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A multijurisdictional approach to predicting benefit-cost ratios for flood retention wetlands in rural Iowa

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A MULTIJURISDICTIONAL APPROACH TO PREDICTING BENEFIT-COST RATIOS FOR FLOOD RETENTION WETLANDS IN RURAL IOWA

by

Max E. Brourman

A thesis submitted in partial fulfillment
of the requirements for the Master of Science
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ABSTRACT

Rural Iowa towns often lack flood mitigation because of a lack of resources and inability to compete for federal assistance funds. The Federal Emergency Management Agency relies on a benefit-cost analysis which produces benefit-cost ratios (BCRs) for proposed projects to determine which communities receive funding, with an emphasis on the economic BCR, which compares potential future benefits with estimated capital costs. The FEMA requirement for an economic BCR is at least 0.75. The economic BCRs for mitigation projects in rural towns are often lower compared to those in urban centers due lower potential future benefits from lower building count and potential exposure. Here we use a multijurisdictional approach which analyzes flood mitigation at a watershed scale to join upstream agricultural potential future benefits with downstream potential avoided benefits in rural towns. We predicted BCRs of simulated flood retention wetlands using HAZUS-MH to find the potential future benefits a range of estimated capital costs via a percent reduction approach and a targeted peak flow approach to calculating wetland effects on peak flow.

The percent reduction approach generated BCRs of over 0.75 in the Mud Creek watershed for estimated capital costs per wetland up to $177,400. However, the simulated flood retention wetlands did not generate BCRs high enough to meet the minimum requirement in the Hinkle Creek watershed by itself. However, a multijurisdictional approach is not limited to each watershed individually. When the simulated flood retention wetland projects in each watershed were combined, the BCRs were high enough to meet the FEMA requirement. The combined BCRs were over 0.75 for estimated capital costs up to $143,300.

The targeted peak flow approach included BCRs which account for dry and wet antecedent soil moisture conditions and minimum, maximum and average peak flow change scenarios. The scenarios with dry antecedent soil moisture conditions created BCRs higher than wet antecedent soil moisture conditions. Further, the maximum peak change scenarios generated BCRs higher than average peak change scenarios, which in turn generated higher BCRs than the minimum peak change scenarios. In the Mud Creek watershed, the only scenario to generate BCRs above 0.75 for any part of the range of estimated capital costs was the maximum peak change scenario under dry antecedent soil moisture conditions. However, the maximum and average peak change scenarios under dry antecedent soil moisture conditions and the maximum peak change scenario under wet soil moisture conditions generated BCRs over 0.75 in the Hinkle Creek watershed. When the simulated flood retention wetland projects for both watersheds were combined, only the maximum peak change scenario under dry antecedent soil moisture conditions generated BCRs above 0.75. We found that a multijurisdictional approach is a viable method for rural watersheds to analyze potential flood mitigation projects to help increase their BCRs.

PUBLIC ABSTRACT

Flood recovery alone is inadequate to preserve rural communities from repetitive floods; however flood mitigation is not commonly adopted due to prohibitive costs and a lack of resources. Further rural communities often lag in their ability to garner funding because the structural values of rural areas do not produce benefit-cost ratios (BCRs) that meet the minimum requirement for flood prevention assistance funds applications. To increase the ability of rural Iowan communities to fund flood prevention projects, we analyzed economic BCRs of simulated flood retention wetlands using a multijurisdictional approach. We simulated before and after flood retention wetland implementation scenarios in two hydrologic unit code 12 watersheds in rural Iowa using two methods to calculate the impacts of the wetland projects. We then used an economic analysis on the avoided damages over the useful lifetime of each project to determine the BCRs over a range of estimated capital costs. The results show that when flood prevention projects are analyzed at a watershed scale rather than a governmental boundary scale, rural flood prevention projects produce BCRs that meet the minimum requirements for flood mitigation assistance funds applications. A multijurisdictional approach to flood mitigation projects can help protect communities that otherwise would not receive flood mitigation benefits.

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1. INTRODUCTION

Flooding is the most common cause of a disaster declaration in the United States, and 62% of all major disaster declarations have been flood related since the Federal Emergency Management Agency (FEMA) began tracking this statistic in 1953 (Brusentsev, 2017). Moreover, the proportion of disaster declarations directly related to flooding in Iowa since 1953 is 74% (Federal Emergency Management Agency, 2019a). Thus, flooding is the most prevalent natural disaster in the United States, which is also one of the costliest since flooding alone has caused $119.9 billion in damages from 1980 to 2017, third only behind tropical cyclones and severe storms, both of which have associated flooding (Smith, 2018). Furthermore, flood intensity is expected to increase with increasing urbanization and a changing climate (Gilroy & McCuen, 2011). Consequently, increased flood frequency and magnitude will cause higher economic impacts in the future in the absence of comprehensive mitigation measures.

1.1 Flood Resilience

Communities can increase their flood resilience by finding ways to mitigate future floods. Resilience is a complex concept that has been defined as the capability to resist, overcome and adapt to adversity and crisis while maintaining function and structure (European Comission, 2012; IPCC, 2012; NIST, 2016; UNISDR, 2012). Historically, flood resilience has been classified as ecological and engineering resilience, focusing on either the capacity to endure or mitigate floods (Hollin, 1973). Currently, flood resilience is defined as the ability for communities to mitigate and recover from flooding in an efficient and timely manner (Aerts et al., 2014; Bertilsson et al., 2018; Schinke et al., 2016). Moreover, high flood resilience relies on minimizing flood risk, which is a function of hazard, exposure and vulnerability (Aerts & Botzen, 2011; Kron, 2005; UNISDR, 2011). Furthermore, flood hazard refers to the frequency and magnitude of the flood; flood exposure refers to the people and properties at risk of suffering from flooding; vulnerability refers to how likely a person or property is to suffer damages. Therefore, flood mitigation to reduce flood risk is a key for any community to increase their flood resilience.

1.2 The Financial Implications of Flood Mitigation Approaches

The premiums collected by the National Flood Insurance Program (NFIP) increased from $81.8M in 1978 to $3,308M in 2017 (Figure 1.1) (Federal Emergency Management Agency, 2019e). The NFIP is the main flood insurance provider in the United States (Horn, 2018), whose claim payments can act as a gauge for how much flood recovery is being expended in the United States. However, payments by the NFIP have exceeded the earned annual premiums collected 14 times over the past 40 years, totaling a deficit of approximately $5 billion (Federal Emergency Management Agency, 2019d). The cause for higher may be due to an increasing number of policy holders, however the number of policy holders has decreased from 2008-2017, during which period, the NFIP has paid more in losses than it has collected in premiums 4 times (Figure 1.2) (Federal Emergency Management Agency, 2019f). Moreover, most NFIP payments are used to rebuild properties to pre-flood conditions, if flood regulations have not changed, thereby leaving them vulnerable to future flooding. Repetitive flood loss properties are projected to cost about $200 million to the NFIP every year (Jenkins, 2004). Thus, even if flood risk remains constant, NFIP payments will increase as properties continue to be flooded repeatedly. Therefore, future mitigation must lower flood risk and lessen the cycle of repetitive losses. Since financial logic dictates that the current method of flood recovery is not sustainable, a holistic, multijurisdictional approach to flood mitigation assessment and decision-making is necessary.

Historically, flood mitigation has been localized to the city or property scale (Aerts & Botzen, 2011; Bertilsson et al., 2018; UNISDR, 2012). Consequently, over 14,000 miles of levees exist in the United States to protect citizens and property, which reduce flood risk at the city scale (Levee Safety Program, 2018). Further, Flood Protection Elevation (FPE) is one of the most common practices of flood mitigation in place (Federal Emergency Management Agency, 2014). FPE is the process of raising the base elevation of a house by raising it onto stilts or extending foundation walls. One key drawback for FPE is that it only reduces flood risk for a single property. While these mitigation practices have been successful, their scopes are limited to single properties or town boundaries. This may force local governments to decide which areas are worth protecting and which will have to suffer the impacts of floods.

A multijurisdictional approach is designed to help mitigate floods across an entire watershed. Therefore, rather than communities being forced to choose which neighborhoods are deserving of flood mitigation, a multijurisdictional approach uses flood mitigation upstream in the watershed to benefit all residents and properties downstream of the mitigation project. By placing flood mitigation upstream in a watershed, there are larger stream segments downstream that benefit from the flood mitigation than if the flood mitigation projects were located further downstream. In turn, upstream flood mitigation can decrease flooding for more residents and properties. The residents and properties that may have been unaffected by localized flood mitigation may experience decreased flood impacts due to the application of a multijurisdictional approach. Thus, a multijurisdictional approach to flood mitigation can reach larger populations and potentially have greater impacts than localized methods.

1.3 Benefit-Cost Analyses and Rural Disparities

FEMA uses a benefit-cost analysis (BCA) to evaluate federal hazard mitigation assistance applications from communities and other entities. A BCA generates a benefit-cost ratio (BCR) by comparing the costs of a proposed project with the expected benefits (Federal Emergency Management Agency, 2018a). Consequently, the overall BCA includes an economic component and an ecosystem services component, where the economic BCA exclusively analyzes the costs and monetary benefits of a project.

$$\text{Economic BCR} = \frac{\text{Projected Future Avoided Damages}}{\text{Total Project Costs}} \qquad \text{Eq. 1.1}$$

An economic BCR of one means that a project has predicted future benefits equal to the costs. BCRs over one indicate the benefits outweigh the costs and the project is often considered "cost effective". On the other hand, a BCR under one indicates that the costs outweigh the benefits and it is often considered "cost ineffective" (Federal Emergency Management Agency, 2013). Furthermore, the economic BCR is required to be at least 0.75 for floodplain restoration and flood mitigation projects (Federal Emergency Management Agency, 2015b). Since an ecosystem services BCR is not conducted if the economic BCR does not exceed 0.75, the dependence on the economic BCR of the total BCR makes the economic part the essential factor when considering which applicants receive assistance for flood mitigation projects. From here on, BCR will refer to the economic BCR unless otherwise stated.

In rural areas, access emergency equipment, shelters, public transportation, vehicles and financial reserves is lower compared to urban areas. In addition, access to medical resources is much more limited in rural areas, which contributes to immediate emergencies during floods and potential health crises after floods (Davis, Wilson, Brock-Martin, Glover, & Svendsen, 2010;

Hsu et al., 2006). Moreover, rural flood victims are often displaced from their homes for longer durations than urban flood victims (Kirsch, Wadhwani, Sauer, Doocy, & Catlett, 2012). Additionally, rural residents may be more vulnerable to flooding because the rarity of rural flood shelters leaves them unprotected during floods (Liu, Behr, & Diaz, 2016). These characteristics increase the flood risk of rural communities, while most efforts to increase rural flood resilience are minimal.

Urban areas, by definition, contain higher population and building densities compared to rural settings in addition to having greater average building and content costs. Consequently, Urban centers experience higher building and content damages from floods than rural towns. As a result, many efforts to increase community flood resilience have focused on urban areas (Balsells, Barroca, Becue, & Serre, 2015; Bertilsson et al., 2018; Mugume, Melville-Shreeve, Gomez, & Butler, 2017). Indeed, the average home values in urban areas are roughly $100,000 greater compared to rural areas (Fuller, 2016). Higher average home values combined with higher building densities result in significantly higher projected future avoided damages for flood mitigation projects, and thus higher BCRs, in urban areas (Eq. 1.1).

1.4 Mechanisms for a Watershed-Based Benefit-Cost Analysis

Hazards in the United States-Multi Hazard (HAZUS-MH) is the primary tool used to estimate damages occurring from natural disasters (Ding, White, Ullman, & Fashokun, 2008; Federal Emergency Management Agency, 2012c; Charles Scawthorn et al., 2006; Tate, Muñoz, & Suchan, 2015). Accordingly, HAZUS-MH can estimate losses for earthquakes, tsunamis, hurricanes, and floods (Federal Emergency Management Agency, 2012a, 2012b, 2012c). HAZUS-MH estimates social impacts, economic losses, and physical damage using geographic information systems (GIS) (Federal Emergency Management Agency, 2018c). Moreover, HAZUS-MH users can perform basic analysis (level one) or advanced analysis (level 2 or level 3) (Federal Emergency Management Agency, 2019b) depending on their skill level and availability of data needed to supplement the default data. The level one analysis is based on data native to HAZUS-MH. It created stream networks based on HAZUS-MH native digital elevation maps, while also using general building stock damages and losses (Federal Emergency Management Agency, 2018d). The general building stock damage function estimates damages based on square footage by building occupancy type, relying on a statewide dataset to determine building count and value. In addition to simplified data sources, a level one analysis does not require extensive knowledge on hydrologic and economic simulations, and can be used as a basis to determine where advanced analysis should be done. The damage estimations in a level 1 analysis are much more generalized than the advanced analysis levels (Federal Emergency Management Agency, 2015a).

A level two analysis requires data from outside sources to update the user defined facilities or flood depth data (Caufield & Hillier, 2011). Therefore, a level two analysis utilizes updated user defined facilities data over using a general building stock analysis to evaluate building and content losses. Furthermore, instead of a dasymetric approach, the user defined facilities analysis calculates flood damages for individual properties rather than blocks of properties. Accordingly, each property is individually analyzed, ensuring that only flooded buildings are included in the loss estimates. However, the user defined facilities analysis is much more accurate than the homogenous or dasymetric analysis. Thus, a level two analysis may require more effort and expertise, but the accuracy benefits gained make level two analysis the preferred level for federal flood mitigation assistance (Ding et al., 2008; C. Scawthorn et al., 2006). A level 3 analysis is similar to a level 2 analysis, however it requires changing the underlying engineering and loss analysis parameters in HAZUS-MH as well as updated data. It requires substantial effort from multiple experts in loss functions, data analysis and data acquisition, often times making a level 3 analysis arduous to perform.

The Comprehensive Data Management System (CDMS) is a complementary tool developed by FEMA to aid the incorporation of user data into HAZUS-MH (Federal Emergency Management Agency, 2018b). CDMS has four modules: aggregate, site specific, backward compatibility and import. The aggregate module enables updating the aggregated data in HAZUS-MH, which includes the square footage, building count, building and content exposure and demographics. Subsequently, the site-specific module enables data at specific geographic locations to be imported for properties and structures. Further, the backward compatibility and import modules ensure that data are compatible with older versions of HAZUS-MH and can be imported properly. Moreover, CDMS requires many different fields in the user defined facilities data to successfully import the data into the UDF inventory for HAZUS-MH (Table 1.1) (Federal Emergency Management Agency, 2019c). Each data field requires a specific data type and field length, which are dictated by HAZUS-MH compatibility. However, once all the required fields are imported into CDMS, the data can be transferred into any HAZUS-MH scenario.

The Agricultural Conservation Planning Framework (ACPF) toolbox was developed by the United States Department of Agriculture to process elevation models and run hydrologic analysis to enable other tools for the usage of watershed management. A primary use of ACPF is to help determine the potential locations for agricultural conservation practices (S.A. Porter, 2015). ACPF has been used in hydrologic unit code (HUC)12 watersheds to determine the best conservation practice scenarios for reducing nutrients in Iowa (Tomer et al., 2015). In addition, ACPF can determine potential locations for flood-first best management practices (BMPs) as part of its ability to locate conservation practices. This has been used to find potential BMP scenarios, which have then been compared to determine which of them impacts flooding the most (Rundhaug et al., 2018). These flood-first BMPs include grassed waterways, water and sediment control basins and flood retention wetlands. Thus, ACPF serves as an imperative tool for watershed resource management and flood mitigation projects of all types.

The Generic Hydrologic Overland-Subsurface Toolkit is a physically-based integrated model—developed by IIHR-Hydroscience & Engineering at the University of Iowa—that can simulate hydrologic phenomena, including the impacts of best management practices on flood peak flows (Iowa Flood Center, 2018a). Accordingly, GHOST includes multiple factors such as topography, different types of soil and land use to model the major hydrologic processes. Moreover, GHOST can model stochastic storm transposition and determine the flows at river segments based on different storm sizes and locations. Historically, rainfall has been modelled using design storms (HS Wheater, 2006; Rahman, Weinmann, Hoang, & Laurenson, 2002). The design storm approach assumes that a rainfall event with a designed return period will produce corresponding floods with the same return period (A. Viglione, 2009). Design storms have previously been used to estimate the impacts of flood mitigation practices (Lucas, 2010; Yang & Chui, 2018). However, the design storm approach may cause inaccurate estimations of flood probabilities (Berk, Špačková, & Straub, 2017; Verhoest et al., 2010). Rather than using design storms, GHOST uses stochastic storm transposition to model rainfall at the HUC8 watershed scale at a 4 km^2 resolution. Stochastic storm transposition uses a catalog of observed storms to determine intensity-duration-frequency relationships (Koutsoyiannis, 1994). Stochastic storm transposition in turn includes spatial and temporal variability to model rainfall rather than just assuming a single precipitation depth across an entire watershed, which better represents extreme rainfall conditions than the use of design storms does (Wright, Smith, Villarini, & Baeck, 2013). GHOST uses stochastic storm transposition to determine the flows at river segments based on different storm sizes and locations from the storm catalog Therefore, simulated flood retention wetlands can be incorporated into the model to find the difference in peak flows for before- and after-implementation scenarios. Further, GHOST has been used to influence hydrologic assessment reports across Iowa in the Upper Wapspinicon and Middle Cedar Hydrologic Assessments prepared by the Iowa Flood Center (Iowa Flood Center, 2018a, 2018b), In consequence of the above, GHOST was used to determine the effects of various BMPs on the annual maximum peak discharges. However, GHOST being limited to modelling HUC8 sized watersheds as the smallest scale for stochastic storm transposition is a drawback. Resultantly, storm magnitude cannot be determined for smaller watersheds before running GHOST. However, the HUC8 results can be narrowed to the HUC12 scale after being run to determine the peak flows in the desired HUC12 watershed.

The Hydrologic Engineering Center's River Analysis System (HEC-RAS) was developed by the U.S. Army Corp of Engineers to model hydrology and water quality for various waterways (Hydrologic Engineering Center, 2016b). It further has the ability to manipulate flow data for individual river reaches, perform flow analysis and create water surface profiles (Hydrologic Engineering Center, 2016a). Moreover, HEC-RAS has previously been used to model the interactions between flow and natural vegetation in addition to being used to model how flow interacts with various environments (Wang, Zhang, Greimann, & Huang, 2018).

1.5 Problem Statement and Objectives

In Iowa, a multijurisdictional approach to performing a benefit-cost analysis has not been widely implemented. Therefore, this lack of a multijurisdictional approach contributes to the disparity between urban and rural flood mitigation. As a result, the disparity between urban and rural flood mitigation has left rural areas in a state of lowered flood resilience. The objectives to remedy this issue are:

- To create credible hydrologic scenarios that analyze the impacts of flood retention wetlands on peak flows;
- To compare average annualized losses between scenarios without, and with, simulated flood retention wetlands;
- To determine if economic BCRs above 0.75 can be achieved in rural HUC12 watersheds using a multijurisdictional approach.

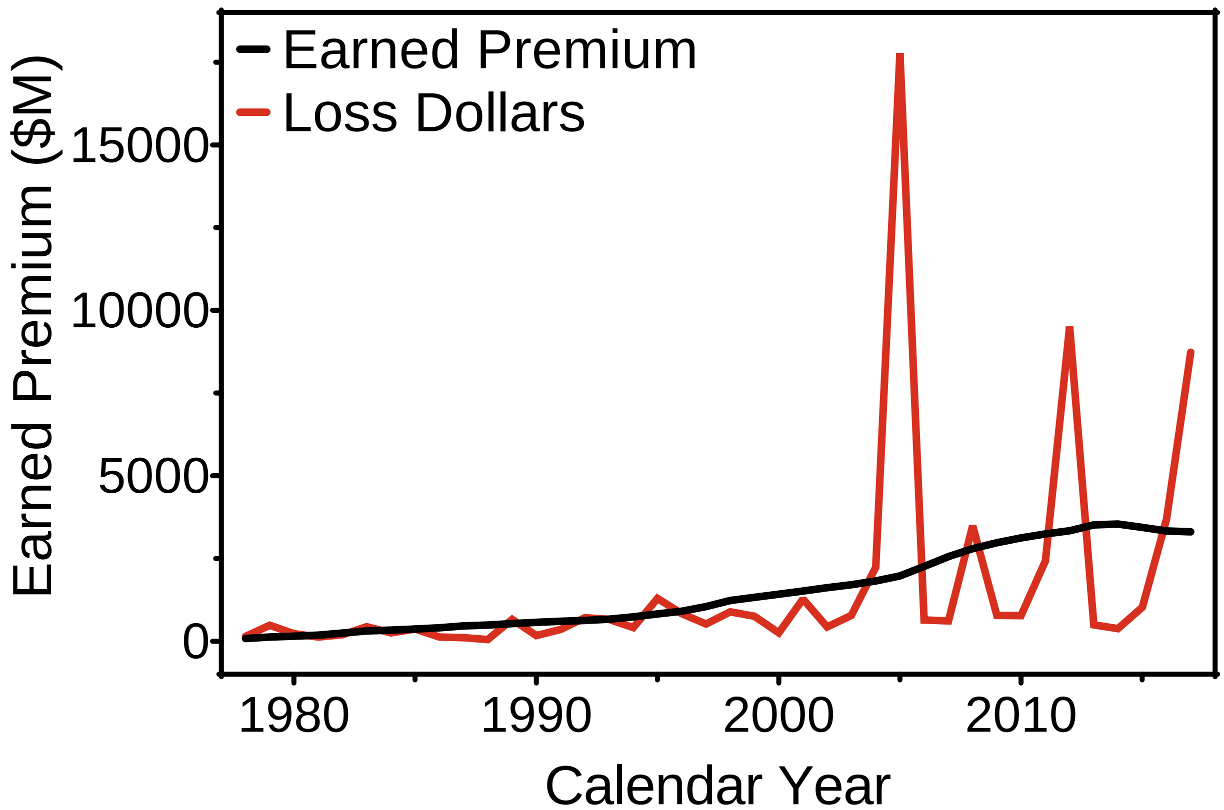

Figure 1.1. NFIP earned premiums compared to loss dollars paid from 1978 to 2017

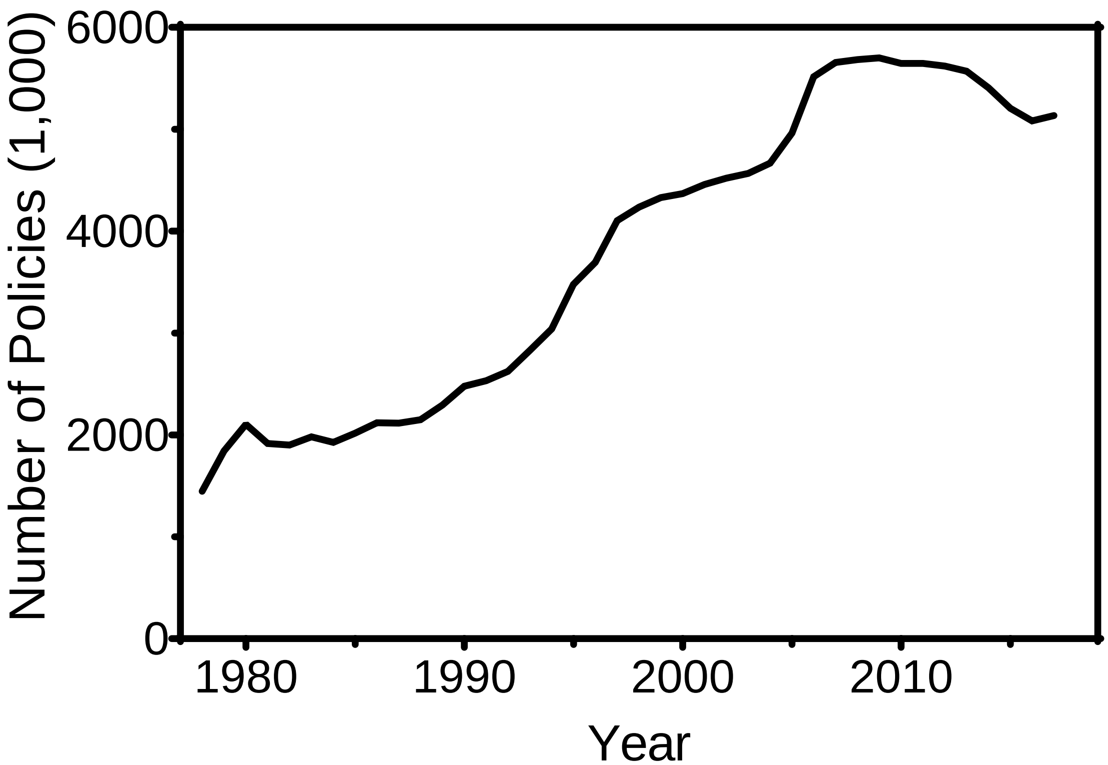

Figure 1.2. Total NFIP policies per year from 1978-2017

Table 1.1. Required user-defined function fields and descriptions

Required Fields for Importing UDF	**Description**
OCCUPANCY	The use of a building, i.e., residential, commercial or industrial.
YEARBUILT	The year in which the building was built.
COST	The cost of the structure of the building.
NUMSTORIES	The number of stories in the building.
BLDGTYPE	The material out of which a building is made.
LATTITUDE	The building's latitude.
LONGITUDE	The building's longitude.
CONTENTCOST	The costs of the contents within the building.
DESIGNLEVEL	Factor field whether a building is pre- or post-FIRM
FOUNDATIONTYPE	The type of foundation that the structure is built upon.
FIRSTFLOODHT	The height of the first floor.
BLDGDAMAGEFNID	The function used to determine the building structure damage.
CONTDAMAGEFNID	The function used to determine the content damage within a building.

2. METHODS

To assess the impacts a multijurisdictional approach has on the economic BCR of flood mitigation projects, HAZUS-MH was used to analyze various flood mitigation scenarios. Before-mitigation and after-mitigation scenarios were simulated to determine the change in flood losses based on the change in peak flow from implementing flood retention wetlands. The change in flood losses were considered avoided losses, which represent the projected future avoided damages in the economic BCR equation. The avoided losses were then compared to a range of total project costs to evaluate the BCRs over a range of capital costs. To determine whether the simulated flood prevention projects would help communities apply for federal aid, the BCRs were then compared to the FEMA minimum requirement of 0.75.

To determine the economic impacts of flood prevention ponds in the Hinkle Creek and Mud Creek watersheds, the difference between the before-implementation and after-implementation scenarios were compared. The effects of flood retention wetlands on flood depth and extent were based on the difference in peak flow. The change in peak flow was calculated through two different approaches, through percent reduction and by matching target peak flows. The percent reduction approach simulated the change in peak flow for the annual peak discharge from the implementation of flood retention wetlands with flood frequency curves to determine by what percent the peak flow decreased. This type of approach is common among applications for federal assistance for flood mitigation. The second approach created target peak flows for before-implementation and after-implementation scenarios and matched the depth grid data to those target peak flows. The same simulation process was performed in HAZUS-MH for both the percent reduction and matching target peak flow approaches. Each approach shared similar depth grid creation processes as well, with minor differences during the data manipulation phase.

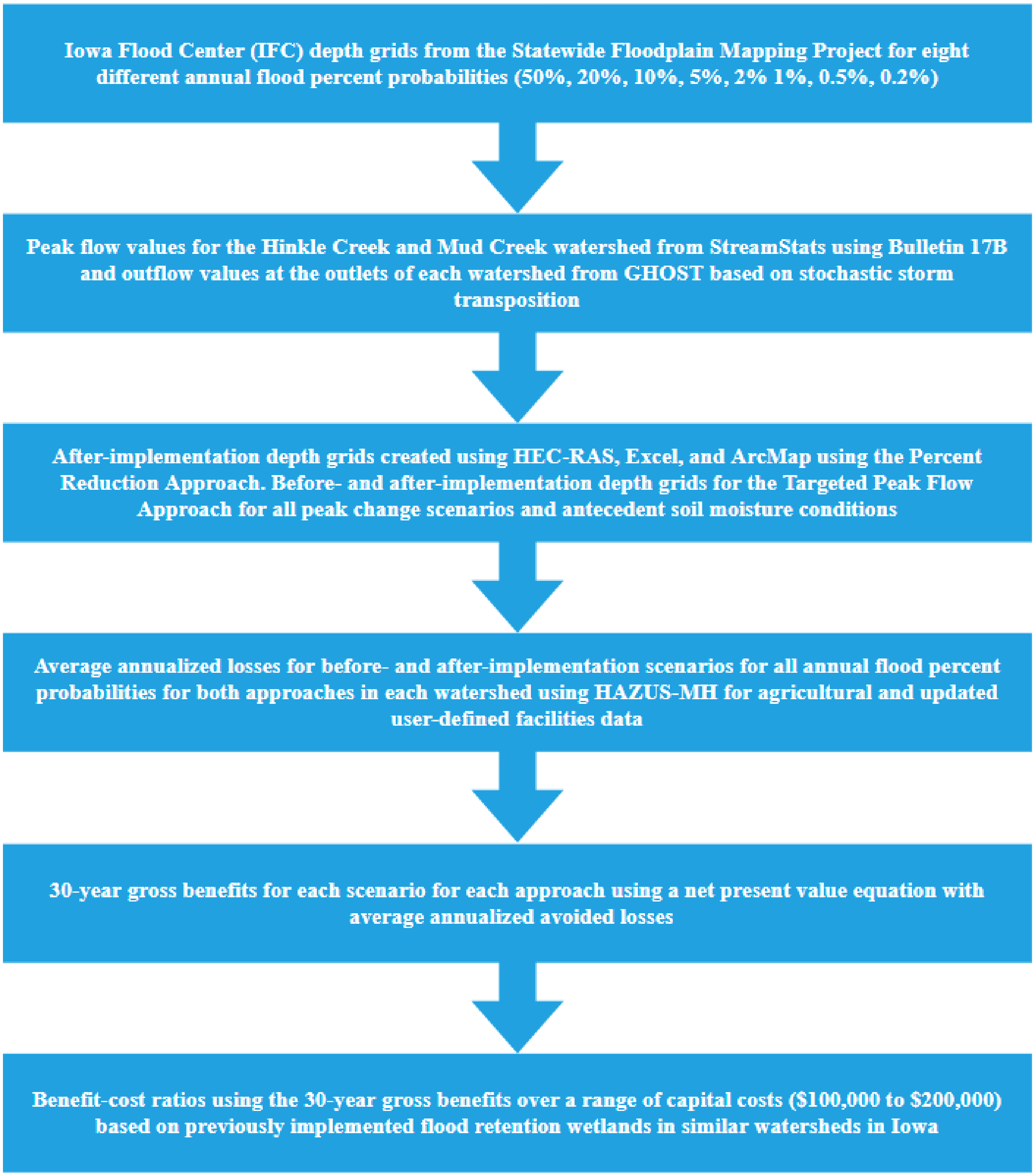

Figure 2.1. BCR workflow

2.1 Study Region

Two Hydrologic Unit Code 12 (HUC12) watersheds located in Iowa were used as the study region. These watersheds are the Mud Creek sub-watershed (HUC 070802051104) and the Hinkle sub-watershed (HUC 070802051102), which are located right next to each other in Iowa (Figure 2.2). Both HUC12 watersheds are predominantly rural. Hinkle Creek is estimated to be 68% covered by row crops, and only 4% impervious surfaces (Middle Cedar Watershed Management Authority, 2018a). Mud Creek is even more rural, at 81% row crops and 3% impervious surfaces (Middle Cedar Watershed Management Authority, 2018b). These HUC12 watersheds not only because of their rural characteristics, but also because they flow through the same rural town; Vinton, IA. Vinton is a small town, with a geographic footprint of 4.74 mi^2 with a population estimate of 5093 (United States Census Bureau, 2019) located in Benton County. Four hundred and forty eight user-defined facilities exist within the city boundaries for Vinton, IA. The total exposure of the user-defined facilities in the city of Vinton is $84,965,800, with $54,249,400 in building costs and $30,716,400 in content costs according to the Homeland Security and Emergency Management Division. The total agricultural exposure in Benton County was $668,085,280 according to HAZUS-MH. The location of Vinton near the outlet of each watershed means that the Hinkle Creek and Mud Creek watersheds have aspects of agricultural and structural flooding. The agricultural and structural characteristics of the Hinkle Creek and Mud Creek watersheds combined with Vinton make this area ideal for simulating the economic benefits of a multijurisdictional approach for flood mitigation.

2.2 Depth Grid Preparation for Analysis

The original depth grid data used for this analysis were created by the Iowa Flood Center (IFC) in 2016 through the Statewide Floodplain Mapping Project. The IFC used light detection and ranging (LIDAR) technology to map all the rivers and floodplains in Iowa. This process was done for all rivers and streams that had a drainage area of at least one square mile. The LIDAR data was then converted into flood depth grids for eight different annual flood percent probabilities (50%, 20%, 10%, 4% 2%, 1%, 0.5% and 0.2%) (Iowa Flood Center). The IFC depth grids served as a starting point for all data manipulation in this study.

To be able to import all the data required for this study, extensive preprocessing was required. Preprocessing was required for all raw depth grid data, no matter the later analysis methods. The IFC data was originally in raster catalog format and was converted data into raster format using the raster catalog to raster dataset tool in ArcCatalog. Within the tool settings, the mosaic operator was set to maximum, to ensure that the peak values were used to create each raster. Next, the pixel type of the raster dataset was changed. To avoid long processing times, each raster was clipped from the HUC8 scale to the study region first (Figure 2.3) using the clip tool in ArcCatalog. To further decrease the processing times, only the tributaries (Figure 2.4) that were affected by the flood prevention wetlands were included. The flood damages in the tributaries unaffected by the wetlands were assumed to be the same before and after the wetlands were implemented. The HUC12 watershed delineations served as boundary regions for the analysis. The clip to region extent option was used so that data outside of the desired watersheds were excluded. The data was then converted from 16-bit to 32-bit float for compatibility with HAZUS-MH by copying the 16-bit data using the ArcCatalog copy tool, while adjusting the data type changed to 32-bit float. The rasters were converted to meters to be compatible with the user-defined structure data. In its raw form, the data was multiplied by 1000 to allow the previous preprocessing steps to be performed. To convert the rasters back to meters, each data point was divided by 1000 in ArcMap using the raster calculator tool. The resulting rasters were ready to be imported into HAZUS-MH or be used as the starting point to create new depth grids. An additional benefit to preprocessing was that it created an intermediary raster at every step, which ensured that if any files were corrupted or lost, the recovery time was as short as possible. HAZUS-MH has many intricacies and sometimes requires that the file names at the final step must start with letters rather than numbers to ensure that they remain compatible with HAZUS-MH.

2.3 Peak Flow Change by Percent Reduction

To find the change in peak flow by percent reduction, simulated wetland impacts were applied to a flood frequency curve to find the amount by which the peak flows decreased. The potential locations of wetlands were found using ACPF. Of the potential locations generated by ACPF, the simulated wetlands were chosen to prioritize placement near the headwaters of each watershed (Figure 2.5). The before-implementation scenario in the percent reduction approach was simply the original IFC depth grids after they had undergone preprocessing. The first step in the percent reduction approach was to create a flood frequency curve for both watersheds. The baseline flood frequency curve (Figure 2.6 & Figure 2.7) were created for the eight annual flood percent probabilities using the peak flow characteristics generated by StreamStats. StreamStats is a tool developed by the United States Geologic Survey (USGS) that estimates streamflow statistics for ungauged sites, which was accessed in Septermber 2018, in accordance to USGS Bulletin 17B (D.P. Turnipseed, 2006; K.G Ries, 2017). A logarithmic function was found that matched the data for each watershed (Eq. 2.1 & Eq. 2.2)

$$y = 2027.4 \ln(x) - 584.06 \qquad \text{Eq. 2.1}$$

$$y = 1892.6 \ln(x) - 309.36 \qquad \text{Eq. 2.2}$$

Where *y* represents the outflow at the outlet of each watershed in cubic feet per second, and *x* represents the annual flood percent probability. The historical peak flow data for the Hinkle Creek and Mud

Creek watersheds showed an average decrease to peak flow by approximately 10% in preliminary flood retention wetland simulations performed in GHOST. To represent a 10% decrease in flooding, the base function of each logarithmic fit was multiplied by 0.9. Using the new equations with decreased base functions, the after-implementation peak flows were calculated. The change in peak flow was then calculated by dividing the after-implementation peak flow by the sum of the before- and after-implementation peak flows to result in a unique reduction factor for each of the eight flood percent probabilities for both watershed (Table 2.2). The reduction factors were largest for the 50% flood in each watershed and decreased as the annual flood percent probability decreased, with another spike in reduction factor for the 0.5% flood in each watershed. The increase in reduction factor for the 0.5% floods was likely because the original logarithmic fit slightly underestimated the 0.5% flood outflow. When the adjusted fit was created, the previously underestimated outflow was further decreased which resulted in a larger reduction factor for the 0.5% floods. This method was like one used by Emmons & Olivier Resources, Inc. (EOR), a consulting firm based in Iowa doing watershed planning in the Middle Cedar watershed.

2.4 Peak Flow Change by Adjustment to Match Target Peak Flows

The target peak flow approach used the simulated wetlands in ACPF and GHOST to predict peak flows for before-implementation and after-implementation scenarios. The location and size of the wetlands were found through ACPF, but the actual peak flows were calculated using GHOST. Stochastic storm transposition was performed in GHOST over the Middle Cedar HUC8 watershed, which contains the Hinkle Creek and Mud Creek watersheds. One river segment was selected from each of the study watersheds to identify the peak flows, outflow 1296 for Hinkle Creek and outflow 1311 for Mud Creek as delineated in GHOST (Figure 2.8). These river segments were chosen because they were as far downstream as possible without being affected by backflow, as determined from the detailed study river profiles (Figure 2.9 & Figure

2.10). Each storm was run for before-implementation and after-implementation scenarios, which when subtracted yield the change in peak flow due to the implementation of flood retention wetlands. The GHOST data was imported into Tecplot 360 to graph the flows at outflow 1296 and 1311 for each different storm transposition (Figure 2.13). The peak flows were classified by flood size based on the lower and upper thresholds for annual flood percent probabilities. StreamStats was used to find the lower and upper peak flows for all eight flood percent probabilities in both watersheds. The flow data from GHOST was then sorted into flood percent probabilities. Any flow under the 50% annual probability minimum flow threshold was excluded. The 0.5% annual probability flood was not simulated in GHOST, so only the 50%, 20%, 10%, 4% 2%, 1%, and 0.2% annual probabilities were used in the target peak flow approach. The maximum, minimum and average change to peak flows for each flood percent probability were found for the Hinkle Creek watershed (Table 2.4) and the Mud Creek watershed (Table 2.5).

2.5 New Depth Grid Generation

To create new depth grids, the original IFC depth grids were manipulated using HEC-RAS, Microsoft Excel and ArcMap. HEC-RAS was used because it could perform the steady state analysis on the data and for export to ArcGIS. Microsoft Excel was used for calculations and conversions that could not be performed with HEC-RAS. ArcMap was used to create the depth grids and to combine individual, tributary depth grids into whole watershed depth grids. The data were opened in HEC-RAS, exported to Microsoft Excel, multiplied by the adjustment factors, imported back into HEC-RAS, and a steady flow simulation was performed on the data. GEO-RAS data files were then exported from HEC-RAS into ArcMap. To create actual depth grids from the data, water surface depth and flood plain extent were calculated in ArcMap. Once the data was imported back into HEC-RAS, the same method used to create new depth grids for the Iowa Floodplain Mapping Project was used. This was done for the main stem of each watershed, as well as all tributaries affected by the modelled flood retention wetlands.

The first step to run HEC-RAS was to open the project file for the desired river segment. This could be dragged directly into HEC-RAS from the file explored. To view the depth grid data, the view/edit steady flow button was used to display the entire dataset. All the data points were then copied into Microsoft Excel. Once in Excel, the data manipulation could occur. The percent reduction approach only needed data manipulation for the after-implementation depth grid creation, as the before-implementation scenario was simply the IFC depth grids once they had been converted into a HAZUS-MH compatible format. The targeted peak flow approach required creating completely new depth grids for the before- and after-implementation scenarios, since the targeted peak flows for both scenarios were different than the peak flows in the IFC depth grids.

To create the after-implementation depth grids for the percent reduction approach, the reduction factors found for each annual flood percent probability and watershed were applied to all the data. Eight data points existed for each river cross section in the original IFC depth grids, one for each flood percent probability. The data points for each flood percent probability were multiplied by one minus the reduction factor for that respective flood percent probability to represent the effects of the simulated flood retention wetlands. The data was then able to be copied and pasted back into HEC-RAS to continue the new depth grid generation. This process had to be done for each tributary individually because they all had individual project files and isolated depth grid data.

To create new depth grids for the targeted peak flow approach, adjustment factors had to be calculated to manipulate the IFC depth grids to reflect the GHOST peak flows. The flows identified for the target river segments in each watershed were divided by the flows for the same river segments in the IFC depth grids to create the adjustment factors. These adjustment factors were unique for each flood percent probability, peak change scenario, and antecedent soil moisture conditions. The targeted peak flow approach used wet and dry antecedent soil moisture conditions, as well as a minimum, average, and maximum peak change scenario. We used these initial conditions to represent a variety of floods. Antecedent soil moisture was chosen as an initial condition to vary because of how important it is to determine flood characteristics (Michele & Salvadori, 2002; Sakazume, Ryo, & Saavedra, 2016). Minimum, average, and peak flow change scenarios were chosen to represent the entire range of effects from flood retention wetlands on flooding. Using just the maximum peak flow change may cause an overestimation in flood retention wetland benefits, while the minimum peak flow change may underestimate the benefits. Therefore, both were used to represent the entire range of potential flood retention wetland benefits as well as the average peak change scenario to represent the average benefits.

The adjustment factor for each flood percent probability was then multiplied by all depth grid data for each respective flood percent probability. The adjustment factors were initially calculated from the main stem data but were used for all of the tributaries as well. Once the adjustment factors were applied to all the data, the newly manipulated data was copied and pasted back into HEC-RAS for the main stem and tributaries of each watershed. This process was performed for both the before- and after-implementation scenario for the targeted peak flow approach. The before-implementation scenario used the GHOST peak flow outputs when flood retention wetlands were excluded from the simulation, and the after-implementation scenario used the GHOST peak flow outputs when they were included. There are 4 affected tributaries in the Hinkle Creek sub-watershed, and 5 affected tributaries in the Mud Creek sub-watershed (Figure 2.2) to total 5 river lengths in the Hinkle Creek watershed and 6 in the Mud Creek watershed. This number of starting condition scenarios and tributaries meant that this process was performed 132 times total.

Once the data was copied back into HEC-RAS after being manipulated, the new flow data was saved as a new file. The new data still had to be processed though, so a steady flow simulation was performed in HEC-RAS using the "perform steady flow simulation" tool. The steady flow simulation had to be saved as a new plan, with the name of each plan reflecting the watershed, antecedent soil moisture conditions, peak flow change scenario, and whether it was data for a before- or after-implementation scenario. The steady flow simulation was then computed, and the results were ready to be exported to ArcMap.

To export the HEC-RAS data into ArcMap, the Export GIS Data tool was used in HEC-RAS. In the Export GIS Data options, all eight return periods needed to be selected, and the same classification of the data used in the naming of the steady flow plan was included in the file name to differentiate it from the other GIS data exported by HEC-RAS. In ArcMap, the GeoRAS toolbar was added to enable processing of the exported HEC-RAS data. Using the Import Ras SDF File button on the GeoRas toolbar, the exported SDF from HEC-RAS was converted into an XML file with the same name as the SDF file. The ArcMap file was then saved so that the Layer Setup tool could be used. The new analysis option was used for each new depth grid within the Layer Setup tool. The Layer Setup was done by selecting the XML file that was just created for the RAS GIS export option. The Layer Setup was then set to a GRID digital elevation map (DEM), with the one-meter DEM that corresponded to the river length the depth grid was being created for. The output directory was set to the river length folder of the river length for which the depth grid was being created, which held all the depth grids for that river length. The Layer Setup was then run. To import the RAS data, the Import RAS Data tool was used, which automatically imported the data because it had already been selected during the Layer Setup step. The Water Surface Generation tool was then used to create the water surface based on the HEC-RAS data previously imported. All eight annual flood percent probabilities must be selected in the options before the Water Surface Generation tool was run. With the water surface successfully created, the Flood Plain Delineation Using Rasters tool was used to create the final depth grids. Again, all eight annual flood percent probabilities must be selected in the options before the Flood Plain Delineation Using Rasters tool was run. The final depth grids that were created were labeled DP01 to DP08, where each represented a different annual flood percent probability (Table 2.3).

This process was run for the main stem of each watershed, as well as all the tributaries affected for each. However, the depth grids were all separated, and needed to be combined before importing them into HAZUS-MH. The depth grids for the main stem and each tributary for each annual flood percent probability were then combined using the ‘mosaic’ tool in ArcMap. It is necessary to use the ‘maximum’ option for this step so that if there is overlap between any of the parts, the larger data points are used. Once mosaicked together, the depth grids were able to be uploaded into HAZUS-MH.

While the new depth grids now represented the before- and after-implementation scenarios, backflow from the Cedar River was not yet accounted for. The river segments that were affected by backflow were determined from the detailed study river profiles created during the Iowa Statewide Floodplain Mapping project (Figure 2.9 & Figure 2.10). Each profile shows a cross section of the creeks for the 0.2%. 1%, 2% and 10% annual flood probabilities. Where the water lever upstream begins to change is where the backflow effects from the Cedar River end. For Mud Creek, the entire detailed study is in the backflow affected area. However, in the Hinkle Creek, the 10% water level begins to rise around 2,000ft above the mouth at the Cedar River, and the 0.2% 1%, and 2% water levels begin to change around 2,500ft above the mouth at the Cedar River. 2,000ft above the mouth correlated to cross section D of the detailed study, and 2,500ft above the mouth at the Cedar River corresponded to cross section F. Thus, the areas downstream from cross section D were designated as backflow affected areas for the 50%, 20%, 10%, and 4% floods (Figure 2.11), while the areas downstream from cross section F were designated as backflow affected areas for the 2%, 1%, 0.5% and 0.2% floods (Figure 2.12). Shape files were created for the downstream segments of Hinkle Creek and Mud Creek affected by backflow. These shape files were used to clip out the backflow affected areas from the before-implementation depth grids. To make sure that the backflow areas did not simulate decreases in peak flow from the implementation of wetlands, the newly clipped backflow rasters segments were mosaicked with the after-implementation rasters giving priority to the backflow raster segments. This created rasters that had adjusted data only for the areas that were affected by the flood retention wetlands, and left backflow areas unaffected. This process was performed on for both the percent reduction and targeted peak flow approach.

2.6 Running HAZUS-MH

This study focuses exclusively on the riverine flood module because both HUC12 watersheds in this study are land locked and have no coastal effects on flooding. The 4.0 version of HAZUS-MH was used for its compatibility with the depth grids data and user-defined facilities data that were available for this study. HAZUS-MH was used to estimate the economic losses alone because the economic BCR exclusively analyzes economic impacts. While HAZUS-

MH was the program which was used to simulate all the economic losses, a number of data sources and tools were needed to create accurate BCRs for this project. These auxiliary tools and datasets were required to meet the level two analysis requirements. Many of these tools were used to pre-process the data to transform it into formats that were compatible with HAZUS-MH.

Updated user-defined facilities (UDFs) were also included in the level two analysis. The Homeland Security Emergency Management Division (HSEMD) collected all of the user-defined facilities data for this study from county assessors' websites. Economic data was collected for every user-defined facility located in the 500-year flood plain for every county in the Middle Cedar watershed. However, only the structural costs were available on the county assessors' websites. The content costs were not included on the assessors' website and are extremely difficult to estimate with high precision because the data is not publicly available, and records of the content costs are rarely kept by home owners. To find completely accurate content costs, the homeowners of every user-defined facility in the 500-year flood plain would have to calculate the dollar value of everything in their home and volunteer this data to HSEMD. To simplify the content costs, they were estimated to be equal to a proportion of the structural costs. For residential homes, the content costs were estimated to be equal to 50% of the structural costs. The content costs for industrial and commercial buildings were estimated to be equal to 100% of the structural costs. Since both the Mud Creek and Hinkle Creek watersheds are located in Benton County, IA, only the data collected from Benton County was used in this study. The user-defined facilities data was originally gathered in a Microsoft Excel spreadsheet. Excel data cannot be directly imported into HASUZ-MH so it was first imported into CDMS to then be imported into HAZUS-MH. CDMS 3.0 was used to ensure that it was compatible with the version of HAZUS-MH 4.0.

However, since the user-defined facilities data was collected from the county assessors' website, data only exists for properties that pay taxes, thus excluding some of the essential facilities in the city of Vinton. The essential facilities in Vinton include the Vinton Police Department, Benton County Sheriff Department, the Vinton Fire Department Fire House, Virginia Gay Hospital, the Lincoln Center, Tilford Middle School, Washington High School and the West Early Childhood Center (Figure 2.14). However, none of these facilities are located in the floodplain that is affected by the flood retention wetlands upstream. Any flooding for the essential facilities either comes from backflow from the Cedar River or from urban runoff that is unaffected by the wetlands upstream. Therefore, they were excluded from the avoided losses calculations, because the flood retention wetlands would not have any impact on their flood damages.

The user-defined facilities data was not ready to be immediately uploaded into HAZUS-MH. The raw user-defined data was saved in a Microsoft Excel sheet which cannot be uploaded directly into HAZUS-MH. To upload the user-defined data into HAZUS-MH, it was first imported into the Comprehensive Data Management System (CDMS) as an intermediary step. Each incompatible data field in the raw data was matched to a compatible data field in CDMS. The user-defined facilities data was stored in the local CDMS database and could be uploaded to any HAZUS-MH file.

To find the avoided losses that each flood prevention project generated, before-implementations and after-implementation scenarios were ran in HAZUS-MH. To find the avoided losses, the total losses for the after-implementation scenario were subtracted from the before-implementation scenario. The method for running HAZUS-MH remained the same for both the before- and after- scenarios for both peak flow change approaches. To create a study region in HAZUS-MH, the geographic location of the study region must first be identified. For this project, all the analysis occurred in Benton County, IA. The study region boundaries were set to Benton County for each scenario because HAZUS-MH does not include watershed boundaries for watersheds smaller than HUC 8. The data was previously clipped in the preprocessing steps to the desired watershed boundaries, so there are no worries about extraneous data being included. Once the study region was created, the user-defined facilities data were be uploaded to the HAZUS-MH files from CDMS. Importing the user-defined facilities data was done before the depth grids were uploaded to be sure that they transfer successfully. To import the user-defined flood depth grids, the flood type must first be set to riverine only, because only riverine flooding occurs in either watershed. The user-defined depth grids were then uploaded for all eight annual percent probabilities, setting the units for each depth grid to meters and inputting the proper annual flood percent probability for each. HAZUS-MH uses return periods rather than annual percent probabilities, but all annual percent probabilities have correlating return periods (Table 2.1).

With all necessary user-defined data uploaded into HAZUS-MH, the model was run for both the Hinkle Creek and Mud Creek watersheds. First, the hazard type was set to riverine only. New scenarios were then created in HAZUS-MH. There were four scenarios created for each HAZUS-MH file that used the percent reduction approach, a FullSuite scenario containing the 10%, 4%, 2%, 1% and 0.2% depth grids, and three individual scenarios for the 50%, 20%, and 0.5% depth grids each. The targeted peak flow approach only needed three scenarios because no data for the 0.5% flood probability existed. Once created, the flood plain was delineated for each scenario before they were ran. The scenarios were then ran, selecting only the user-defined facilities and agricultural losses options to minimize processing time. In total, four HAZUS-MH scenarios were required to perform the generic approach, the before-implementation and after-implementation for both the Mud Creek and the Hinkle Creek watersheds. The percent reduction approach only required four different HAZUS-MH files to be created, but targeted peak flow approach required 24 HAZUS-MH files to be ran. The results could be viewed for each annual flood percent probability individually. The user-defined facilities and agricultural loss reports were opened using the "view summary reports" tool. The maximum agricultural loss function was used to generate the largest agricultural avoided losses as possible. The 7 day, 14 day, and maximum loss functions all used the same calculation, and thus would result in the same agricultural damages. Higher agricultural avoided losses led to higher gross benefits which in turn would generate higher BCRs, which is one of the goals for this project.

The scenarios were ran in HAZUS-MH on the in simulation date of June 9th. This date was chosen to represent maximum crop losses according to their growth cycles. From 2014-2018, soybeans, corn and oats have reached 100% emergence just before mid-June in Iowa (National Agricultural Statistics Service, 2019). Emergence is one of the earliest phases of the crop growth cycle, during which crops are extremely vulnerable to floods (Khosravi & Anderson, 1990; Nanjo et al., 2014; Tamang, Magliozzi, Maroof, & Fukao, 2014). Thus, running HAZUS-MH on June 9th resulted in high agricultural damages because of crop growth cycle. Changes to peak flow from flood retention wetlands would then have the largest impact on avoided losses from agricultural products on this date, generating higher BCRs later on than other simulation dates may have. Further, mid-June marks the end of the moist phase and the beginning of the drying phase in Iowa soil in terms of soil moisture content (Khong, Wang, Quiring, & Ford, 2015). Thus using both wet and dry antecedent soil moisture conditions as varying initial conditions necessitates a HAZUS-MH simulation date that can encompass both soil moisture conditions, which June 9th can provide based on the annual soil moisture cycle.

2.7 Average Annualized Losses and Estimated Project Costs

Once the before-implementation and after-implementation scenarios were finished running in HAZUS-MH, the results were ready for economic analysis. To find the total avoided losses for each annual flood probability, the total losses for each annual flood probability from the after-implementation scenario were subtracted from the total losses of the before-implementation scenario. To find the average annualized avoided losses (AALs), the total avoided losses for each annual probability were inputted into the augmented AAL equation. HAZUS-MH uses an AAL equation to estimate yearly damages for the 10%, 4%, 2%, 1% and 0.2% annual flood probabilities (Eq. 2.3).

$$AAL = (f_{10} - f_{25})\frac{(L_{10}+L_{25})}{2} + (f_{25}-f_{50})\frac{(L_{25}+L_{50})}{2} + (f_{50}-f_{100})\frac{(L_{50}+L_{100})}{2} + (f_{100}-f_{500})\frac{(L_{100}+L_{500})}{2} + L_{500}\, f_{500} \qquad \text{Eq. 2.3}$$

To include the 50%, 20%, and 0.5% annual flood probabilities, an augmented AAL equation was created. The augmented equation uses the same approach to losses as the original equation but adds three terms to include all eight annual probabilities, all of which are bolded (Eq. 2.4).

$$AAL = \mathbf{(f_2-f_5)\frac{(L_2+L_5)}{2}} + \mathbf{(f_5-f_{10})\frac{(L_5+L_{10})}{2}} + (f_{10} - f_{25})\frac{(L_{10}+L_{25})}{2} + (f_{25}-f_{50})\frac{(L_{25}+L_{50})}{2} + (f_{50}-f_{100})\frac{(L_{50}+L_{100})}{2} + \mathbf{(f_{100}-f_{200})\frac{(L_{100}+L_{200})}{2}} + \mathbf{(f_{200}-f_{500})\frac{(L_{200}+L_{500})}{2}} + L_{500}\, f_{500} \qquad \text{Eq. 2.4}$$

The augmented equation was used to generate average annualized avoided losses ($AAL_{avoided}$), which represent yearly dollars saved because of the implementation of the simulated flood prevention wetlands. This could be done using the percent reduction approach since depth grids for all eight annual flood percent probabilities existed for that approach. However, the GHOST results did not have data for the 200-yr flood, thus a new $AAL_{avoided}$ equation was needed that omitted the 0.5% flood probability terms (Eq. 2.5).

$$AAL = (f_2 - f_5)\frac{(L_2 + L_5)}{2} + (f_5 - f_{10})\frac{(L_5 + L_{10})}{2} + (f_{10} - f_{25})\frac{(L_{10} + L_{25})}{2} + (f_{25} - f_{50})\frac{(L_{25} + L_{50})}{2} + (f_{50} - f_{100})\frac{(L_{50} + L_{100})}{2} + (f_{100} - f_{500})\frac{(L_{100} + L_{500})}{2} + L_{500}\, f_{500} \qquad \text{Eq. 2.5}$$

To estimate the lifetime benefit of each wetland project, the $AAL_{avoided}$ were projected over the useful lifetime of each wetland, which was 30 years. To account for the time value of money, the present value of the $AAL_{avoided}$ was found for every year over the useful lifetime of the wetlands using the net present value equation (Eq. 2.6).

$$\text{Present Value} = \frac{\text{Future Value}_N}{(1+I)^N} \qquad \text{Eq. 2.6}$$

Where I is the inflation rate (2.3% (US Bureau of Labor Statistics, 2018)) and N is the future period. To find the gross lifetime benefit for each wetland project, the sum of the $AAL_{avoided}$ for all 30 years of useful lifetime was calculated.

To find the economic BCR for each project, the projected future benefits were divided by the estimated project costs. In this study, the estimated project costs were equivalent to the capital costs for immediate implementation. Previous studies have been conducted on the Hinkle Creek and Mud Creek watershed that estimate the cost of implementing flood retention wetlands (Middle Cedar Watershed Management Authority, 2018a, 2018b). The capital costs were estimated to range between \$100,000 and \$200,000 depending on size and location. This is the same range that this study uses to analyze the BCRs of the simulated flood retention wetlands.

Table 2.1. Annual flood percent probabilities and correlating return periods

Probability Percent	50%	20%	10%	4%	2%	1%	0.5%	0.2%
Return Period	2yr	5yr	10yr	25yr	50yr	100yr	200yr	500yr

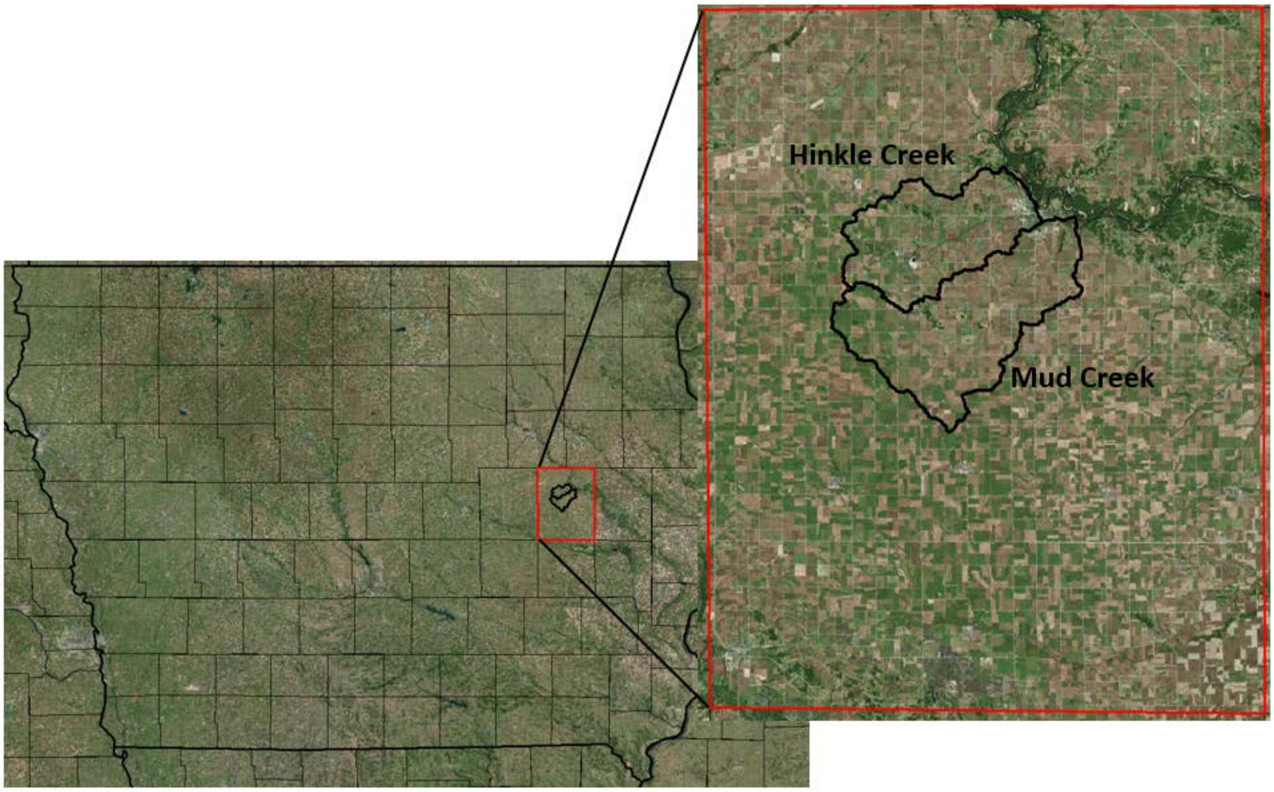

Figure 2.2. Hinkle Creek and Mud Creek watershed locations

Table 2.2: Generic adjustment factors for Hinkle Creek and Mud Creek

Annual Flood Percent Probability	Hinkle Creek	Mud Creek
50.0%	43.74%	34.05%
20.0%	8.46%	6.92%
10.0%	6.04%	6.07%
4.0%	8.96%	9.22%
2.0%	8.21%	8.10%
1.0%	7.14%	7.01%
0.5%	16.66%	16.22%
0.2%	9.62%	9.11%

Table 2.3. Newly created depth grid numbering and corresponding return periods

Depth Grid Numbering	DP01	DP02	DP03	DP04	DP05	DP06	DP07	DP08
Return Period	2yr	5yr	10yr	25yr	50yr	100yr	200yr	500yr

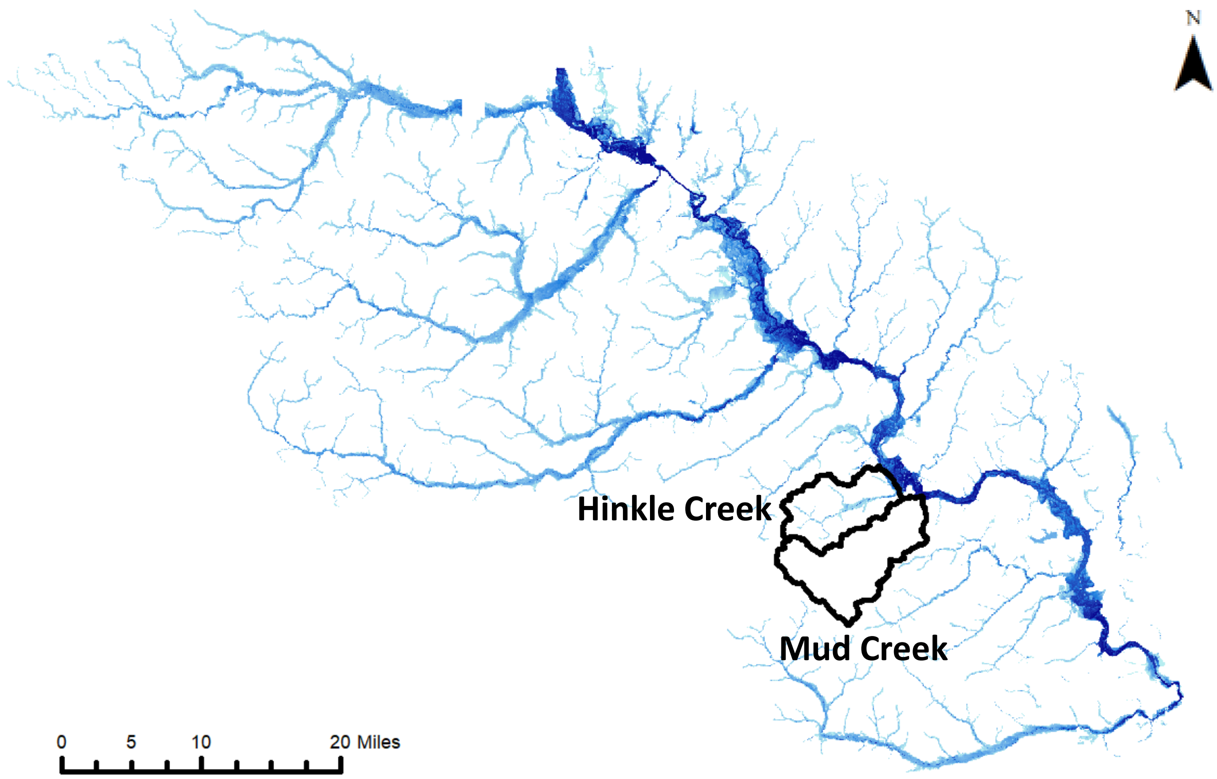

Figure 2.3: The boundaries for the Hinkle Creek and Mud Creek watersheds compared to the size of the raw depth grid data for the Middle Cedar watershed

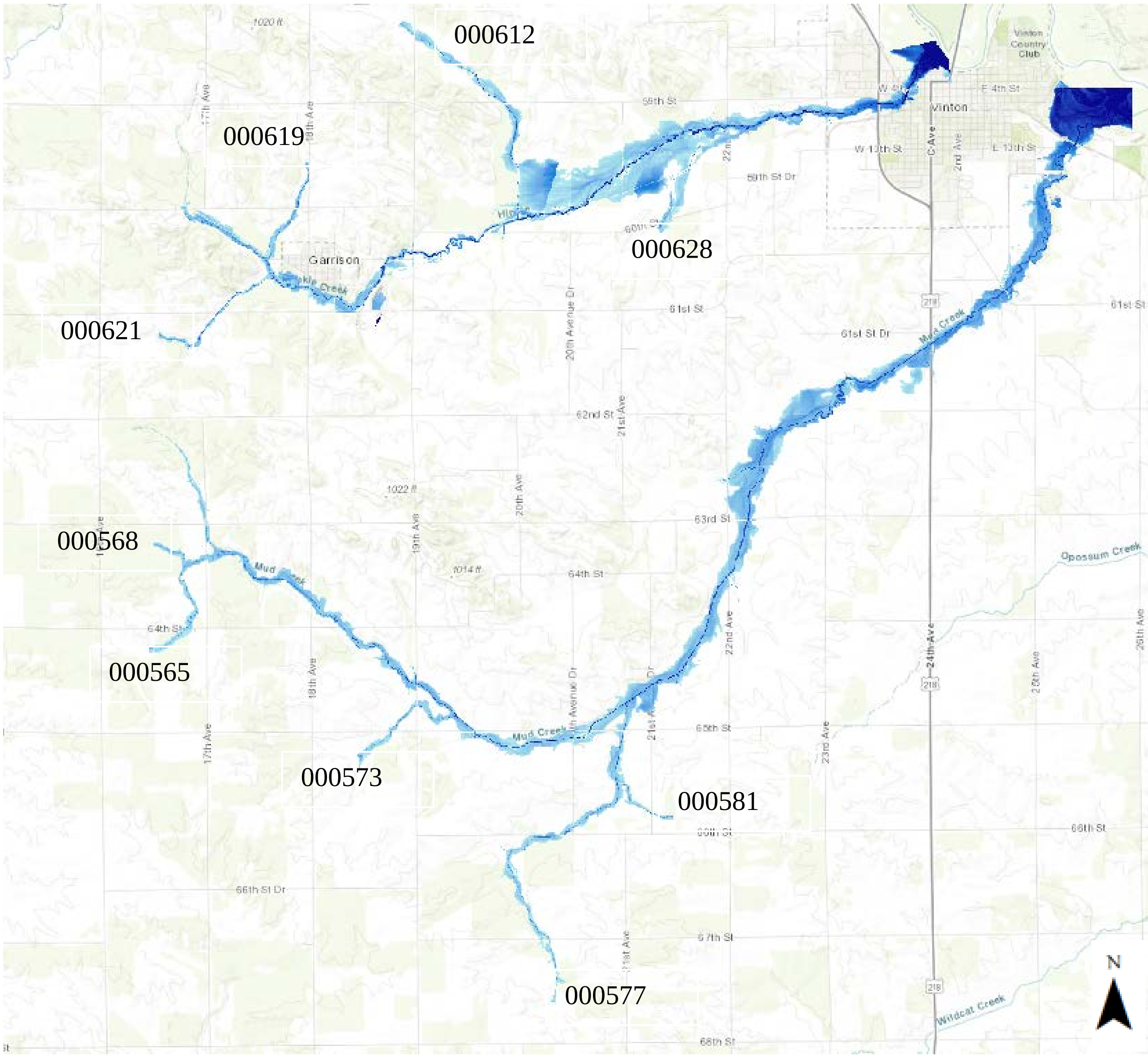

Figure 2.4: Tributary locations and identification numbers for the Hinkle Creek and Mud Creek

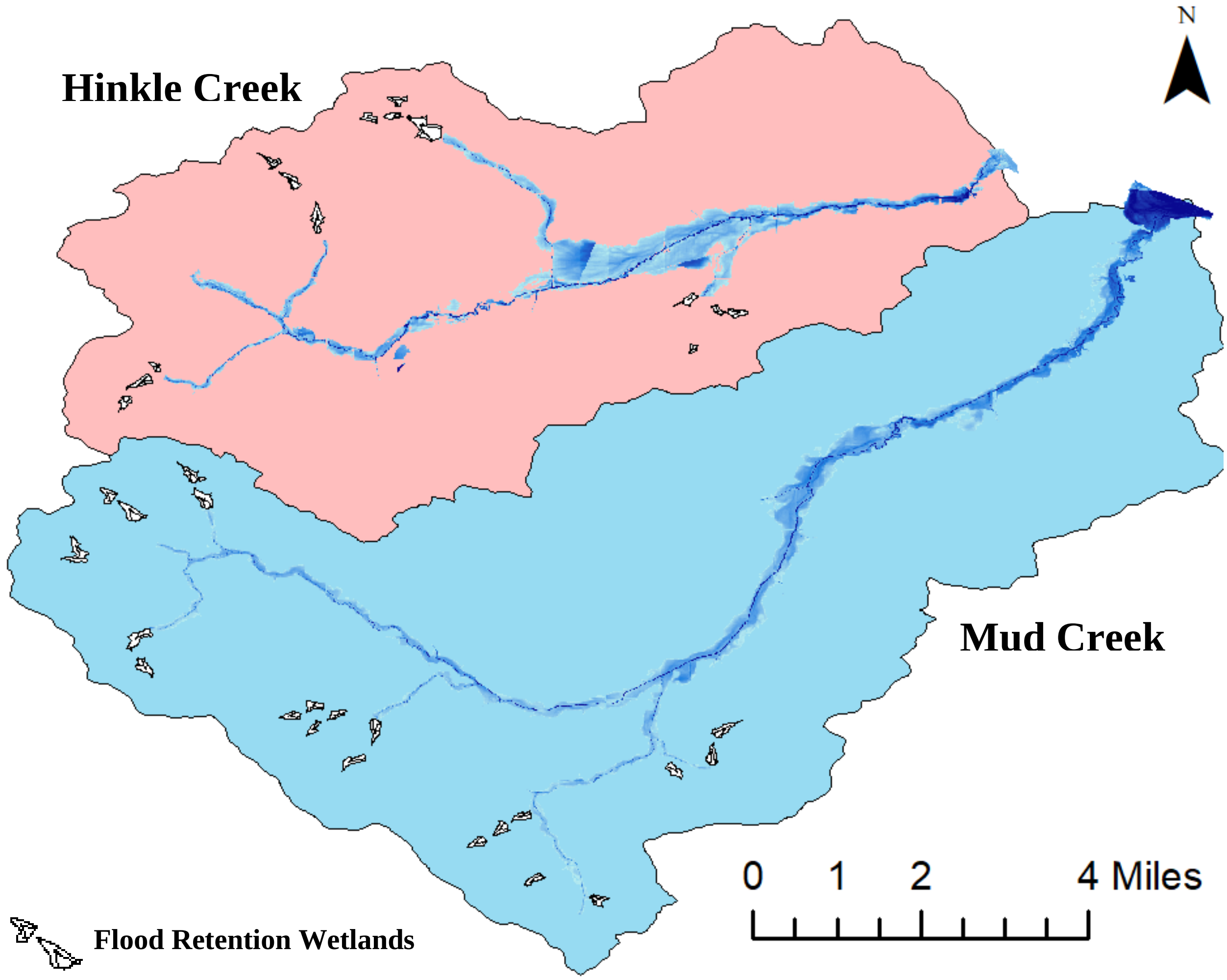

Figure 2.5. Flood retention watershed locations

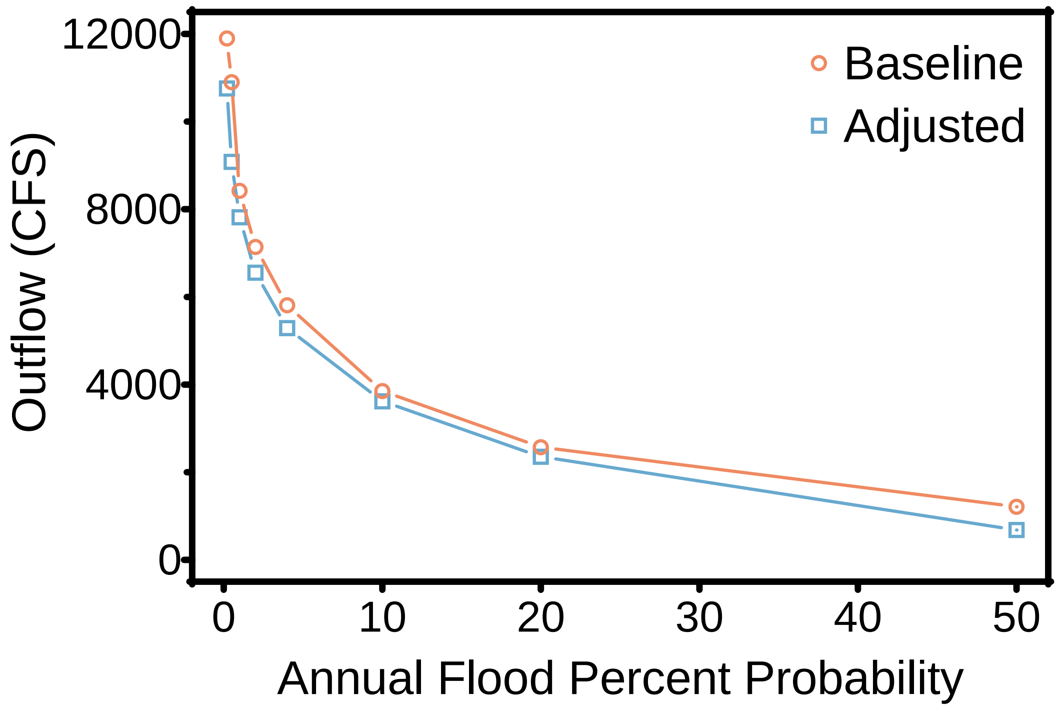

Figure 2.6. Generic baseline and adjusted flood frequency curves for Hinkle Creek

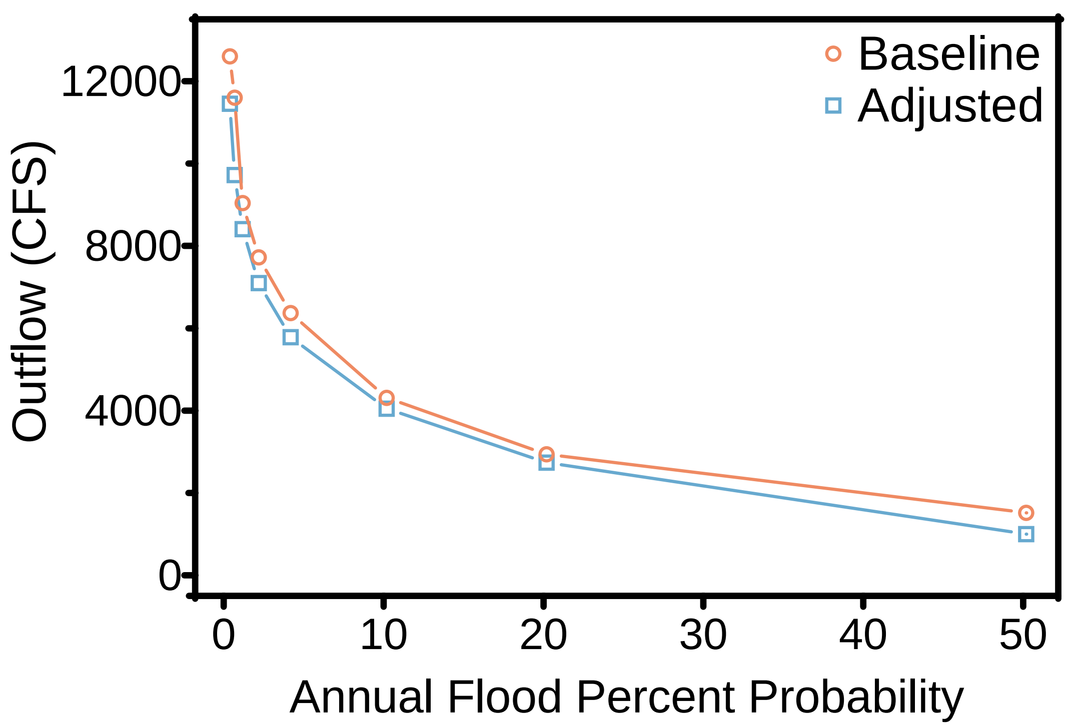

Figure 2.7: Generic baseline and adjusted flood frequency curves for Mud Creek

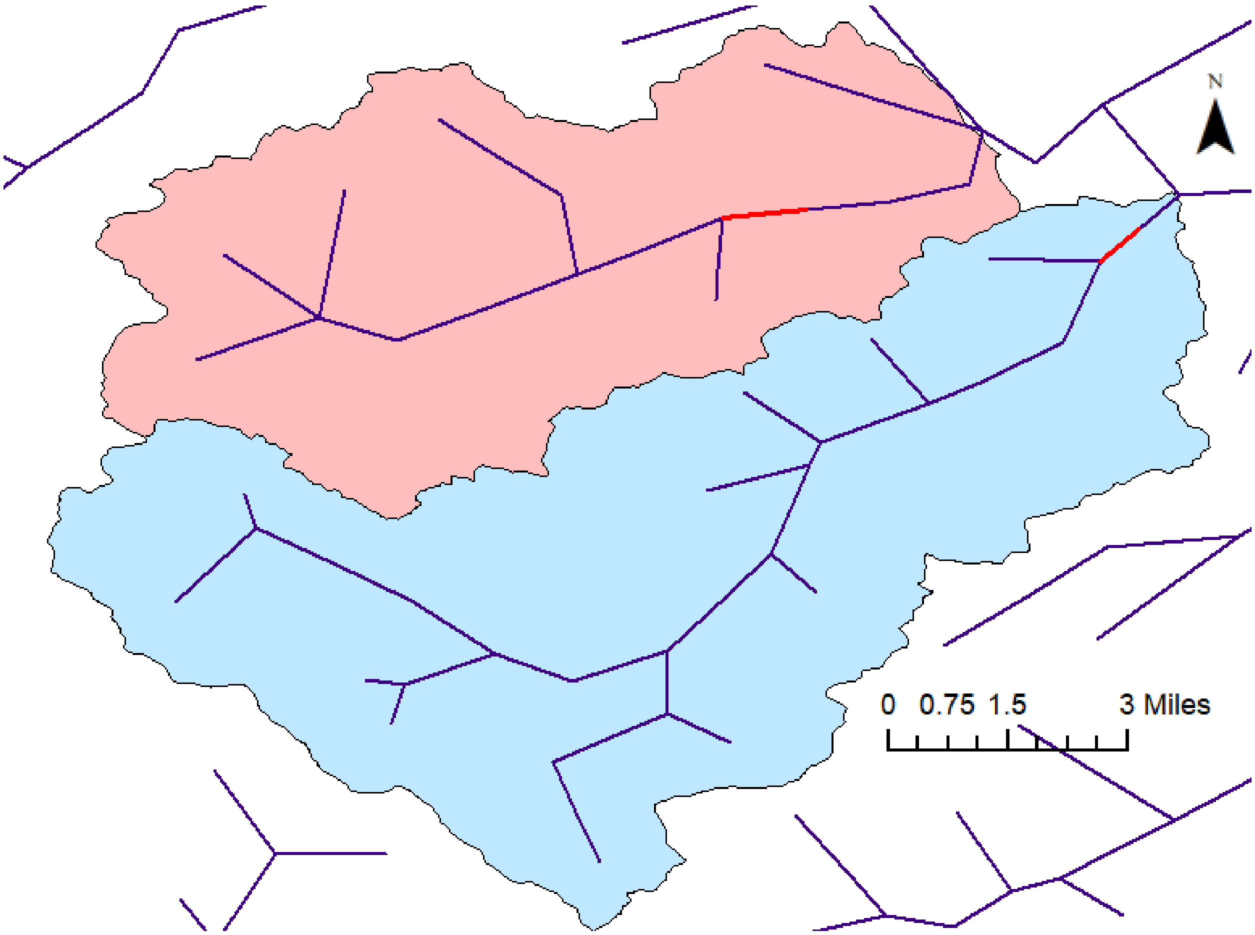

Figure 2.8: The chosen river segments for the Hinkle Creek and Mud Creek watersheds

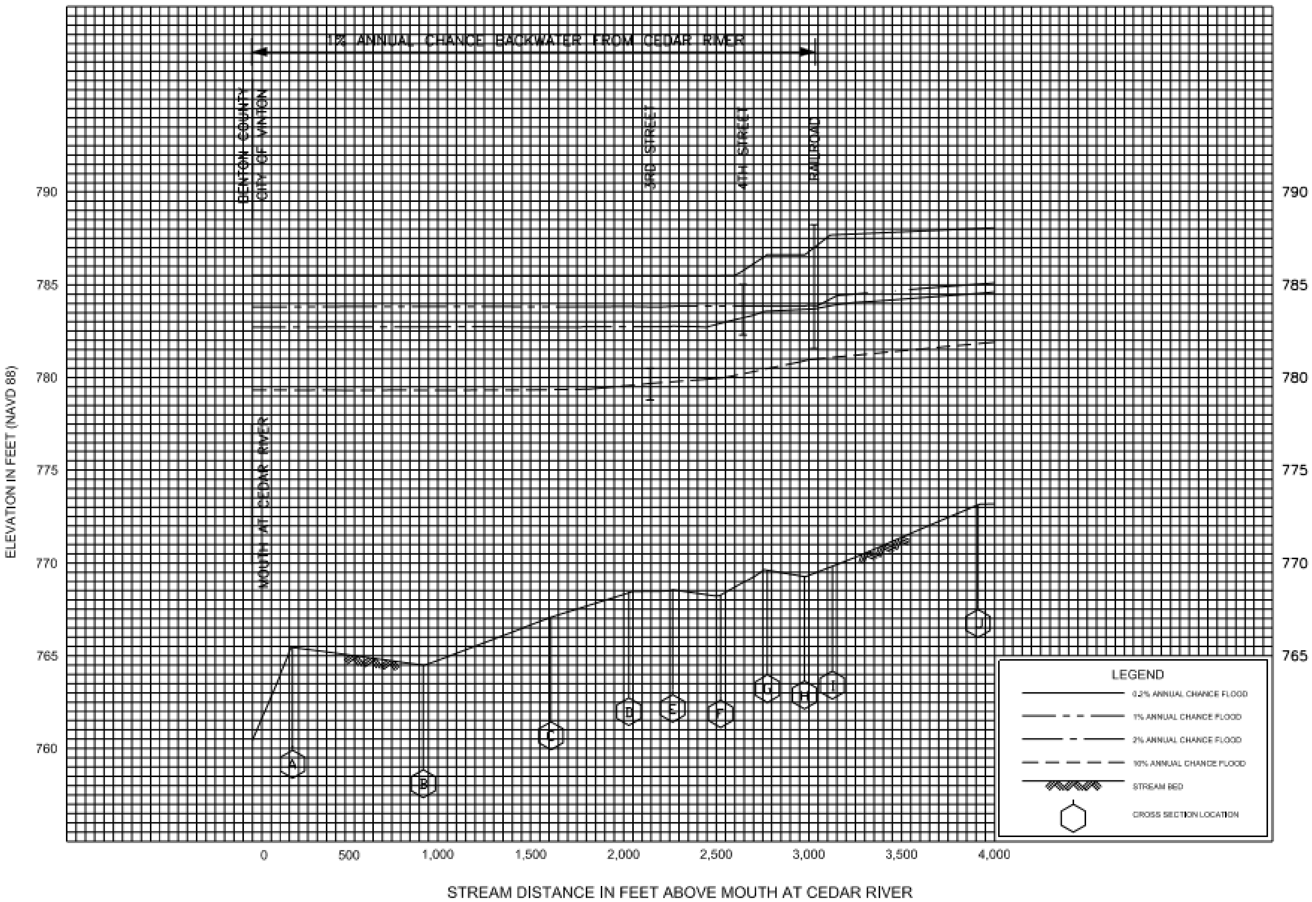

Figure 2.9: Detailed study profile for Hinkle Creek

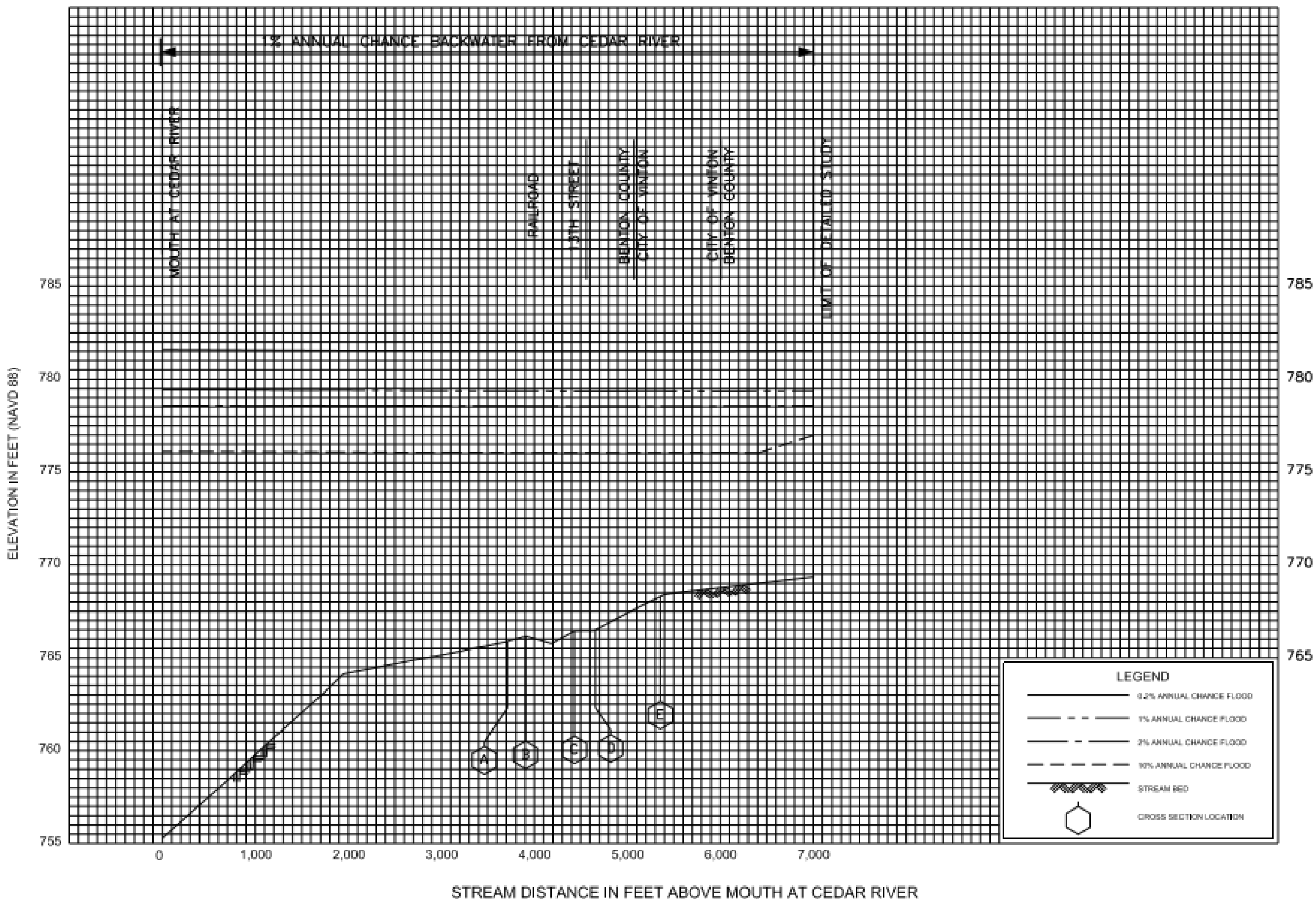

Figure 2.10: Detailed study profile for Mud Creek

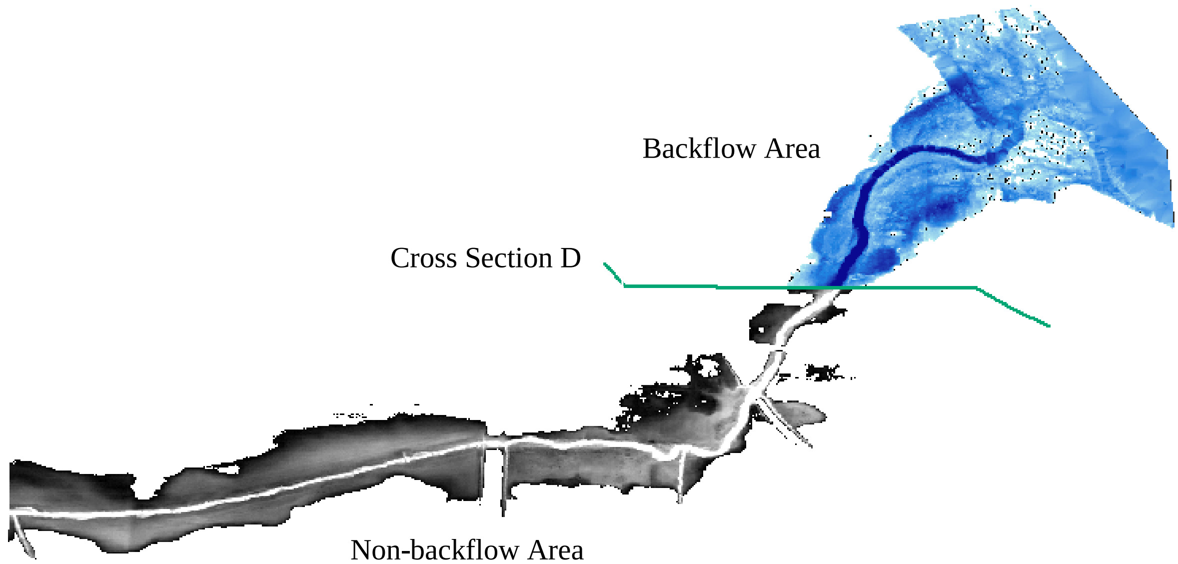

Figure 2.11: Backflow area for the 50%, 20%, 10%, and 4% floods in Hinkle Creek

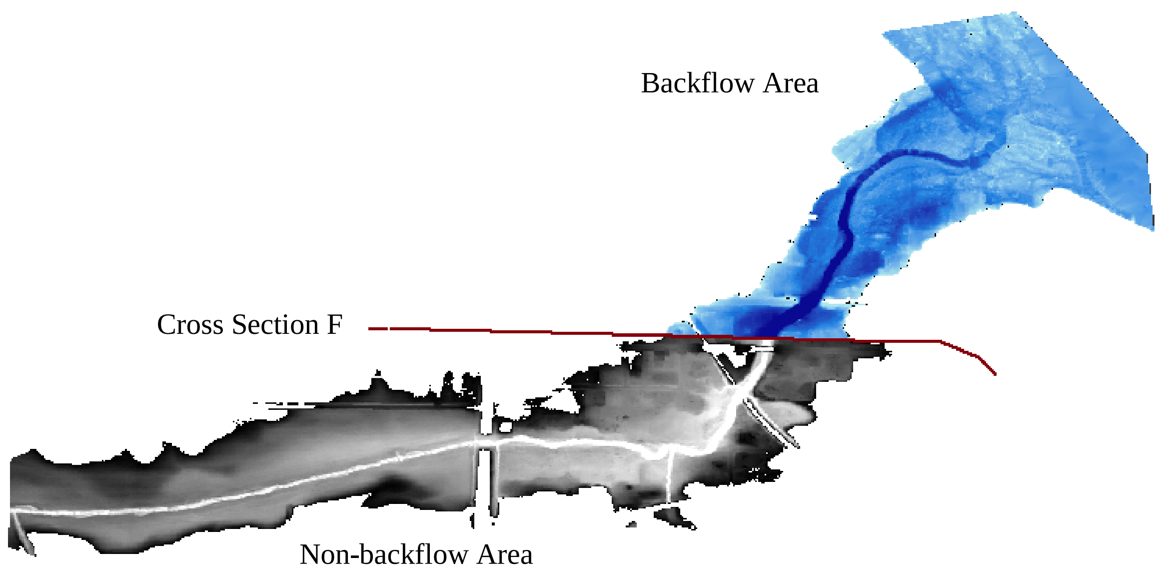

Figure 2.12: Backflow area for the 2%, 1%, 0.5% and 0.2% floods in Hinkle Creek

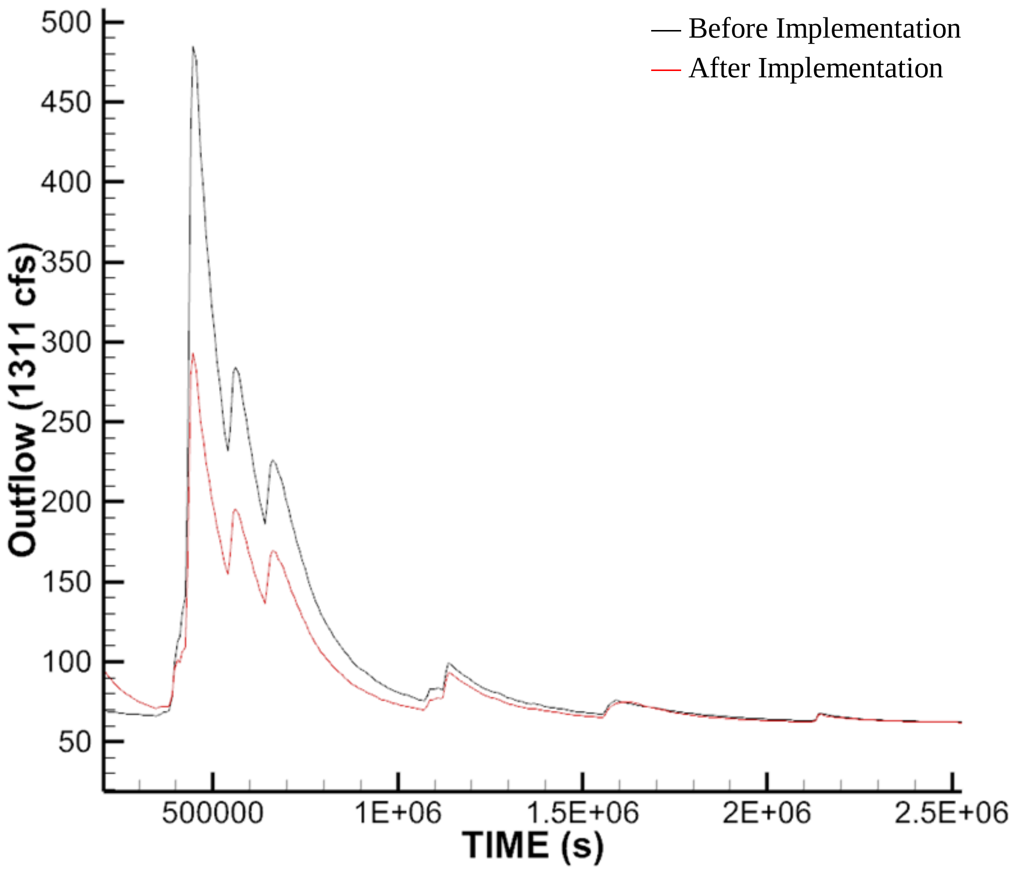

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Figure 2.13: Example of GHOST flow data at river segment 1311 with before and after implementation scenarios

Table 2.4: Target GHOST peak flows for Hinkle Creek in cfs

Annual Percent Probability	50.0%	20.0%	10.0%	4.0%	2.0%	1.0%	0.2%
Dry Minimum Baseline	1224.91	2677.70	3861.94	6763.45	8034.09	9837.44	12122.00
Dry Minimum Ponds	1273.32	2618.35	3748.58	6267.07	6149.55	8060.17	10634.00
Dry Maximum Baseline	2547.92	3875.35	4148.75	6480.14	7771.96	8731.53	11352.00
Dry Maximum Ponds	1078.57	1566.66	1714.45	2636.32	5782.16	4860.94	9642.00
Dry Average Baseline	1718.75	3188.31	4643.51	6391.69	7903.02	9284.49	15236.67
Dry Average Ponds	1504.98	2664.21	3474.41	4395.46	5965.86	6460.55	13064.67
Wet Minimum Baseline	1280.60	3526.02	4458.99	6049.86	7681.27	8670.13	12483.00
Wet Minimum Ponds	2251.33	3913.18	4923.50	6439.76	6975.65	8230.63	12034.00
Wet Maximum Baseline	2515.39	2908.17	5407.12	6252.14	7501.48	9865.28	10918.78
Wet Maximum Ponds	2175.95	2255.82	3804.16	4502.23	4647.19	7884.30	5924.10
Wet Average Baseline	1752.65	3195.35	4722.79	6121.92	7535.48	9185.94	15221.45
Wet Average Ponds	2092.24	3313.32	4441.32	5547.74	5798.96	8122.55	12888.52

Table 2.5: Target GHOST peak flows for Mud Creek in cfs

Annual Percent Probability	50.0%	20.0%	10.0%	4.0%	2.0%	1.0%	0.2%
Dry Minimum Baseline	1576.65	4233.49	5041.42	7619.59	7721.95	10259.33	14414.00
Dry Minimum Ponds	1945.17	4729.94	5602.19	6574.85	7246.61	8998.91	11706.54
Dry Maximum Baseline	1880.95	3021.68	5201.01	7074.07	8475.37	10324.57	13741.87
Dry Maximum Ponds	873.15	1772.12	3533.60	4742.76	1737.87	6769.11	6074.68
Dry Average Baseline	2067.92	3629.93	5348.59	7212.33	8160.54	10356.46	15800.53
Dry Average Ponds	1961.07	3322.59	4708.94	5518.06	6010.74	8363.09	11122.89
Wet Minimum Baseline	1593.52	2986.17	4517.72	6497.82	8401.60	11186.22	15840.69
Wet Minimum Ponds	1985.04	3340.80	4919.83	6832.77	8563.80	10716.27	14270.65
Wet Maximum Baseline	2871.73	3810.40	4896.08	6826.29	8134.97	9908.05	17433.38
Wet Maximum Ponds	2936.13	3464.14	4202.58	5883.12	6585.25	8358.79	13740.83
Wet Average Baseline	2111.36	3582.06	5131.61	6801.75	8312.33	10362.48	17123.09
Wet Average Ponds	2404.83	3779.97	5214.84	6580.77	7848.32	9436.41	14622.96

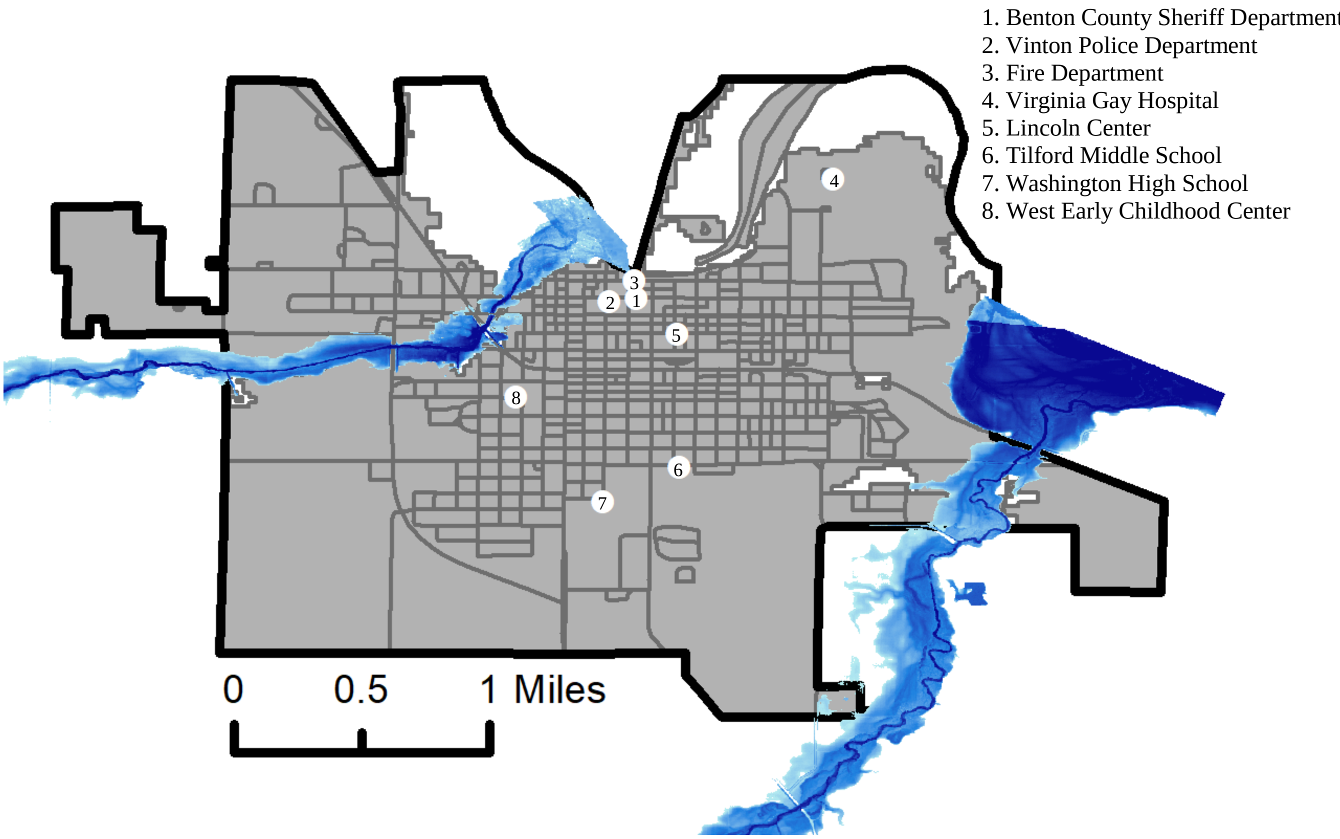

Figure 2.14. All essential facilities located in Vinton relative to the 0.2% probability flood

3. RESULTS AND DISCUSSION

3.1 BCRs from Percent Reduction

The first approach that we analyzed found the avoided losses from flood retention wetlands by simulating peak flow changes using the percent reduction approach. To determine the effects of a multijurisdictional approach on the BCRs of proposed flood retention wetlands, we simulated before- and after-implementation scenarios using the percent reduction approach. The total 30-year net benefit of implementing flood retention wetlands in Hinkle Creek was $969,700. Moreover, the avoided losses increased as the annual flood percent probability decreased (Figure 3.1). Accordingly, the avoided losses for each annual flood percent probability were positive, implying that the wetlands were saving money downstream despite the size of the flood. Furthermore, agricultural avoided losses constituted the majority of the total avoided losses for the higher annual percent probability floods, but the total avoided losses were predominantly from the user-defined facilities for the smaller percentage probability floods (Figure 3.5). In addition, the avoided losses were predominantly agricultural in the higher probability floods because HAZUS-MH calculated agricultural losses by extent over depth. Therefore, while the higher probability floods were not deep enough to cause substantial user-defined facilities, they extended into the agricultural lands, thereby causing higher damages. On the other hand, in the lower probability floods, the depth was much greater, thereby causing higher user-defined losses.

In Mud Creek, the 30-year net benefit of the simulated wetlands was $2,793,700. Interestingly, the relationship between avoided losses and annual flood percentage probability existing in the Hinkle Creek results did not exist for the Mud Creek results, which remained constant as the annual flood percentage probability changed (Figure 3.2). The average total avoided losses were $282,570 with a standard deviation of only $38,272. Similarly, in Mud Creek, the total avoided losses for each annual flood percentage probability in the percent reduction approach were all positive. This was expected as only decreases to peak flow were considered in the percent reduction approach, which would make all avoided losses positive. Therefore, the total avoided losses were predominantly agricultural for the higher probability floods in Mud Creek as well (Figure 3.6). However, the agricultural and user-defined facilities avoided losses split was much more even in the lower probability floods in Mud Creek. This may have been because the Mud Creek watershed had fewer user-defined facilities compared to Hinkle Creek, resulting in the proportion of agricultural avoided losses being higher in the lower probability floods.

Individually, the Mud Creek watershed met the BCR requirement over a range of wetland costs and managed to yield BCRs of at least 0.75 for capital costs per wetland up to $177,400. However, the Hinkle Creek watershed did not meet the FEMA BCR requirement for even the lowest end of the range of capital costs per wetland (Figure 3.3). Consequently, the highest capital cost per wetland that would yield a BCR of 0.75 was $92,300 in the Hinkle Creek watershed. Moreover, although the multijurisdictional approach had raised the BCRs of Mud Creek enough to create competitive applications for federal assistance for a wide range of wetland costs, the properties affected by Hinkle Creek flooding would not receive any benefits.

While flood mitigation efforts in the Hinkle Creek did not create BCRs above 0.75 on their own, the multijurisdictional approach does not limit the analysis to a single HUC12 watershed. Thus, the Hinkle Creek and Mud Creek watersheds can be considered together since they both surround the same downstream town. When the net benefits are compared to the capital costs across both wetlands, the resulting BCRs are high enough meet the FEMA requirement (Figure 3.4). In addition, the maximum capital cost per wetland still yielding BCRs of at least 0.75 was $143,300 when the simulated flood retention wetland projects for the Hinkle Creek and Mud Creek watersheds were considered together.

3.1. BCRs from Targeted Peak Flows

To determine how using targeted peak flow approach results impacted the BCRS of simulated flood retention wetlands, we used HAZUS-MH to compare before- and after-implementation scenarios for the minimum, maximum and average decrease to peak flows as well as wet and dry antecedent soil moisture conditions. As expected, in Hinkle Creek, the maximum decrease scenarios yielded the highest total avoided losses in both the wet and dry antecedent moisture conditions, and the minimum decrease scenarios yielded the lowest avoided losses (Figure 3.7). Consequently, the majority of the avoided losses in Hinkle Creek from the targeted peak flows approach were agricultural (Figure 3.9). The avoided losses were predominantly agricultural for higher probability floods with an even split in the lower probability floods. The average agricultural proportion for the 50% flood scenarios were 83%, which decreased to 49% for the 0.2% flood scenarios. In addition, the avoided losses were more agricultural in the dry antecedent soil moisture conditions with an average of 77%, 73% and 72% for the minimum, average and maximum peak flow change scenarios, respectively. Moreover, the average agricultural proportions under wet antecedent soil moisture conditions were 60%, 75% and 60% for the minimum, average and maximum peak flow change scenarios, respectively.

Interestingly, in some cases, the total avoided losses were negative, indicating that the flood losses in the after-implementation scenario were larger compared to the before-implementation scenario. Therefore, the flood retention wetlands have caused higher downstream damages in some cases. Accordingly, for both the Hinkle Creek and Mud Creek watersheds, negative avoided losses occurred most often under wet antecedent soil moisture conditions. As a result, we believe that overtopping of the wetland outlet structure during floods was the cause of increased damages in the wet condition. When the soil is wet, it is likely that underflow is exiting the wetlands and the water will infiltrate poorly when the soil is saturated. Such poor infiltration may cause the wetlands to fill quickly and overtop, combining with the underflow to increase the total outflow. Moreover, negative avoided losses occurred for 50% flood under minimum peak change and dry antecedent soil moisture conditions. In accordance with the above, the wetlands may be holding water such that the peak outflow is delayed to simultaneously occur with peak outflows from elsewhere in the watershed. Subsequently, the peak outflows from the wetlands may occur simultaneously to combine and create one larger peak flow downstream. Therefore, we believe that negative avoided losses occur due to wetland overtopping under wet antecedent soil moisture and peak outflow delay while simultaneously releasing under dry antecedent soil moisture.

As regards the minimum peak changes, the avoided losses increased as the annual flood percentage probability decreased (Figure 3.9). This relationship was less pronounced in the average peak change scenarios for both antecedent soil moisture conditions. However, in the maximum peak change scenario, this result only occurred in the wet soil moisture condition. Consequently, the avoided losses did not follow this relationship for dry soil moisture conditions, with the 4.0% probable flood generating the largest avoided losses. Further, the average decrease to peak flow for the dry maximum conditions was 46% with a standard deviation of 17%. Thus, the high decreases in peak flow and the large standard deviation led to high avoided losses without a clear trend.

In the Mud Creek watershed, as expected, the avoided losses were greatest for the maximum peak change scenarios for both antecedent soil moisture conditions as well (Figure 3.8). Similar to the results of the Hinkle Creek watershed, the dry antecedent soil moisture conditions generated larger avoided losses compared to the wet antecedent soil moisture conditions in all three peak change scenarios. Moreover, the avoided losses increased as the annual flood percentage probability decreased, except for in the maximum peak change scenario for the dry antecedent soil moisture conditions (Figure 3.10). In addition, the magnitude of the avoided losses for the maximum change of the dry soil moisture conditions in Mud Creek were significantly larger than any of the other avoided losses in either watershed. Accordingly, the average peak flow decrease in Mud Creek with dry antecedent soil moisture was 47% with a 16% standard deviation. While the magnitude in peak flow change was similar in Mud Creek compared to Hinkle Creek, the avoided losses were substantially larger in the Mud Creek watershed due to higher building and content exposure. The avoided losses were predominantly agricultural in Mud Creek (Figure 3.12). Subsequently, the average agricultural proportion of the total avoided losses for all annual flood probabilities in all scenarios was 84%. Hence, neither the antecedent soil moisture nor the peak flow change scenario had much impact on the proportion of agricultural damages. Furthermore, the average agricultural proportion of avoided losses were 87%, 73% and 86% for the minimum, average and maximum peak flow scenarios, respectively, under dry antecedent soil moisture condition, and 84%, 85% and 87%, respectively, under wet antecedent soil moisture conditions.

To determine how the returns on investment varied between the different targeted peak flow scenarios, the benefit-cost ratios were calculated for each of the six conditions based on a range of estimated capital costs per wetland, stretching from $100,000 to $200,000. In the Hinkle

Creek watershed, dry antecedent soil moisture conditions with the maximum change to peak flow (Figure 3.13) produced the highest BCRs. Moreover, the dry maximum scenario maintained BCRs over 0.75 for the entire range of capital costs. In fact, the BCRs were over 1.0 for the entire range of capital costs, implying that in the dry maximum scenario, the wetlands saved more money over their lifetimes than it cost to implement them. Accordingly, the dry maximum scenario produced BCRs over 0.75 until the capital costs per wetland reached $360,750. However, not all the scenarios returned such high BCRs. Only the dry average scenario and the wet maximum scenarios generated BCRs of over 0.75 (Figure 3.14). In addition, the dry average scenario maintained a BCR of over 0.75 until the capital costs reached $100,100 while the maximum wet scenario maintained BCRs of over 0.75 until the capital costs reached $145,000. None of the other targeted peak flow approach scenarios had benefits high enough for the BCRs to ever reach 0.75. Further, the wet minimum and wet average scenarios had negative BCRs, which is unsurprising since their 30-year gross benefits were also negative.

Similar to the Hinkle Creek results, the dry maximum conditions generated the highest BCRs (Figure 3.17) in Mud Creek, where the dry maximum scenario was the only targeted peak flow approach scenario that generated BCRs of over 0.75. Moreover, the highest capital cost for the dry maximum scenario that still produced BCRs of over 0.75 was $184,800. However, all the other scenarios failed to meet the FEMA requirement. Additionally, the dry average conditions produced the next highest BCRs after the dry maximum conditions, followed by the wet maximum conditions (Figure 3.18). Although neither of those two scenarios generated BCRs of over 0.75, they were still positive while all the other targeted peak flow scenarios in Mud Creek generated negative BCRs.

When the benefits from the projects in both Mud Creek and Hinkle Creek were combined, only the dry maximum scenario generated BCRs of over 0.75 for the targeted peak flow approach (Figure 3.21). Consequently, although the combined benefits for the wet maximum and dry average scenarios were high enough to generate positive BCRs, the rest of the scenarios still only created negative BCRs.

3.2 Comparing BCRs from Each Peak Flow Adjustment Approach

The results of each approach were compared to determine which peak change approach generated higher gross benefits and BCRs. In the Hinkle Creek, the percent reduction method yielded a 30-year gross benefit of $924,504. Furthermore, the dry maximum, dry average and wet maximum scenarios exceeded the benefits of the percent reduction approach. Moreover, the dry average scenario 30-year gross benefit of $1,051,373.78 in Hinkle Creek was the closest to the 30-year gross benefit found in the percent reduction approach (Figure 3.7). Surprisingly, the dry maximum scenario was the targeted peak flow scenario that differed the most from the peak reduction results, despite some scenarios producing negative 30-year gross benefits. The percent reduction results were greater than the dry minimum, wet average and wet minimum condition benefits. However, the average of all the 30-year benefits for the targeted peak flow approach was $884,660, which was closer to the percent reduction benefit than any of the individual scenario benefits. Accordingly, the BCRs of the percent reduction approach were closest to the BCRs of the dry average scenario owing to having the closest 30-year gross benefit.

In the Mud Creek watershed, the percent reduction method yielded a gross benefit of $2,793,700. Consequently, the dry maximum scenario was the only targeted peak flow approach in Mud Creek to exceed the benefit from the percent reduction approach, thereby generating a 30-year gross benefit of $2,960,533. Interestingly, the dry maximum scenario benefit was also the closest to the percent reduction approach benefit. Accordingly, the average 30-year benefit of all six scenarios in Mud Creek was only $387,066.77, which was significantly lower than the percent reduction approach benefit. The percent reduction approach was more economically appealing in Mud Creek compared to all other targeted peak flow scenarios aside from the dry maximum conditions. The maximum capital cost per wetland for the dry maximum targeted peak flow scenario that still created BCRs of over 0.75 was $184,800. Therefore, compared to the percent reduction approach, which showed a maximum capital cost per wetland of $177,400, the dry maximum scenario performed slightly better.

3.3 Effects of Backflow

To find the impact that backflow from the Cedar River had on the finances of flood prevention in the Hinkle Creek and Mud Creek watershed, we compared the gross benefits and BCRs of the targeted peak flow approach scenarios with backflow to those without backflow. In Hinkle Creek, the BCRs slightly increased for all targeted peak flow based scenarios when backflow was excluded (Figure 3.15 & Figure 3.16). Moreover, the changes in BCR were consistent for both the dry and wet antecedent soil moisture conditions. The BCRs for the dry maximum scenario were still over one for the entire range of wetland capital costs. However, the maximum capital costs that yielded BCRs of over 0.75 were significantly higher for the wet maximum and dry average conditions. In addition, the maximum capital cost that yielded a BCR of 0.75 in the dry average scenario without backflow was $111,500, which was $11,400 higher compared to when backflow had been included. Further, the maximum capital costs of the wet maximum scenario without backflow was $173,500, which was $28,500 higher than with backflow being accounted for. Moreover, the scenarios that included backflow had lower BCRs because the areas affected by backflow were unaffected by any peak flow reductions caused by upstream flood retention wetlands. Thus, when backflow was included, the flood level did not change in the areas close to the Cedar River when upstream flood retention wetlands were implemented. Accordingly, unchanged flood levels meant no change to flood damages, thus resulting in the lack of financial benefit in the backflow affected areas. Since the scenarios that did not include backflow decreased the peak flow in the areas that would have otherwise had unchanged peak flows, the flood damages decreased when backflow was excluded, while they would have remained constant with backflow included. However, the changes to peak flow were still included in the cases that the peak flow increased because of the flood retention wetlands. Changes were included for these scenarios because when the peak flows increased, more water was being delivered to all downstream areas, including the backflow affected areas. In turn, the flood damages for the backflow affected areas increased whenever the flood retention wetlands caused increases in the peak flow.

In addition, the BCRs in Mud Creek watershed increased when backflow effects were not included (Figure 3.19 & Figure 3.20). However, the differences in BCR in the Mud Creek watershed were smaller compared to the Hinkle Creek watershed. Further, the largest difference between BCRs when backflow effects were excluded occurred in the wet minimum scenario. On the other hand, the BCRs for the dry maximum scenario slightly increased whenever backflow was excluded. Thus, when backflow was excluded, the maximum capital cost per wetland for the dry maximum scenario increased to $188,000, which was $3,200 greater than whenever backflow was included. Consequently, none of the other scenarios met the FEMA BCR requirement even when backflow was excluded. Moreover, the percent reduction approach results were closer to the dry maximum scenario with backflow compared to the dry maximum scenario without backflow, which is reasonable since the percent reduction approach included backflow as well. Therefore, the difference between the 30-year benefit from the percent reduction approach and the dry maximum 30-year benefit increased from $116,731 to $166,833 when backflow was excluded.

In accordance with the above, decreased BCRs indicate that the effects of upstream flood retention wetlands are likely to be most economical in areas where backflow is not an issue. Thus, HUC12 scale watersheds that do not have cities close to the outlets may have higher BCRs since they do not have to deal with backflow effects from larger rivers. However, the decrease in BCRs due to backflow effects being included were not large enough to disregard flood mitigation in cities that must deal with backflow from a larger river downstream. Additionally, upstream flood mitigation can still be economically viable even when backflow from a large river source is present. Therefore, upstream flood retention can be financially viable in both the Hinkle Creek and Mud Creek watersheds despite the effects of backflow being accounted for.

However, when analyzing the effects of flood retention wetlands on flooding in the Hinkle Creek and Mud Creek watershed, backflow must be excluded in the actual application for federal funding. As mentioned earlier, the wetlands would not have any effect on the flooding of the backflow areas. Thus, including damages from backflow from the Cedar River would include damages outside of the scope of the flood retention wetland projects in the Hinkle Creek and Mud Creek watershed. In turn, the BCRs of the flood retention wetlands in each watershed would decrease because of outside factors that the wetlands would have no factor in controlling. By excluding backflow, the flood damages are limited to just the area in which the flood retention wetlands affect peak flows, and the benefits accurately reflect the impacts that the wetlands would have.

3.4 Avoided Losses Based on Variable Storage

To determine the economics of flood storage, we compared the amount of money saved per acre-feet (ac-ft) of variable storage in each watershed. In the Hinkle Creek watershed, the avoided losses per acre foot of storage, ranging from a maximum of $13,348/ac-ft to a minimum of $(3,198)/ac-ft (Table 3.3), were substantially variable. Interestingly, the avoided losses per ac-ft of storage had a narrower range in the Mud Creek watershed, which were a maximum of $5,841/ac-ft and a minimum of $(1,628)/ac-ft. Thus, the smaller range of avoided losses per ac-ft of storage may be due to the higher amount of total variable storage in the Mud Creek watershed. Accordingly, the Mud Creek watershed had 498 ac-ft of total variable storage whereas the Hinkle Creek watershed only had 283 ac-ft of total variable storage. However, interestingly, the average variable storage was similar between the two watersheds with 23.7 ac-ft in the Mud Creek and 20.3 ac-ft in the Hinkle Creek. Since the average variable storage was similar in both watersheds, the higher total variable storage in the Mud Creek watershed likely was the cause of the decreased variability of avoided losses per ac-ft of storage.

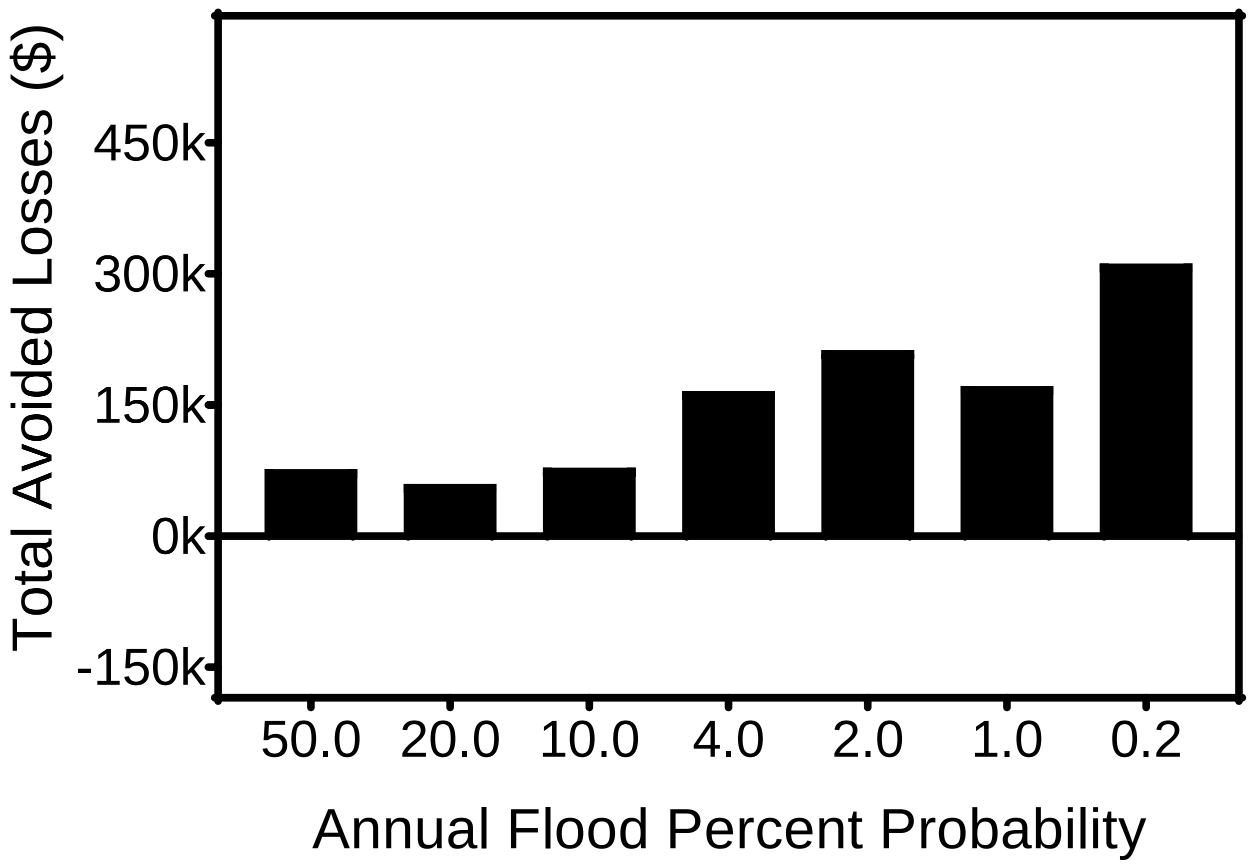

Figure 3.1. Total avoided losses in the Hinkle Creek watershed for the percent reduction approach to simulating flood reduction

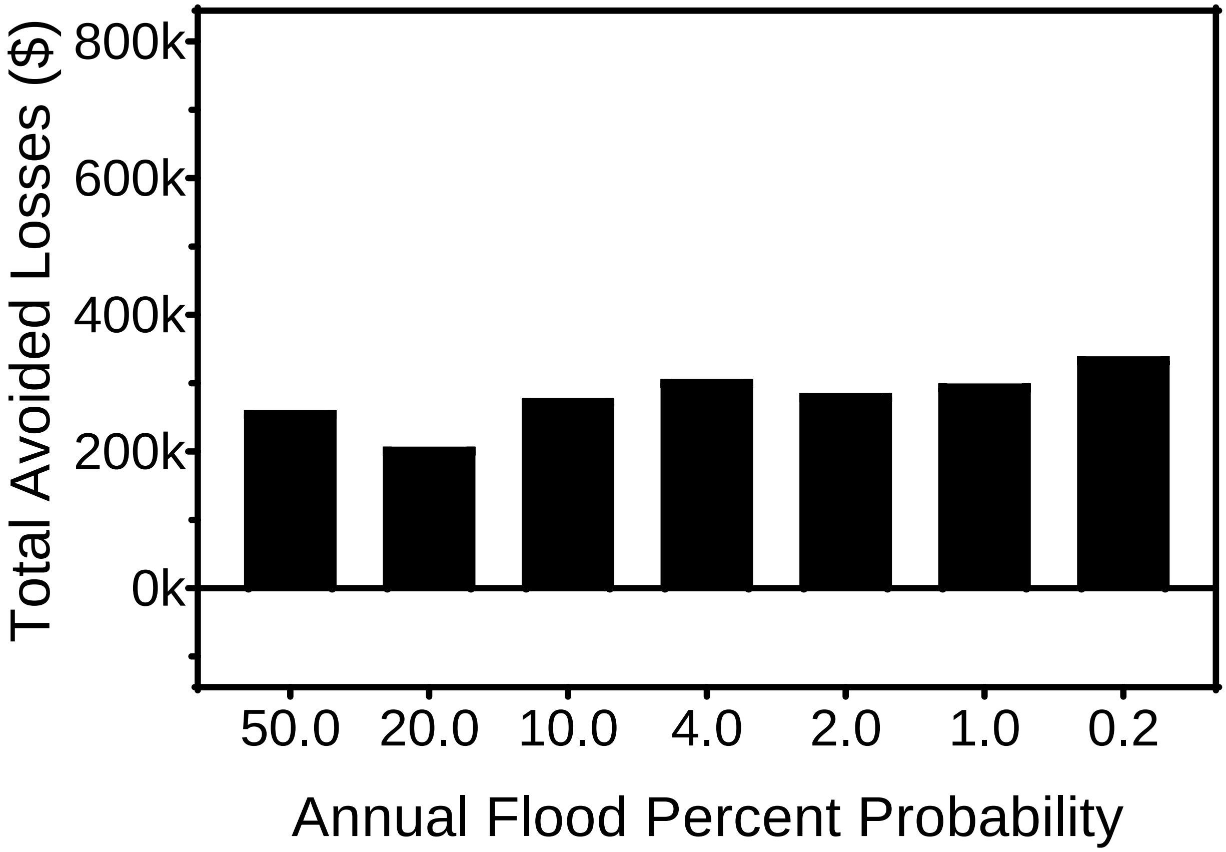

Figure 3.2. Total avoided losses in the Mud Creek watershed for the percent reduction approach to simulating flood reduction

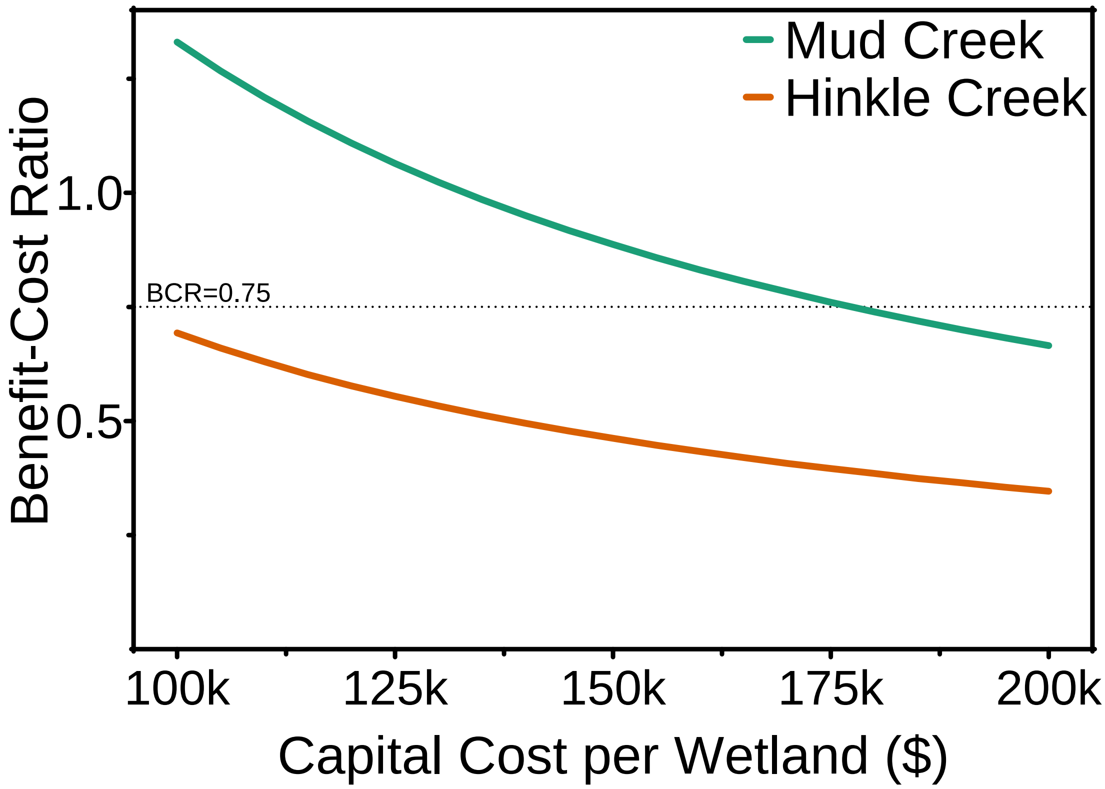

Figure 3.3. Benefit-cost ratios for the percent reduction approach in the Hinkle Creek and Mud Creek watersheds

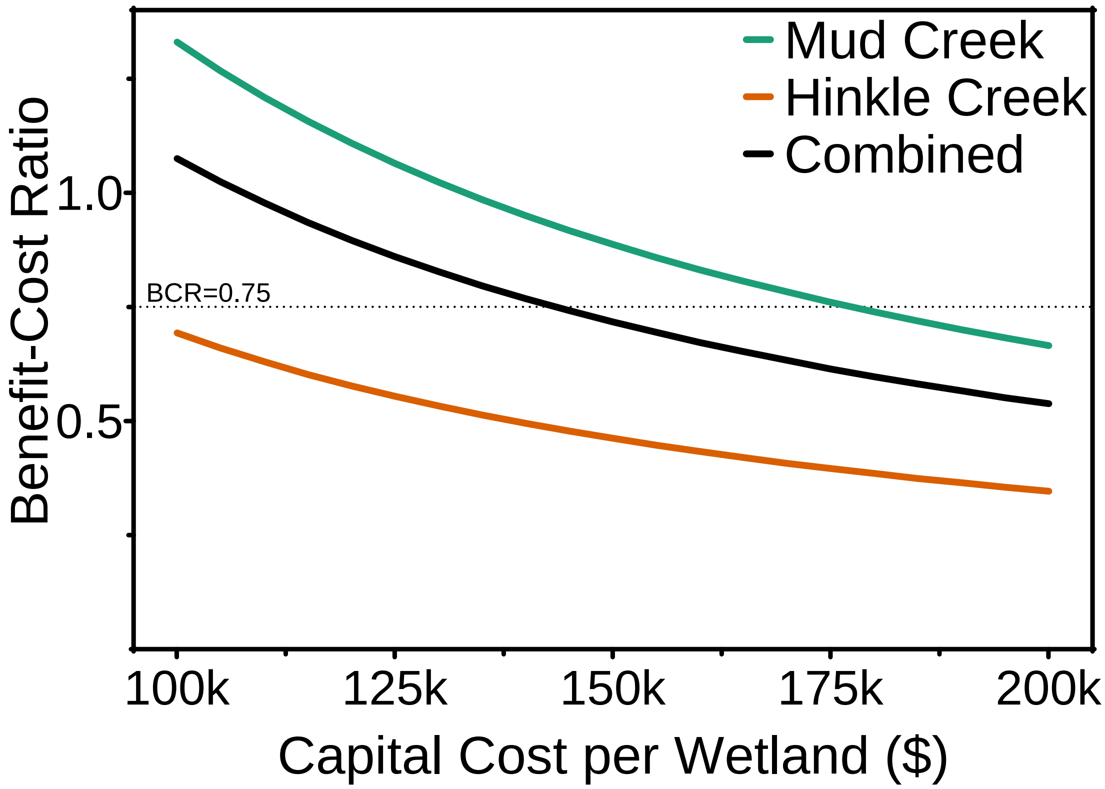

Figure 3.4. Benefit-cost ratios for the percent reduction approach combining the Mud Creek and Hinkle Creek mitigation projects

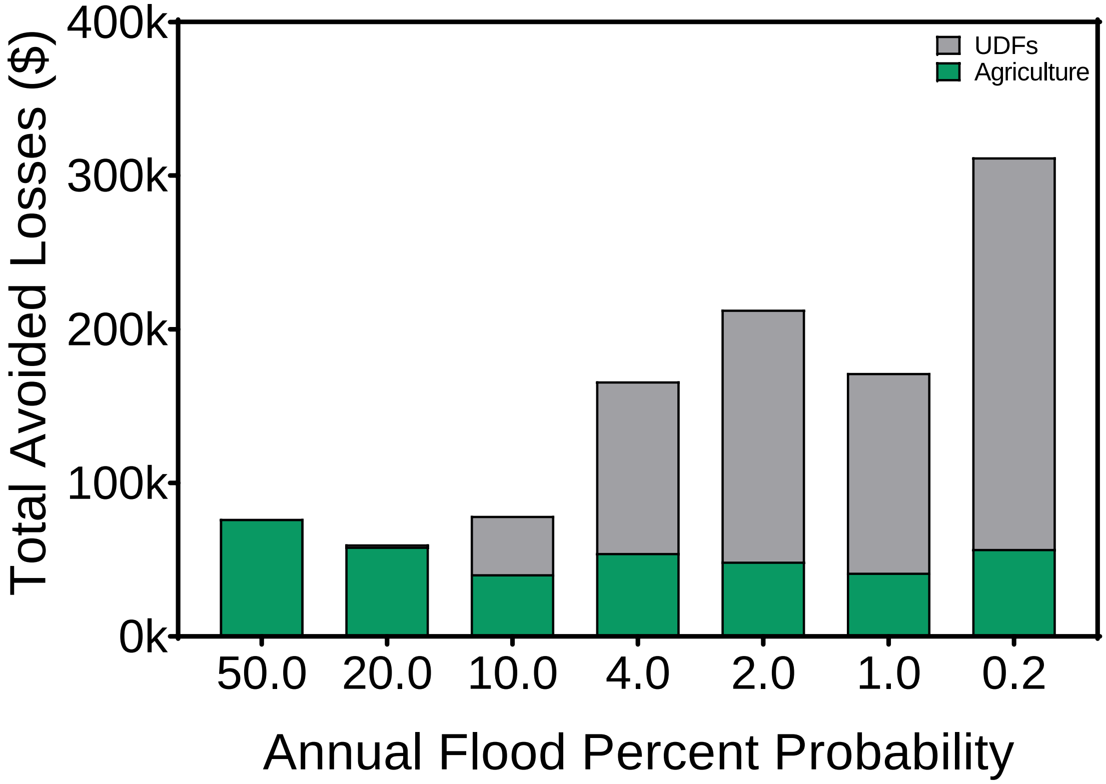

Figure 3.5. Agricultural and user-defined facilities avoided losses in the Hinkle Creek watershed using the percent reduction approach

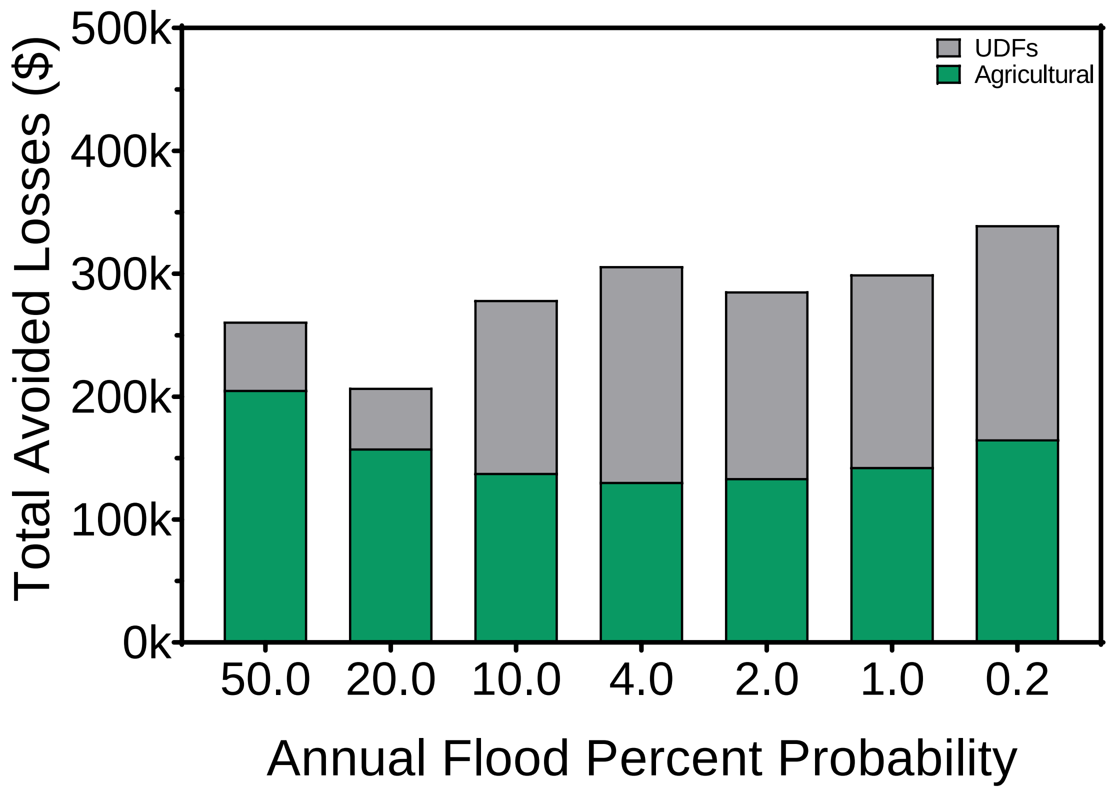

Figure 3.6. Agricultural and user-defined facilities avoided losses in the Mud Creek watershed using the percent reduction approach

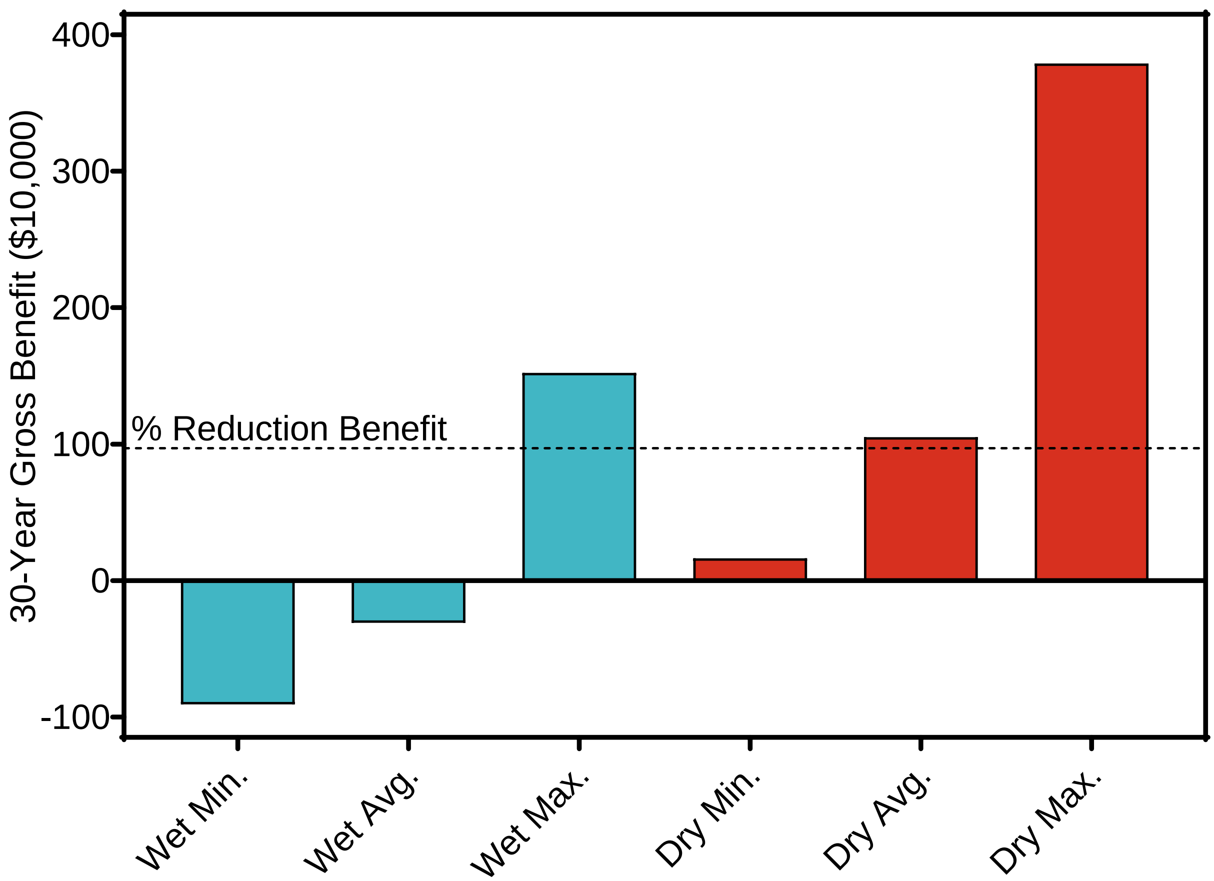

Figure 3.7. The gross benefit of the wetlands in Hinkle Creek over the useful lifetime of 30 years for all six antecedent moisture and peak change conditions from the targeted peak flow approach

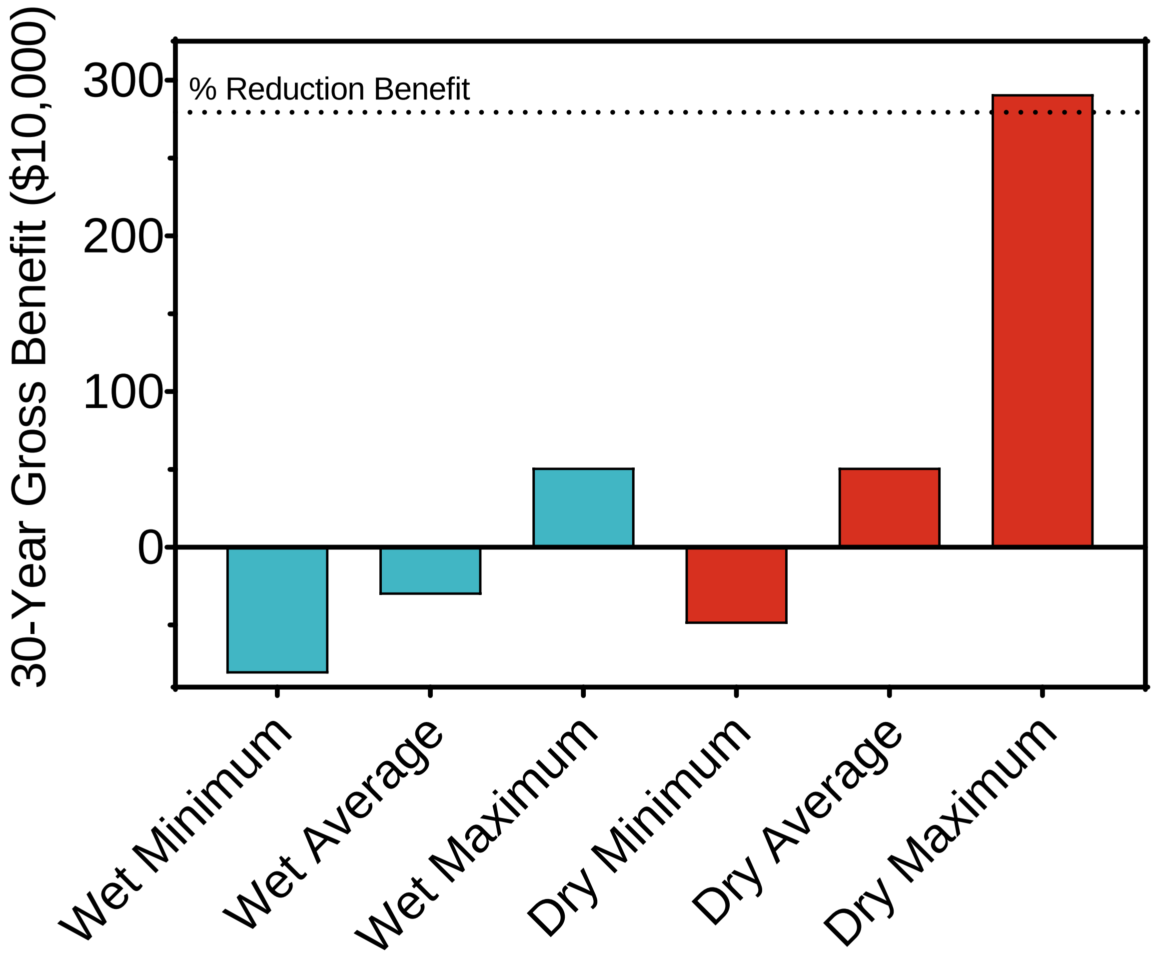

Figure 3.8. The gross benefit of the wetlands in Mud Creek over the useful lifetime of 30 years for all six antecedent moisture and peak change conditions from the targeted peak flow approach

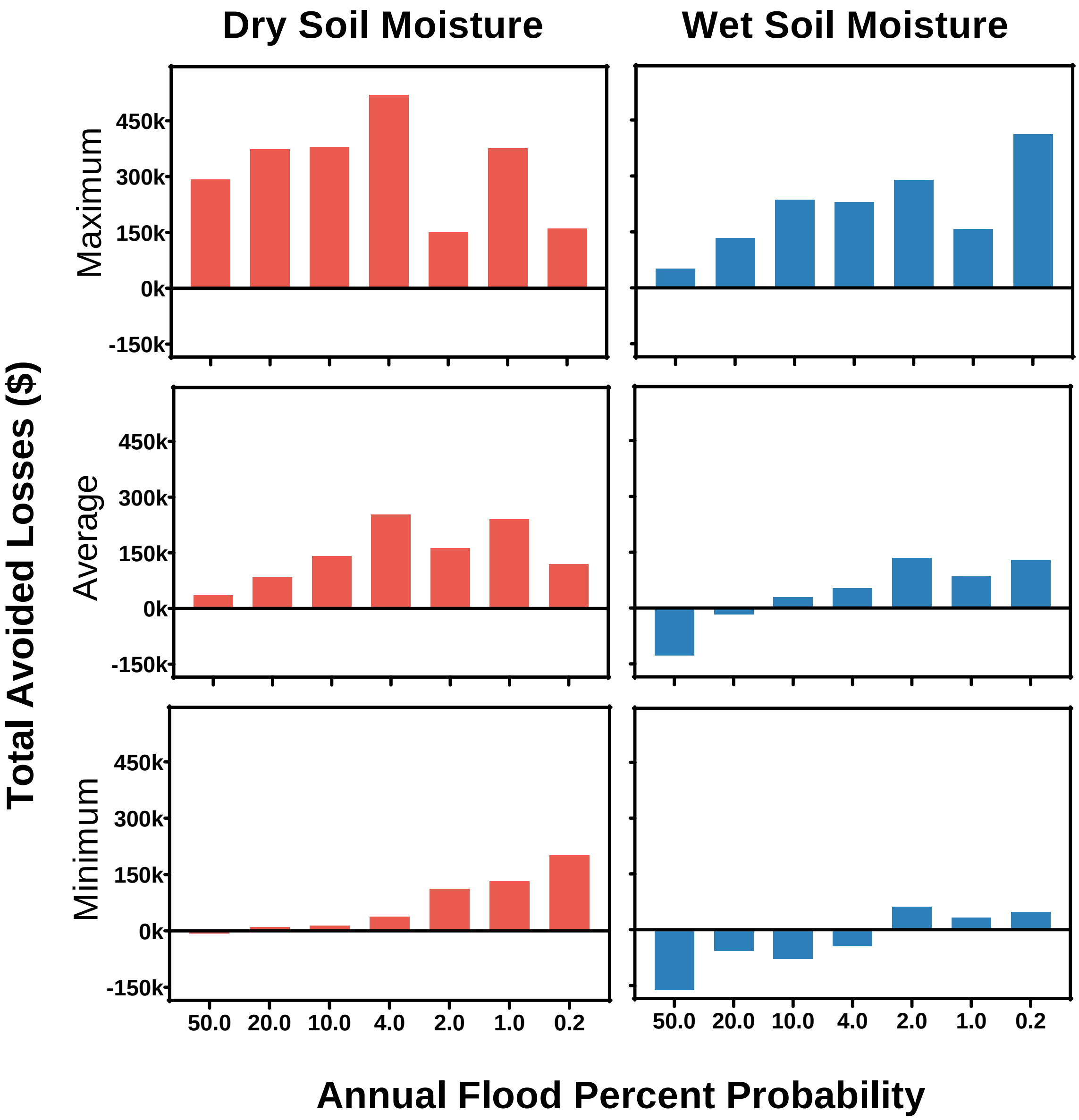

Figure 3.9. Total avoided losses for the Hinkle Creek watershed for dry and wet antecedent soil moisture and the minimum, average and maximum changes to peak flow

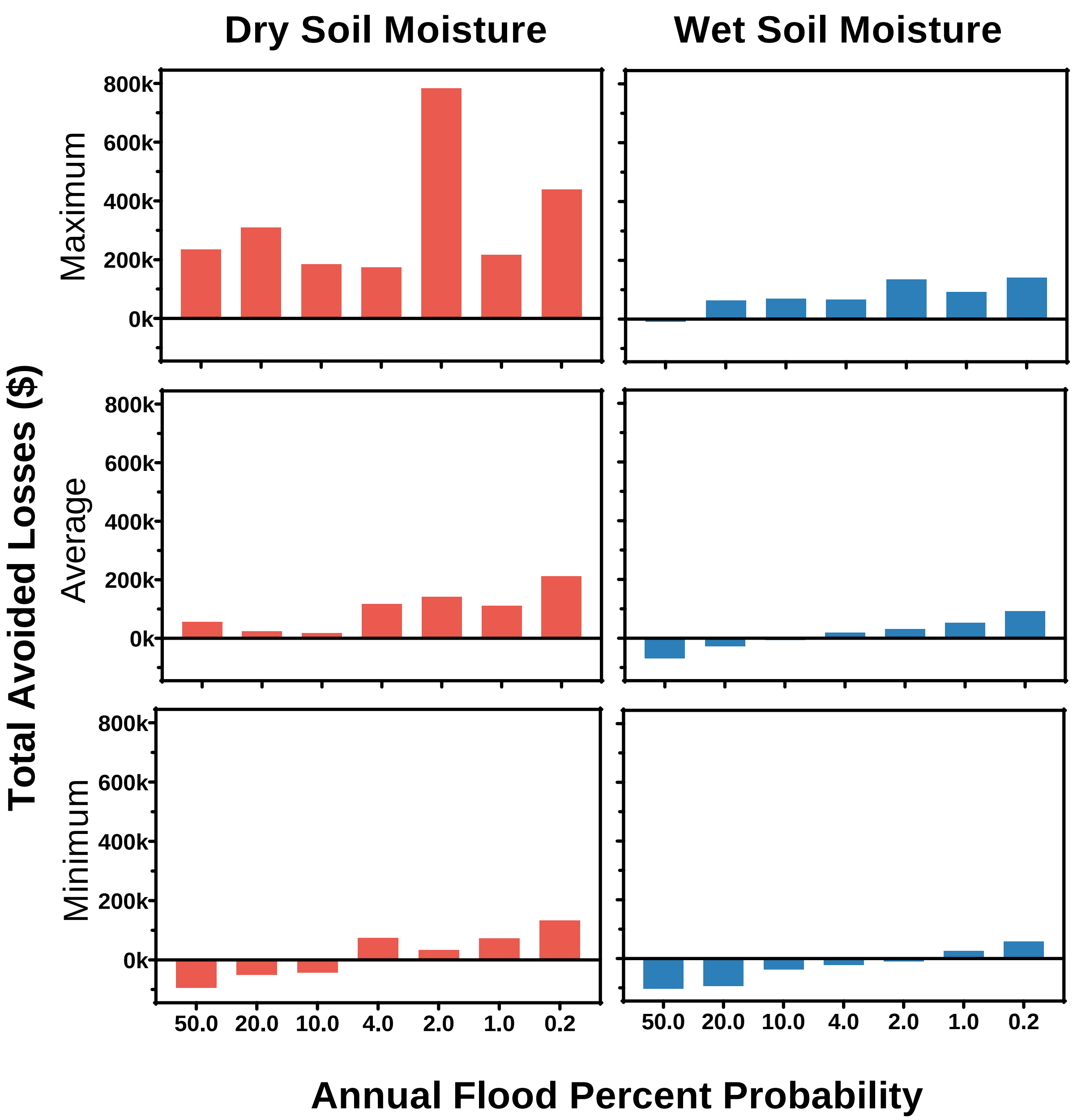

Figure 3.10. Total avoided losses for the Mud Creek watershed for dry and wet antecedent soil moisture and the minimum, average and maximum changes to peak flow

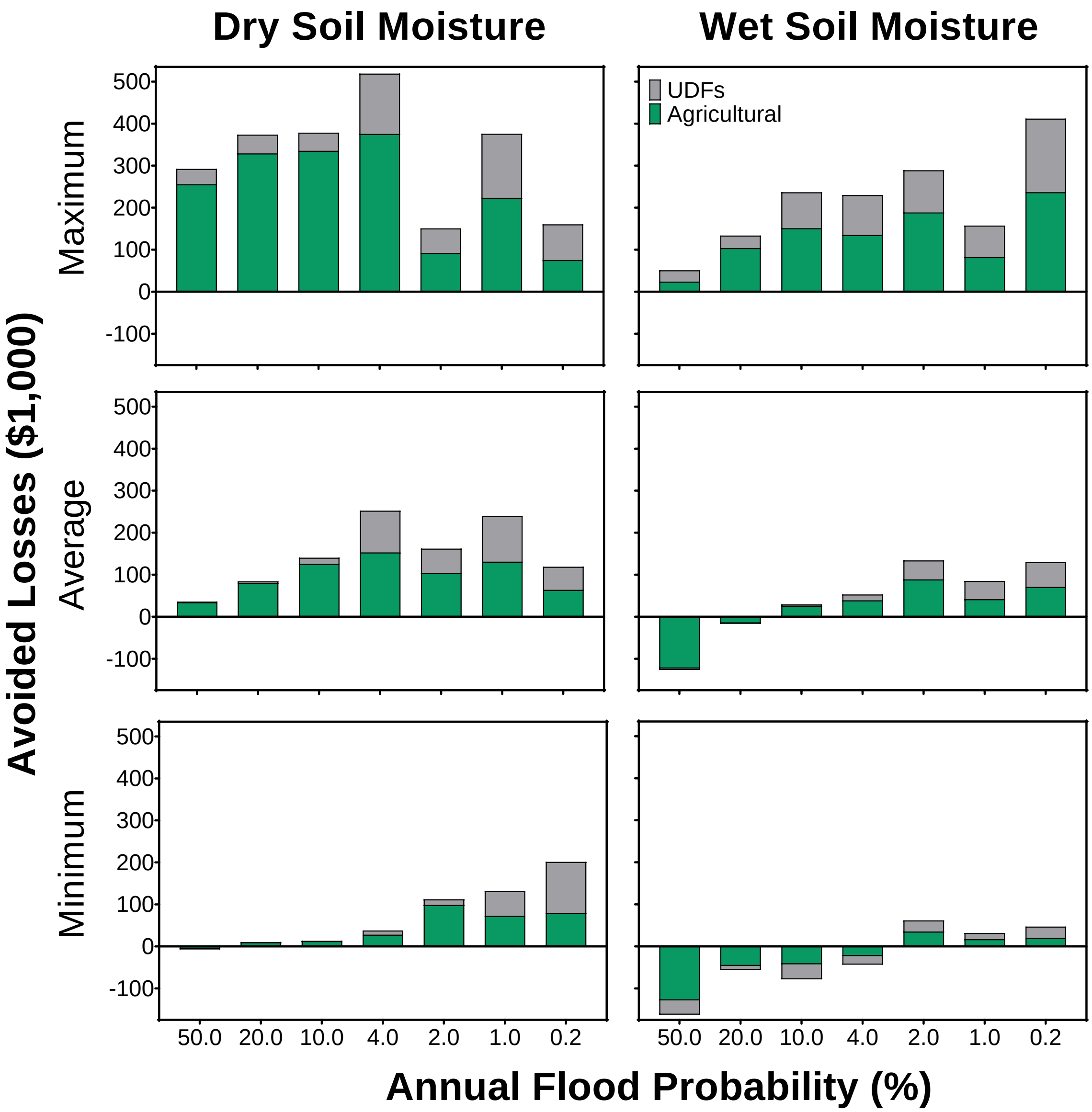

Figure 3.11. Agricultural and user-defined facilities avoided losses in Hinkle Creek by annual flood probability for dry and wet antecedent soil moisture and the minimum, average and maximum changes to peak flow

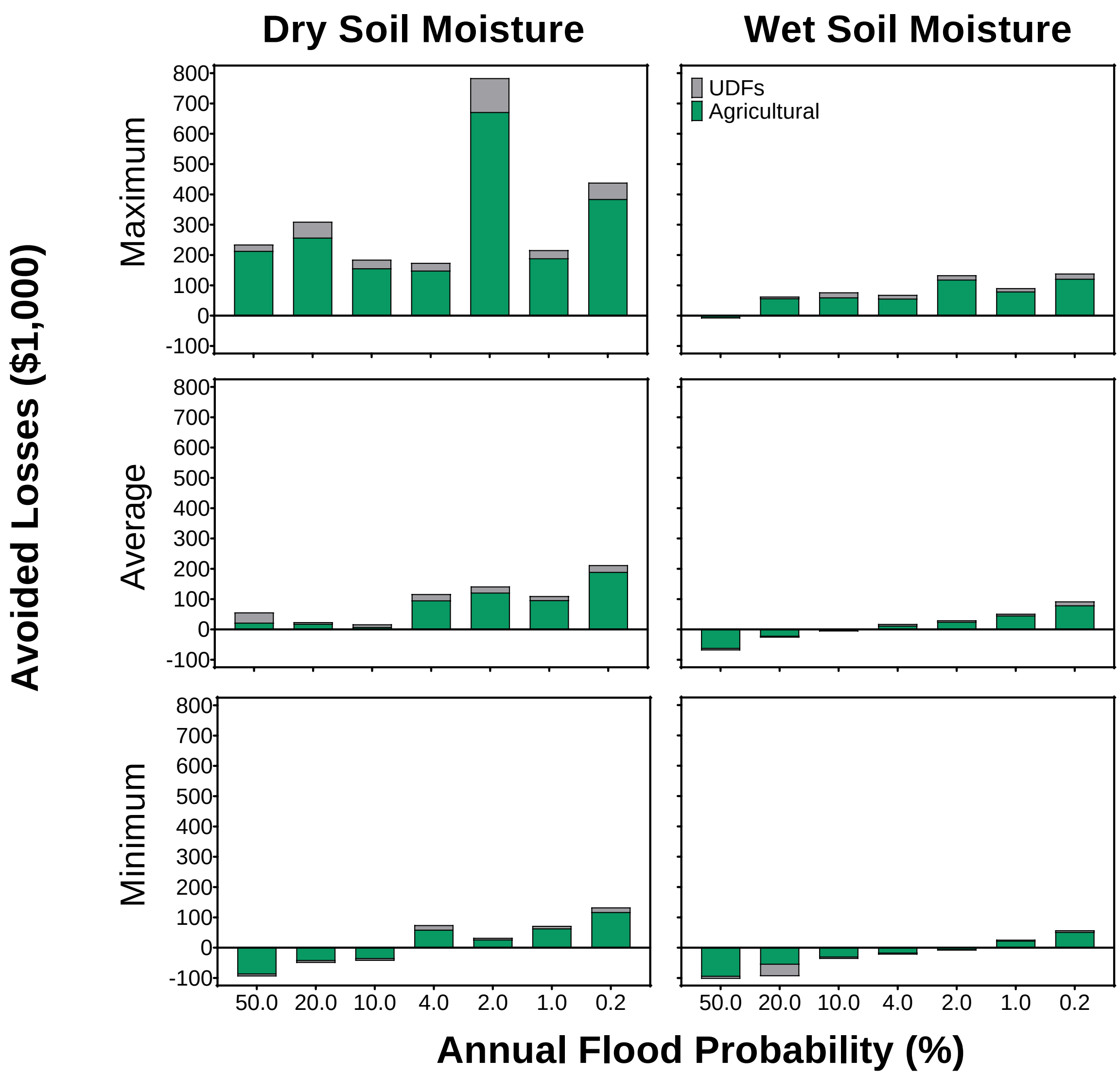

Figure 3.12. Agricultural and user-defined facilities avoided losses in Mud Creek by annual flood probability for dry and wet antecedent soil moisture and the minimum, average and maximum changes to peak flow

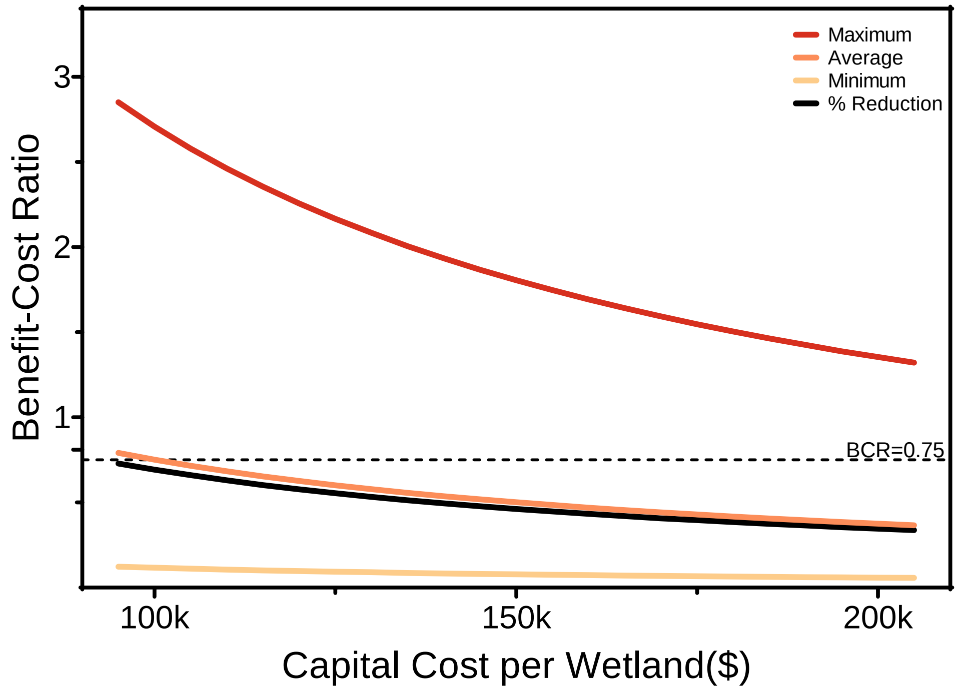

Figure 3.13. Benefit-cost ratios for the dry conditions in Hinkle Creek

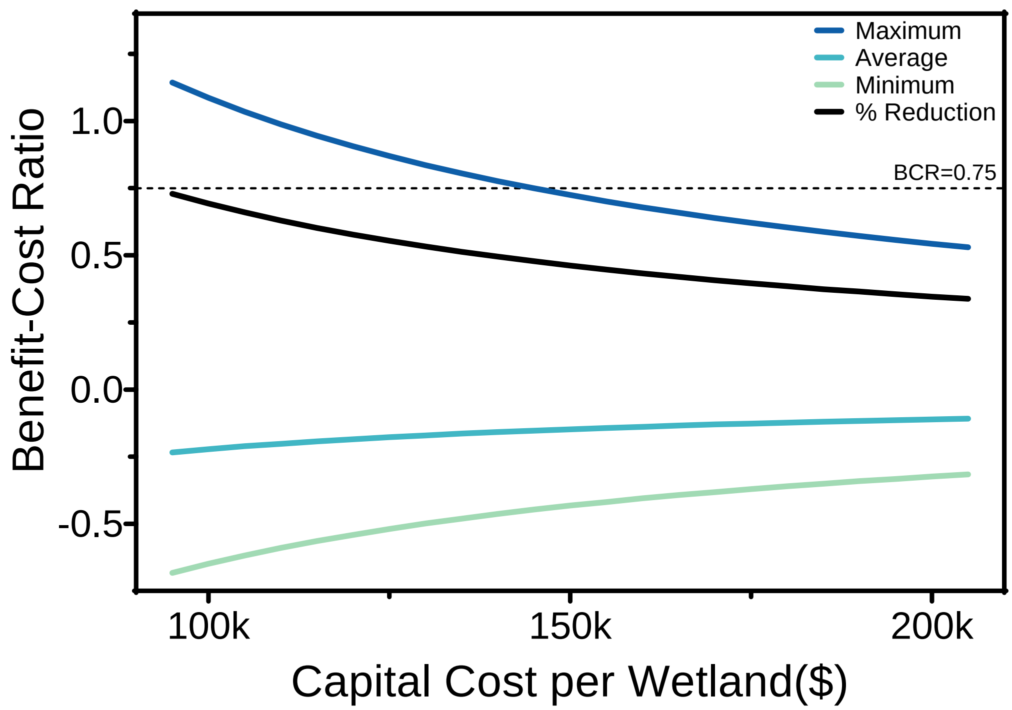

Figure 3.14. Benefit-cost ratios for the wet conditions in Hinkle Creek

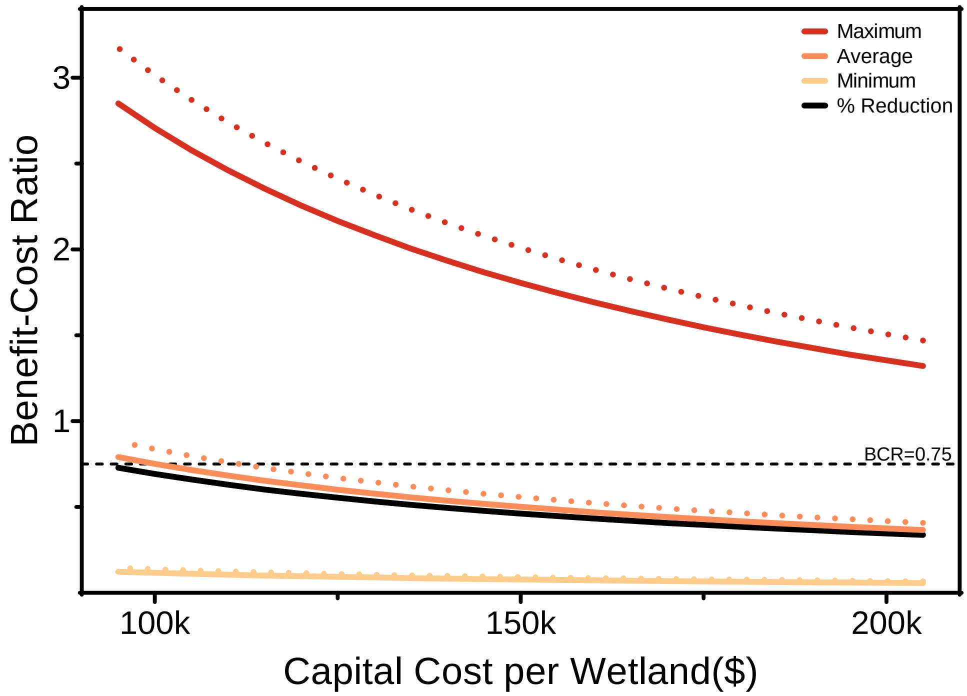

Figure 3.15. Benefit-cost ratios for the dry conditions in Hinkle Creek with (solid lines) and without backflow (dashed lines)

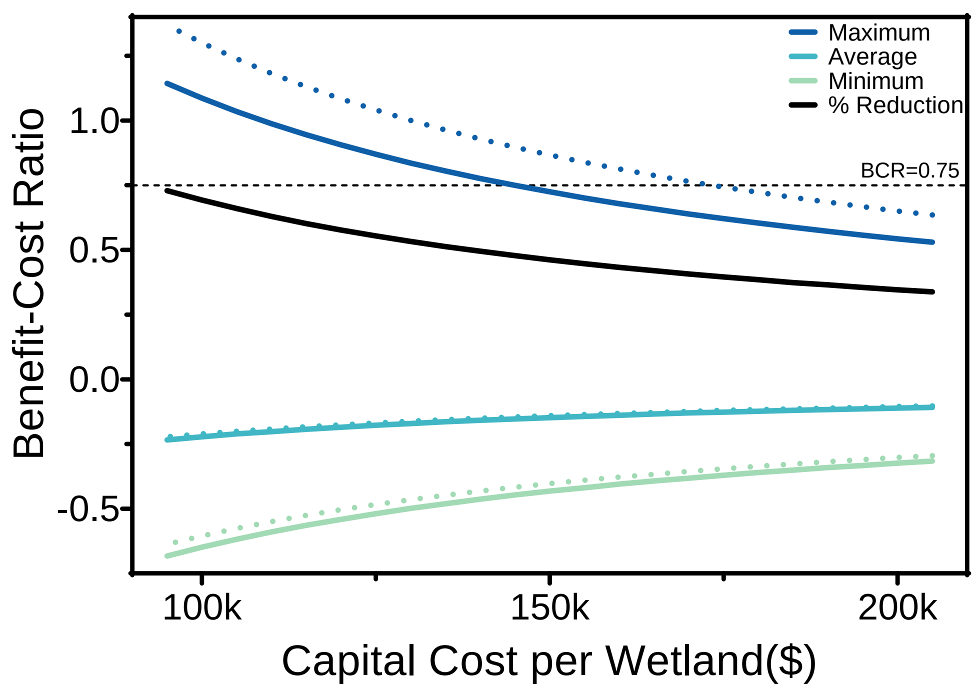

Figure 3.16. Benefit-cost ratios for the wet conditions in Hinkle Creek with (solid lines) and without backflow (dashed lines)

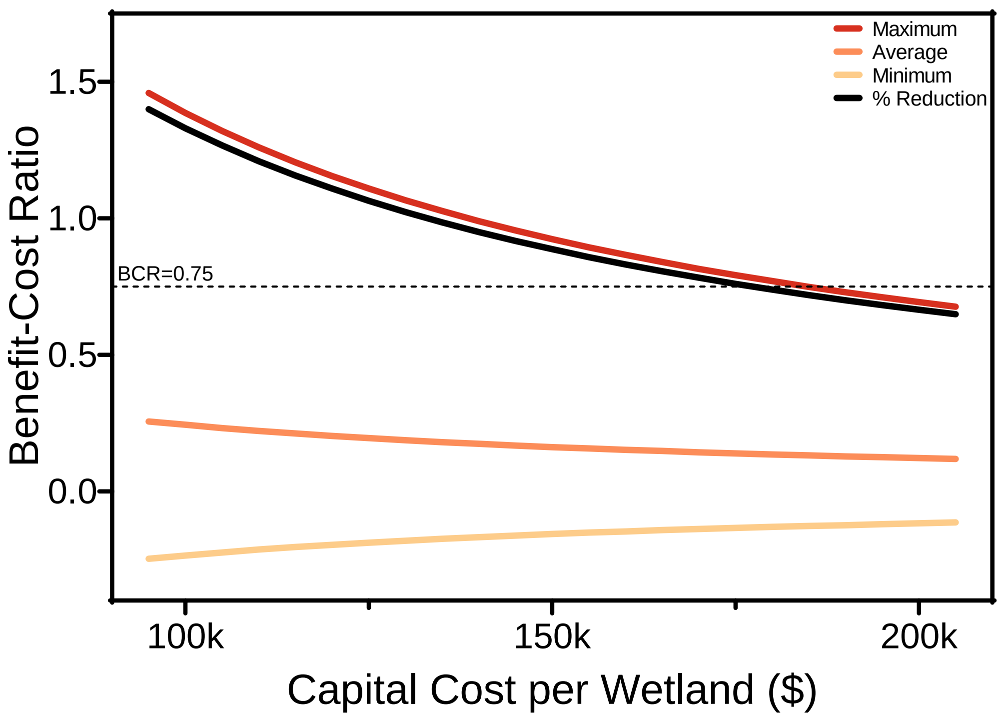

Figure 3.17. Benefit-cost ratios for dry conditions in Mud Creek

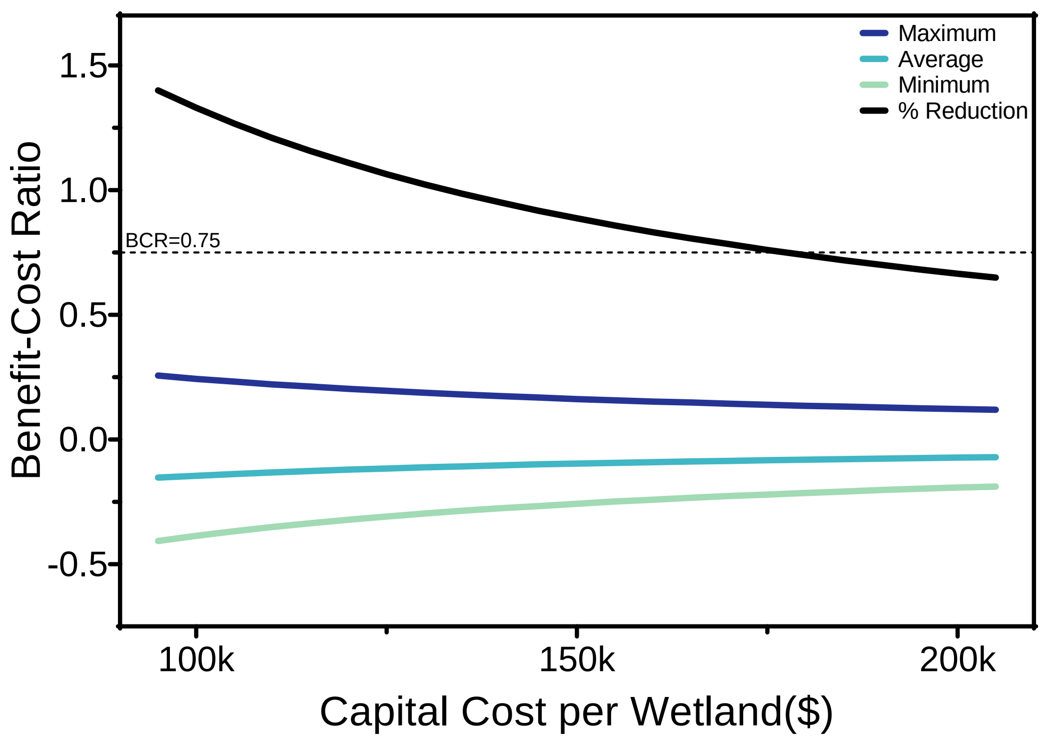

Figure 3.18. Benefit-cost ratios for wet conditions in Mud Creek

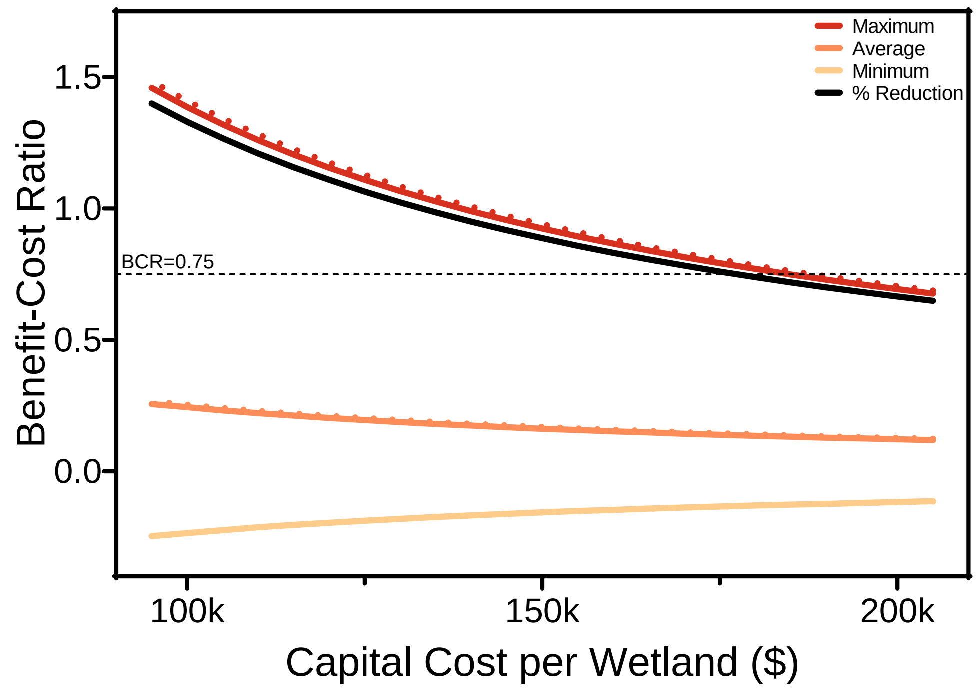

Figure 3.19. Benefit-cost ratios for dry conditions in Mud Creek with (solid lines) and without backflow (dashed lines)

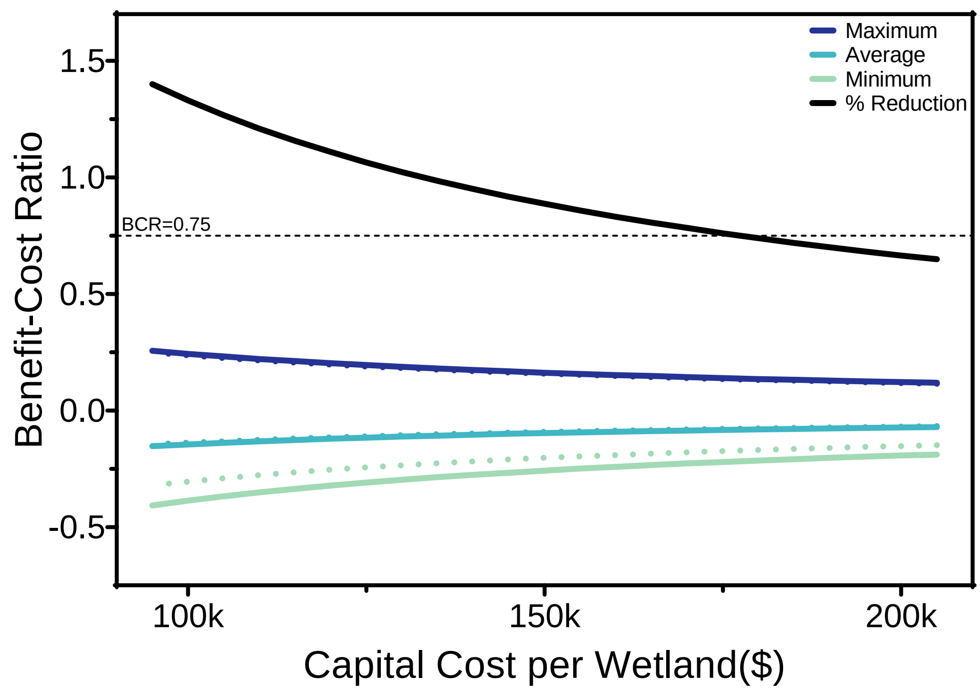

Figure 3.20. Benefit-cost ratios for wet conditions in Mud Creek with (solid lines) and without backflow (dashed lines)

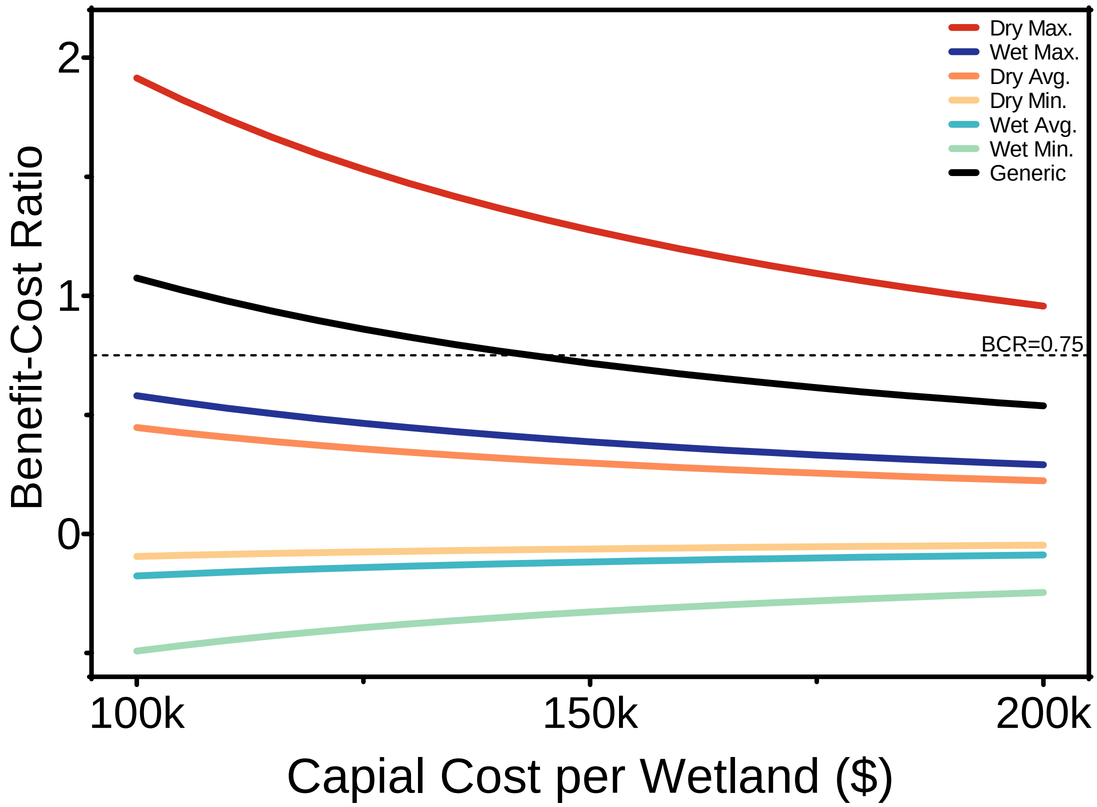

Figure 3.21. Benefit-cost ratios for the combined benefits of both the Mud Creek and Hinkle Creek watersheds

Table 3.1. 30-year gross benefits for the targeted peak flow approach in Hinkle Creek

	Without Bacfklow	With Backflow
Dry Minimum	$ 193,147.32	$ 163,363.19
Dry Maximum	$ 4,220,137.21	$ 3,790,352.16
Dry Average	$ 1,171,416.08	$ 1,051,373.78
Wet Minimum	$ (905,463.08)	$ (908,216.62)
Wet Maximum	$ 1,821,016.20	$ 1,521,652.03
Wet Average	$ (294,917.46)	$ (310,564.38)

Table 3.2. 30-year gross benefits for the targeted peak flow approach in Mud Creek

	Without Bacfklow	With Backflow
Dry Minimum	$ (494,440.27)	$ (492,901.99)
Dry Maximum	$ 2,960,533.42	$ 2,910,490.66
Dry Average	$ 532,101.91	$ 511,389.38
Wet Minimum	$ (640,628.09)	$ (811,824.41)
Wet Maximum	$ 496,923.72	$ 511,126.53
Wet Average	$ (308,358.43)	$ (305,879.56)

Table 3.3. Avoided losses per Ac-ft of storage in the Hinkle Creek watershed for scenarios with and without backflow included

	With Backflow	Without Backflow
Dry Minimum	$ 575.32	$ 680.22
Dry Maximum	$ 13,348.66	$ 14,862.25
Dry Average	$ 3,702.67	$ 4,125.43
Wet Minimum	$ (3,198.51)	$ (3,188.81)
Wet Maximum	$ 5,358.87	$ 6,413.16
Wet Average	$ (1,093.73)	$ (1,038.62)

Table 3.4. Avoided losses per Ac-ft of storage in the Mud Creek watershed for scenarios with and without backflow included

	With Backflow	Without Backflow
Dry Minimum	$ (989.23)	$ (992.31)
Dry Maximum	$ 5,841.19	$ 5,941.62
Dry Average	$ 1,026.33	$ 1,067.90
Wet Minimum	$ (1,629.29)	$ (1,285.70)
Wet Maximum	$ 1,025.80	$ 997.30
Wet Average	$ (613.88)	$ (618.86)

4. CONCLUSIONS AND FUTURE WORK

The overall goal of this project was to use a multijurisdictional approach to determine the benefit-cost ratios of flood retention wetlands in small, rural watersheds in Iowa. This type of approach has not been implemented before in Iowa yet could improve how Iowan communities apply for mitigation assistance funds. To address this goal, we set forth three objectives:

- To create credible hydrologic scenarios that analyze the impacts of flood retention wetlands on peak stream flows;
- To compare average annualized losses between scenarios without, and with, simulated flood retention wetlands;
- To determine if economic BCRs above 0.75 can be achieved in rural HUC12 watersheds using a multijurisdictional approach.

4.1 Credible Hydrologic Scenarios

To create credible hydrologic scenarios, we created and compared multiple approaches to find the avoided losses from simulated flood prevention wetlands. ACPF and GHOST were used to locate potential flood retention wetlands and determine their impacts on peak flow. We used a percent reduction approach and a targeted peak flow approach to create hydrologic scenarios based on the results from ACPF and GHOST. The percent reduction approach created before- and after-implementation scenarios following a method like one used by watershed management authorities in Iowa. Conversely, the targeted peak flow approach used more in-depth GHOST results to manipulate depth grid data to match the resulting GHOST outflows. Each method utilized HEC-RAS to generate new depth grids that represented before- and after-implementation scenarios for various peak flow change scenarios and antecedent soil moisture conditions. The BCRs of the simulated flood retention wetlands relied strongly on which type of approach was used to calculate the change in peak flow. The percent reduction approach was easy to implement and can be performed in a much smaller time frame. The ease of use and small implementation times makes the percent reduction approach much more appealing for watershed management authorities. However, we found that the percent reduction approach may overestimate the lifetime benefits because it does not account for any scenarios in which the peak flow increases, which occurs often for wet antecedent soil moisture conditions. Further, the percent reduction approach was based on manipulating flood frequency curves based on statistics rather than simulated before- and after-implementation peak flow data. The targeted peak flow approach exceled in determining peak flow change and the various factors that can be incorporated into the model. The changes in peak flow from GHOST are based on stochastic storm transposition, meaning that all the peak flows and changes to peak flows are rooted in simulations rather than statistical frequency curves. While this study focused on antecedent soil moisture, GHOST also can incorporate temperature, land use, solar radiation, and many other factors. These factors will change depending on the watershed that is being analyzed, which allows the targeted peak flow approach to be tailored to the specifics of each study region. However, running GHOST is computationally intensive. While the targeted peak flow approach is more versatile than the percent reduction approach, the time, expertise, and computational requirements limits the usefulness of this approach.

4.2 Average Annualized Loss Generation

To generate average annualizes losses for this study, we created before- and after-implementation scenarios and created an average annualized loss equation to include auxiliary storm data. We used HAZUS-MH to determine the before- and after-implementation flood damages to determine the avoided losses from simulated flood prevention wetlands in the Mud and Hinkle Creek watersheds. We found the avoided losses for seven annual flood percentage probabilities to use in our augmented average annualized losses equation to find the average annualized avoided losses ($AAL_{avoided}$). The $AAL_{avoided}$ were then discounted over 30 years to find the total potential benefits of the flood retention wetlands over their entire useful lifetime.

We found that for the percent reduction approach, the $AAL_{avoided}$ depended on the exposure within watershed the most. The avoided losses in the Hinkle Creek watershed increased as the flood percent probability decreased. However, in the Mud Creek watershed, the avoided losses were constant across all flood percent probabilities, with no clear relationship between the two. The Mud Creek watershed had higher total exposures, causing similar damages for higher probability and lower probability floods. Furthermore, in the targeted peak flow approach, the avoided losses per annual flood percent probability varied depending on peak change scenario and antecedent soil moisture. For the wet soil moisture conditions, the avoided losses increased as the annual flood percent probability decreased across all peak change scenarios. The avoided losses increased as the flood percent probability decreased for the minimum dry scenario as well, but the avoided losses for the average and maximum dry scenarios did not have a clear relationship between avoided losses and annual flood percent probability.

The $AAL_{avoided}$ also depended on the watershed exposure in the targeted peak flow approach, with the Mud Creek watershed achieving higher $AAL_{avoided}$ than Hinkle Creek. Within each watershed, $AAL_{avoided}$ for the targeted peak flow approach depended on the peak change and antecedent soil moisture conditions the most. The $AAL_{avoided}$ from the targeted peak flow approach were the greatest for the maximum dry scenarios in each watershed. The maximum peak change scenarios produced higher $AAL_{avoided}$ than the average peak change scenarios, which in turn produced higher $AAL_{avoided}$ than the minimum peak change scenarios. Further, dry antecedent soil moisture conditions generated higher $AAL_{avoided}$ than wet antecedent soil moisture conditions for the same peak flow change scenarios. The dry maximum, dry average, and wet maximum gross benefits from the targeted peak flows approach were greater than the percent reduction benefits in the Hinkle Creek watershed. Only the benefit from dry maximum scenario in the targeted peak flows approach was larger than the benefits from the percent reduction approach in the Mud Creek watershed. Further, some scenarios in the targeted peak flows approach generated negative average annualized avoided losses, indicating that the simulated flood retention wetlands could increase downstream losses after implementation. This primarily occurred for the minimum and average peak flow change scenarios under wet antecedent soil moisture conditions, however the $AAL_{avoided}$ were also negative for the minimum dry scenario in the Mud Creek watershed. We believe that negative $AAL_{avoided}$ were due to overtopping of the wetland outflow structure in the wet antecedent soil moisture conditions and the peak outflow delay resulting in simultaneous peak flows in the dry antecedent soil moisture conditions. The average annualized avoided losses were able to serve as the potential future benefits in the BCR equation when calculating financial viability.

4.3 BCRs of a Multijurisdictional Approach

To calculate the economic BCRs of the simulated flood retention wetland projects, we compared the projected future benefits to the estimated capital costs. The potential future benefits for the BCR calculation were simply the lifetime average annualized avoided losses of each wetland scenario. The estimated capital costs were based on previous wetland implementation projects in rural Iowa and on engineering estimates for the Iowa Watershed Approach project. We found that the BCRs of the simulated flood retention wetlands depend on which peak flow change approach was used. Similarly to the $AAL_{avoided}$, the BCRs from the percent reduction approach were dependent on the watershed exposures. For the targeted peak flow approach, the BCRs depended on both the antecedent soil moisture conditions and the amount by which the peak flows change. Consequently, dry scenario BCRs were higher than wet scenario BCRs, and the BCRs increased as the peak flow reductions increased.

The BCRs generated by the two approaches used in this study were high enough for some of the scenarios that they met or exceeded the FEMA requirement. The dry average scenario with backflow included was the closest to the percent reduction approach in the Hinkle Creek watershed, whereas the dry maximum scenario with backflow included was the closest to the percent reduction approach in the Mud Creek watershed. The BCRs for the percent reduction approach fall within the range of BCRs from the minimum to maximum peak change scenarios for both watersheds. We believe that the percent reduction approach may be useful and accurate for evaluating the economics for flood prevention wetlands in similarly sized and located wetlands as the ones in this study. Corroborating the percent reduction approach to determine the changes to peak flows will allow consultants and watershed management authorities to evaluate their own projects with much more confidence. The ease of use of a validated percent reduction approach also enables more competitive applications for federal assistance because those applications will no longer have doubts about the credibility of their methods. More credible applications will potentially lead to better flood prevention and increased flood resilience for rural communities.

When calculating the BCRs of flood retention wetlands that are upstream of areas that are affected by backflow from a larger water source downstream, backflow must be excluded in the economic BCR. Including backflow would include damages from water bodies that are unaffected by the upstream flood retention wetlands. The higher damages would then generate lower gross benefits, and in turn lower BCRs. By including the effects of backflow, the effects of the upstream flood retention wetlands would be underestimated, decreasing how well the applications for federal funding based on flood retention wetlands could compete with others. Thus, if the results from this study were to be used to compose an application for federal assistance, the BCRs that exclude backflow must be used to accurately portray the effects of the flood retention wetlands.

A multijurisdictional approach such as the one performed in this study can be applied to various flood prevention projects. A key metric that many flood prevention projects are measured by is their ability to decrease peak flow. The multijurisdictional approach demonstrated in this study can be used for any change to peak flow to determine the economic viability of all types of flood prevention projects. A multijurisdictional approach can be used if the proposed projects give benefits to agricultural lands and downstream towns. Further, this type of approach could be used in rural watersheds across the United States. Many rural towns lack flood resilience because they cannot prevent future floods. Vinton, IA serves as an example to show that the multijurisdictional approach can be used to increase the BCR of flood mitigation projects.

4.4 Future Work

One next step for this work would be to determine the ideal location and size of flood retention wetlands within the Hinkle Creek and Mud Creek watersheds. This study used only one flood retention wetland placement and size scenario. Various ACPF scenarios could be run to find the ideal wetland scenarios from a hydrologic standpoint. Those scenarios could then all be put through a multijurisdictional approach to find their BCRs and determine which would be idea from a financial standpoint. The ideal hydrologic and financial scenarios could then be compared to find a potential relationship between hydrologic impact and financial viability.

A multijurisdictional approach, while limited to analyzing flood retention wetlands in this study, can also be applied to other types of flood mitigation. GHOST can model numerous other types of flood-first best management practices and return the peak flows for before- and after-implementation scenarios. The methods used in this study to create new depth grids for various starting conditions could be used for the GHOST results for other types of flood mitigation practices. BCRs could be calculated assuming that accurate capital cost estimates exist for those types of projects. Those BCRs could then be compared to one another to determine which type of flood mitigation practices are the most financially sound.

This study exclusively analyzed the economic BCR portion of the total BCR used to apply for federal mitigation assistance funds. Another future step would be to analyze the ecosystem services BCR of flood retention wetlands using a multijurisdictional approach. This study demonstrated that the economic BCRs of simulated flood retention wetlands through a multijurisdictional approach were high enough to encourage an ecosystem services BCR analysis. This would create a total BCR which could be compared to the total BCRs of localized flood mitigation efforts to further assess how well a multijurisdictional approach works for rural communities in their applications for federal mitigation assistance funds.

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