying the peak timing, with an average 5% reduction in peak flow in the headwaters and a 4% reduction in peak flow in the outlet reaches. The maximum impact of this restoration was a 35% reduction in peak flow in a headwater reach. The restoration actions also increased the time for the flood to propagate by up to 6 hours, with a mean increase of 0.4 hours near the outlet.

b. Determine reaches in a real watershed which can produce the largest impact on attenuation through floodplain reconnection and roughness addition.

The analysis indicated that the recent restorations have targeted key reaches, bringing additional flood attenuation up to 35% through their restoration actions. Many of the reaches in the watershed had a healthy wood supply, with only one reach (r9) not currently slated for restoration that had degraded wood supply. Reaches r3, r5 and r10 were identified as high attenuation reaches for preservation.

c. Determine the impact of “snagging” on the propagation of flash floods at the watershed scale.

Removal of wood from the watershed had a strong accelerating and magnifying effect on flash floods across the watershed. The most extreme model result indicated that wood removal increased peak discharge 8-fold near the watershed outlet, with the average prediction indicating an increase of 35%. This average increase caused by snagging was roughly equal to the maximum impact of recent wood additions, highlighting the severe impacts of snagging.

5.3 Future work recommendations

This work naturally led to new lines of inquiry that should be explored by researchers moving forward. One of the assumptions I made throughout the study was that peak discharge is the key variable for flood safety and damage. This decision was informed by current practices in the flood modeling world, but the monetary and safety implications of flooding do not scale perfectly by these factors. We addressed the safety implications of flooding using changes in time to peak which would allow for a longer reaction time for evacuation, but further research investigating the time required to evacuate could better determine the impacts of these shifts for specific reaches. My study focused on changes in roughness at the network scale, but geometric changes are also common throughout our watersheds and future studies are needed to understand the impacts these geometric changes have on flash flood propagation. The reach-scale simulations I conducted involved reaches which were previously beaver dominated but currently have no beaver. Comparisons with reaches with more recent beaver activity are needed to understand how beaver influence extreme flash floods like those I studied. I also assumed the stability of the system's geometry throughout flood simulations at all scales. One way I was able to understand these floods without this assumption was through the field observations of flash floods in chapter 4, but I was unable to incorporate the mobile beds into simulations. Future

studies should incorporate mobile beds first through reach-scale modeling and hopefully eventually with network-scale models.