Floodplain Risk Analysis Using Flood Probability and Annual Exceedance Probability Maps

Christopher M. Smemoe
Brigham Young University - Provo
FLOODPLAIN RISK ANALYSIS USING FLOOD PROBABILITY
AND ANNUAL EXCEEDANCE PROBABILITY MAPS

by

Christopher M. Smemoe

A dissertation submitted to the faculty of

Brigham Young University

in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

Department of Civil and Environmental Engineering

Brigham Young University

April 2004
This dissertation has been read by each member of the following graduate committee and by majority vote has been found to be satisfactory.

Date

E. James Nelson, Chair

Date

A. Woodruff Miller

Date

Norman L. Jones

Date

Alan K. Zundel

Date

Wayne C. Downs
As chair of the candidate’s graduate committee, I have read the dissertation of Christopher M. Smemoe in its final form and have found that (1) its format, citations, and bibliographical style are consistent and acceptable and fulfill university and department style requirements; (2) its illustrative materials including figures, tables, and charts are in place; and (3) the final manuscript is satisfactory to the graduate committee and is ready for submission to the university library.

Date

E. James Nelson
Chair, Graduate Committee

Accepted for the Department

A. Woodruff Miller
Department Chair

Accepted for the College

Douglas M. Chabries
Dean, College of Engineering and Technology
ABSTRACT

FLOODPLAIN RISK ANALYSIS USING FLOOD PROBABILITY
AND ANNUAL EXCEEDANCE PROBABILITY MAPS

Christopher Martin Smemoe
Department of Civil and Environmental Engineering
Doctor of Philosophy

This research presents two approaches to determining the effects of natural variability and model uncertainty on the extents of computed floodplain boundaries. The first approach represents the floodplain boundary as a spatial map of flood probabilities—with values between 0 and 100%. Instead of representing the floodplain boundary at a certain recurrence interval as a single line, this approach creates a spatial map that shows the probability of flooding at each point in the floodplain. This flood probability map is a useful tool for visualizing the uncertainty of a floodplain boundary. However, engineers are still required to determine a single line showing the boundary of a floodplain for flood insurance and other floodplain studies. The second approach to determining the effects of uncertainty on a floodplain boundary computes the annual exceedance probability (AEP) at each point on the floodplain. This spatial map of AEP values represents the flood inundation probability...
for any point on the floodplain in any given year. One can determine the floodplain boundary at any recurrence interval from this AEP map. These floodplain boundaries include natural variability and model uncertainty inherent in the modeling process. The boundary at any recurrence interval from the AEP map gives a single, definite boundary that considers uncertainty.

This research performed case studies using data from Leith Creek in North Carolina and the Virgin River in southern Utah. These case studies compared a flood probability map for a certain recurrence interval with an AEP map and demonstrated the consistency of the results from these two methods. Engineers and planners can use floodplain probability maps for viewing the uncertainty of a floodplain boundary at a certain recurrence interval. They can also use AEP maps for determining a single boundary for a certain recurrence interval that considers all the natural variability and model uncertainty inherent in the modeling process.

**Keywords:** Floodplain delineation, Hydrology, Hydraulics, Hydrologic and Hydraulic Modeling, Uncertainty, Risk Analysis, Stochastic Modeling, Rainfall, Runoff.
ACKNOWLEDGMENTS

No great accomplishment is possible without the help of other people. I have received help and support from many people during the time it took to complete this dissertation. I will be forever grateful for their help. The people who have helped include the professors, co-workers, and student employees in the EMRL. In addition, several of the employees at the Hydrologic Engineering Center in Davis, California have assisted and given feedback concerning this research. My advisor, Jim Nelson, has offered me encouragement and hours of help in my efforts. The members of my family and friends here in Utah have given me encouragement to finish. I am especially grateful for my family and my Lord. I could not have completed this dissertation without their friendship, love, sustaining encouragement, and help.
# TABLE OF CONTENTS

Title ........................................................................................................................................ i
Copyright................................................................................................................................. ii
Graduate Committee Approval .............................................................................................. iii
Final Reading Approval and Acceptance ................................................................................ iv
Abstract .................................................................................................................................. v
Acknowledgments ................................................................................................................... vii
Table of Contents .................................................................................................................... viii
List of Figures ........................................................................................................................ xiii

1. Introduction ....................................................................................................................... 1

2. Review of Current Methods ............................................................................................. 13
   2.1 Determining the Scope of the Flood Study ................................................................. 15
   2.2 Data Collection ............................................................................................................ 16
   2.3 Hydrologic Analysis ................................................................................................. 16
      2.3.1 Precipitation ....................................................................................................... 19
      2.3.2 Runoff/Infiltration Percentages ......................................................................... 24
   2.4 Hydraulic Analysis .................................................................................................... 29
      2.4.1 Cross Section/Elevation Data .......................................................................... 30
      2.4.2 Roughness Coefficient ..................................................................................... 31
   2.5 Determining Flood Elevations .................................................................................. 33
   2.6 History of Floodplain Delineation Algorithms ......................................................... 33
   2.7 Creating the (Digital) Flood Insurance Rate Map (FIRM/DFIRM) ......................... 34
   2.8 Risk Analysis in Floodplain Mapping and Flood Damage Studies ......................... 36
2.9 Current Methods for Computing AEP ......................................................... 38
  2.9.1 Computing AEP Using the Annual-Flood Sampling Procedure .......... 38
  2.9.2 Computing AEP Using the Function Sampling Procedure ............... 39
  2.9.3 Geotechnical Uncertainty ................................................................. 41
2.10 Quantifying Uncertainty in Floodplain Delineation ............................. 41
2.11 Research Objectives .............................................................................. 42

3. Risk Analysis in Floodplain Studies ......................................................... 47
  3.1 Probability ............................................................................................... 48
    3.1.1 What is Probability? ........................................................................... 48
    3.1.2 Natural Variability and Knowledge Uncertainty ............................... 49
  3.2 Probability Density Functions ............................................................... 50
    3.2.1 Normal Distribution .......................................................................... 52
    3.2.2 Linear Distribution ............................................................................ 53
    3.2.3 Lognormal Distribution ...................................................................... 54
    3.2.4 Loglinear Distribution ....................................................................... 56
  3.3 Stochastic Analysis Methods ................................................................. 57
    3.3.1 Monte Carlo Simulation ..................................................................... 57
    3.3.2 Latin Hypercube Simulation ............................................................... 61
  3.4 Determining Variable Values for Each Run ........................................... 64
  3.5 Annual Exceedance Probability (AEP) .................................................... 64
  3.6 Stochastic Floodway Delineation ............................................................ 69
  3.7 Chapter Summary .................................................................................... 74

4. Model Implementation ............................................................................... 75
  4.1 HEC-1 ..................................................................................................... 76
    4.1.1 HEC-1 Basin Data .............................................................................. 77
    4.1.2 HEC-1 Routing Data .......................................................................... 78
  4.2 HEC-RAS ............................................................................................... 79
    4.2.1 Using HEC-1 Output for HEC-RAS Modeling ................................. 80
4.3 The WMS Floodplain Delineation Model ........................................................... 81
  4.3.1 Floodplain Delineation Model Input .......................................................... 82
  4.3.2 Interpolating Water Surface Elevations ..................................................... 82
  4.3.3 Determining the Floodplain Boundary ...................................................... 87
4.4 Combining HEC-1, HEC-RAS, and Floodplain Delineation ......................... 90
  4.4.1 Linking HEC-1 and HEC-RAS ................................................................. 90
  4.4.2 Linking HEC-RAS and the Floodplain Delineation Model ....................... 94
4.5 High Resolution Elevation Data ................................................................. 95
  4.5.1 XY Distance Method ............................................................................... 97
  4.5.2 Normal Angle and Z-Distance Methods ................................................... 99
  4.5.3 Laplacian Filter Method ........................................................................... 102
  4.5.4 Modifying Elevation Data ........................................................................ 105

5. Stochastic Modeling Applications ................................................................... 109
  5.1 Variables Modeled ...................................................................................... 110
  5.2 Computing a Flood Probability Map ............................................................ 112
  5.3 Computing the Spatial Distribution of the Annual Exceedance Probability
      (AEP) ........................................................................................................... 114
  5.4 Determining Precise Floodplain Extents at Any Recurrence Interval from
      the AEP Map .............................................................................................. 118
  5.5 Computing Expected Annual Damage (EAD) from an AEP Simulation ...... 120
  5.6 Solutions for Some Recommendations by the National Research Council
      (NRC) ........................................................................................................... 121

6. Case Studies ....................................................................................................... 127
  6.1 The Leith Creek Model ................................................................................ 128
    6.1.1 Developing the Hydrologic Model ............................................................ 132
    6.1.2 Developing the Hydraulic Model .............................................................. 145
    6.1.3 Determining the Floodplain Boundary .................................................... 153
    6.1.4 Running the Stochastic Simulations ......................................................... 156
6.1.5 Results and Analysis ................................................................. 160

6.2 Virgin River .................................................................................. 182

6.2.1 Location .................................................................................... 183

6.2.2 Hydrologic Data ........................................................................ 184

6.2.3 Developing the Hydraulic Model .............................................. 187

6.2.4 Generating the Annual Exceedance Probability (AEP) Map ......... 189

6.2.5 Results ....................................................................................... 191

6.3 Conclusions ................................................................................... 210

7. Contributions and Conclusions ....................................................... 215

7.1 Technical Contributions ................................................................. 216

7.2 Applications .................................................................................. 219

7.3 Future Research ........................................................................... 220

8. References ....................................................................................... 223

A. North Carolina Case Study Results ............................................... 233

A.1 Stochastic Model 1: Latin Hypercube Simulation with Sub-Basin

Precipitation as a Stochastic Variable ............................................. 234

A.1.1 Input Values ............................................................................. 234

A.1.2 Peak Flow Values .................................................................... 235

A.1.3 Hydraulic Model Results ......................................................... 236

A.1.4 Floodplain Delineation Results ............................................... 237

A.2 Stochastic Model 2: Latin Hypercube Simulation with Sub-Basin Curve

Number as a Stochastic Variable ..................................................... 244

A.2.1 Input Values ............................................................................. 244

A.2.2 Peak Flow Values .................................................................... 245

A.2.3 Hydraulic Model Results ......................................................... 247

A.2.4 Floodplain Delineation Results ............................................... 248
A.3 Stochastic Model 3: Latin Hypercube Simulation with Material Manning’s Coefficient as a Stochastic Variable

A.3.1 Input Values

A.3.2 Peak Flow Values

A.3.3 Hydraulic Model Results

A.3.4 Floodplain Delineation Results
LIST OF FIGURES

1-1 Precipitation-frequency curve with observed data for Laurinburg, NC ............... 2
1-2 A flood probability map for the 100-year floodplain............................................ 4
1-3 Annual exceedance probability contours for the Virgin River near Virgin, UT ......................................................................................................................... 6
1-4 An AEP map showing the floodplain boundaries for different recurrence intervals................................................................................................................. 7
1-5 A comparison between the 100-year floodplain boundary on the AEP map and the 100-year flood probability map (1000 simulations each) ........................ 9
2-1 Procedure for floodplain delineation .................................................................. 14
2-2 Flowchart for a FEMA hydrologic analysis........................................................ 18
2-3 A depth-duration-frequency curve for Austin, Texas (from Smemoe, 1995) .... 20
2-4 A log-linear fit to 180-minute storm totals in Austin, Texas (from Smemoe, 1995) ................................................................................................................... 21
2-5 Antecedent runoff condition (ARC) adjustment for varying type II ARC curve numbers. Adapted from Mockus (1964, 1972, 1985) ......................... 28
2-6 Variation in cross-section elevations .................................................................. 31
2-7 Obtaining a discharge value from an exceedance probability and an error function .................................................................................................................... 38
2-8 Obtaining a stage value from the discharge and an error function ..................... 39
2-9 Finding discharge values from an instance of the discharge-probability curve .................................................................................................................... 40
2-10 Finding stage values from an instance of the stage-discharge curve .............. 40
2-11 Creating the stage-probability curve and finding the exceedance probability .... 40
3-1 Stochastic modeling procedure ........................................................................... 48
3-2 Natural variability and knowledge uncertainty represented on a discharge-probability curve ........................................................................................................... 50
3-3 A possible PDF for a CN with an average value of 65 ........................................ 51
3-4 A normal distribution curve with \( \mu = 5.0 \) and \( \sigma = 2.0 \) ...................... 53
3-5 A linear distribution curve with min = 3.0 and max = 7.0.............................. 54
3-6 A lognormal distribution curve with \( \mu \) (of logs) = 5.3 and \( \sigma \) (of logs) = 0.6 .... 56
3-7 A loglinear distribution curve with min = 3.0 and max = 300.0..................... 57
3-8 Determining the probabilities of a floodplain reaching certain extents .......... 58
3-9 Range of floodplain extents for 6-8 inches of precipitation in a 24-hour, 100-year recurrence interval ................................................................. 59
3-10 A uniform probability distribution ................................................................... 59
3-11 A normal probability distribution .................................................................... 60
3-12 A Monte Carlo simulation with an even distribution of values ..................... 61
3-13 A Monte Carlo simulation with an uneven distribution of values ................. 62
3-14 The Latin Hypercube method .......................................................................... 63
3-15 Obtaining a discharge value from an exceedance probability and an error function ......................................................................................................... 65
3-16 Obtaining a stage value from the discharge and an error function .................... 65
3-17 Function sampling procedure ............................................................................. 66
3-18 Determining discharge values from a discharge-probability curve and its uncertainty ......................................................................................................... 68
3-19 Determining the floodway .................................................................................. 69
3-20 The ineffective flow zone along the banks of a floodplain.............................. 70
3-21 Effect of the ineffective flow zone size on floodway extents ...................... 71
3-22 Cross section view showing the effect of the ineffective flow zone size on floodway extents ........................................................................................................ 72
3-23 A stochastic approach to ineffective flow determination for floodways ......... 73
4-1 Floodplain delineation process ............................................................................ 76
4-2 HEC-1 components ........................................................................................... 77
4-3 HEC-1 sub-basin input ......................................................................................... 78
<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
</tr>
</thead>
<tbody>
<tr>
<td>4-4</td>
<td>HEC-RAS input and output</td>
</tr>
<tr>
<td>4-5</td>
<td>Linking HEC-1 model data to an HEC-RAS model</td>
</tr>
<tr>
<td>4-6</td>
<td>Using computed versus interpolated water surface elevations to delineate a floodplain</td>
</tr>
<tr>
<td>4-7</td>
<td>Interpolating the HEC-RAS solution along a cross section</td>
</tr>
<tr>
<td>4-8</td>
<td>Interpolating the HEC-RAS solution between two cross sections</td>
</tr>
<tr>
<td>4-9</td>
<td>A junction with three water surface solution points to interpolate</td>
</tr>
<tr>
<td>4-10</td>
<td>Interpolating water surface elevation points at a junction</td>
</tr>
<tr>
<td>4-11</td>
<td>Determining the main stem at a river junction</td>
</tr>
<tr>
<td>4-12</td>
<td>Water surface elevation point selection criteria</td>
</tr>
<tr>
<td>4-13</td>
<td>A hydrograph generated from HEC-1</td>
</tr>
<tr>
<td>4-14</td>
<td>Entering the hydrograph peak flow value in HEC-RAS</td>
</tr>
<tr>
<td>4-15</td>
<td>The floodplain modeling process—data transfer between HEC-1, HEC-RAS, and the floodplain delineation model</td>
</tr>
<tr>
<td>4-16</td>
<td>The XY distance method of removing points</td>
</tr>
<tr>
<td>4-17</td>
<td>Merging two vertices by averaging their values</td>
</tr>
<tr>
<td>4-18</td>
<td>The normal angle method of reducing data points</td>
</tr>
<tr>
<td>4-19</td>
<td>Step 1 of the Z-distance method</td>
</tr>
<tr>
<td>4-20</td>
<td>Step 2 of the Z-distance method—determining the difference in original and interpolated Z-values</td>
</tr>
<tr>
<td>4-21</td>
<td>Step 3 of the Z-distance method—swapping the edges and determining the new interpolated Z-values</td>
</tr>
<tr>
<td>4-22</td>
<td>Neighborhood ranking in Southard's method (1991)</td>
</tr>
<tr>
<td>4-23</td>
<td>Interpolating point features to elevation data</td>
</tr>
<tr>
<td>4-24</td>
<td>Interpolating linear features to elevation data</td>
</tr>
<tr>
<td>5-1</td>
<td>HEC-1 sub-basin input</td>
</tr>
<tr>
<td>5-2</td>
<td>HEC-RAS input</td>
</tr>
<tr>
<td>5-3</td>
<td>Defining a stochastic variable in the WMS</td>
</tr>
<tr>
<td>5-4</td>
<td>Floodplain probability map showing the location of the 50% probability contour</td>
</tr>
<tr>
<td>Page</td>
<td>Description</td>
</tr>
<tr>
<td>------</td>
<td>-------------</td>
</tr>
<tr>
<td>5-5</td>
<td>Annual exceedance probability contours for the Virgin River near Virgin, UT</td>
</tr>
<tr>
<td>5-6</td>
<td>A discharge-probability curve with uncertainty</td>
</tr>
<tr>
<td>5-7</td>
<td>A stage-discharge curve with uncertainty</td>
</tr>
<tr>
<td>5-8</td>
<td>An AEP map showing the floodplain boundaries for different recurrence intervals</td>
</tr>
<tr>
<td>5-9</td>
<td>Sub-basin hydrographs for the Leith Creek HEC-1 model</td>
</tr>
<tr>
<td>6-1</td>
<td>Location of Laurinburg, North Carolina and the Leith Creek model</td>
</tr>
<tr>
<td>6-2</td>
<td>Approximate boundary of the watershed and floodplain model areas</td>
</tr>
<tr>
<td>6-3</td>
<td>Data requirements for the watershed, hydraulic, floodplain, and the stochastic models</td>
</tr>
<tr>
<td>6-4</td>
<td>DEM contours with TOPAZ-computed flow directions and flow accumulations</td>
</tr>
<tr>
<td>6-5</td>
<td>Stream and sub-basin definitions for the Leith Creek watershed model with basin names and hydrograph combine names</td>
</tr>
<tr>
<td>6-6</td>
<td>Precipitation versus recurrence interval for 24-hour storms for Laurinburg, NC</td>
</tr>
<tr>
<td>6-7</td>
<td>Precipitation versus recurrence interval for 24-hour storms for Moore County, NC</td>
</tr>
<tr>
<td>6-8</td>
<td>100-year, 24 hour precipitation values from the eastern United States (from USDA NRCS, 1986)</td>
</tr>
<tr>
<td>6-9</td>
<td>Antecedent runoff condition (ARC) adjustment for varying type II ARC curve numbers. Adapted from Mockus (1964, 1972, 1985)</td>
</tr>
<tr>
<td>6-10</td>
<td>Sub-basin hydrographs for the Leith Creek HEC-1 model</td>
</tr>
<tr>
<td>6-11</td>
<td>Section of the triangulated, contoured elevation values in the Leith Creek floodplain</td>
</tr>
<tr>
<td>6-12</td>
<td>Leith Creek hydraulic model river reaches and cross sections</td>
</tr>
<tr>
<td>6-13</td>
<td>Extracting cross sections from TIN (LIDAR) data</td>
</tr>
<tr>
<td>6-14</td>
<td>Floodplain map of the Leith Creek floodplain—100 year, 24 hour storm</td>
</tr>
</tbody>
</table>
6-15 Land use types used for determining Manning's roughness values for the
HEC-RAS model .................................................................................................. 158
6-16 Precipitation values used for each segment ................................................. 162
6-17 Curve number values used for each segment ................................................ 162
6-18 Manning's coefficient values used for each segment.................................... 163
6-19 Minimum water depth contours (all values in meters) ............................... 169
6-20 Maximum water depth contours (all values in meters) ............................... 170
6-21 Averaged water depth contours from all floodplain delineations (all values
in meters) .......................................................................................................... 171
6-22 Probability of flooding (values in percent) ................................................. 172
6-23 Probability of flooding—close-up area (values in percent) ............................ 173
6-24 Average flood depth histogram showing the number of vertices on the TIN
with different water depth values for simulation 4 ........................................... 174
6-25 Probability histogram showing the number of vertices on the TIN with
different probability values for simulation 4 ................................................. 175
6-26 A comparison of the 100-year floodplain boundary from the North Carolina
database with the flood probability contours generated for simulation 4 .......... 176
6-27 A close-up of the comparison of the 100-year floodplain boundary from the
North Carolina database with the flood probability contours .......................... 177
6-28 Precipitation input value histogram used to create AEP map for the Leith
Creek floodplain .................................................................................................. 179
6-29 Comparison between the AEP map and the 100-year floodplain probability
map for simulation 4 ......................................................................................... 180
6-30 Comparison between the locations of the contour of the 1% (100-year)
floodplain on the AEP map, the contour of the 50% probability on the 100-year
dafloodplain probability map, and the 100-year floodplain from the North
Carolina database .............................................................................................. 181
6-31 Location of the Virgin River model ............................................................... 183
6-32 Watershed model boundary with location of the hydraulic and floodplain
models ............................................................................................................... 185
6.33 A discharge-probability curve with uncertainty ........................................... 187
6.34 Elevation and cross section data for the Virgin River hydraulic model .......... 188
6.35 Determining a discharge value from discharge-probability curve data .......... 190
6.36 Canvassing the space of the discharge-probability curve ................................ 191
6.37 Flow histograms for 100, 200, 500, and 1000 simulations to produce an AEP map ........................................................................................................... 192
6.38 AEP maps for 100, 200, 500, and 1000 simulations ........................................ 194
6.39 Determining floodplain boundaries at different recurrence intervals using the AEP map produced from 1000 simulations ........................................... 197
6.40 Average water depth maps for 100, 200, 500, and 1000 AEP simulations ..... 198
6.41 Flow histograms for 100, 200, 500, and 1000 simulations to produce 100-year floodplain probability map ........................................................................ 200
6.42 100-year flood probability maps created by running 100, 200, 500, and 1000 simulations ........................................................................................................... 201
6.43 RMS of probability values for different numbers of simulations ...................... 203
6.44 Mean of probability values for different numbers of simulations .................... 203
6.45 Standard deviation of probability values for different numbers of simulations ........................................................................................................... 204
6.46 Comparison between the 50% probability contours on the flood probability map for different numbers of simulations ........................................... 205
6.47 A comparison between the 100-year floodplain boundary on the AEP map and the 100-year flood probability map (1000 simulations each) ................. 206
6.48 Comparison between the 100-year floodplain created from the AEP map, a single simulation with mean values, and a flood probability map .................. 208
6.49 Average water depth maps for 100, 200, 500, and 1000 100-year floodplain simulations ........................................................................................................... 209
7.1 A discharge-probability curve with uncertainty at multiple probabilities ....... 217
A-1 Precipitation values for each set of model runs (segment numbers correspond with a set of model runs) ................................................................. 234
A-2 Minimum water depth contours (all values in meters) .................................. 238
A-3  Maximum water depth contours (all values in meters)................................. 239
A-4  Averaged water depth contours from all floodplain delineations (all values
     in meters) .................................................................................................................... 240
A-5  Probability of flooding (values in percent)..................................................... 241
A-6  Probability of flooding—close-up area (values in percent)......................... 242
A-7  Average flood depth histogram showing the number of vertices on the TIN
     with different water depth values for simulation 1.................................................. 243
A-8  Probability histogram showing the number of vertices on the TIN with
     different probability values for simulation 1 ............................................................ 244
A-9  Curve number values used for each segment............................................. 245
A-10 Minimum water depth contours (all values in meters) ............................. 250
A-11 Maximum water depth contours (all values in meters)............................ 251
A-12 Averaged water depth contours from all floodplain delineations (all values
     in meters) .................................................................................................................... 252
A-13 Probability of flooding (values in percent).................................................. 253
A-14 Probability of flooding—close-up area (values in percent)....................... 254
A-15 Average flood depth histogram showing the number of vertices on the TIN
     with different water depth values for simulation 2.................................................. 255
A-16 Probability histogram showing the number of vertices on the TIN with
     different probability values for simulation 2 ............................................................ 256
A-17 Manning's coefficient values used for each segment............................... 257
A-18 Minimum water depth contours (all values in meters)............................. 262
A-19 Maximum water depth contours (all values in meters)............................ 263
A-20 Averaged water depth contours from all floodplain delineations (all values
     in meters) .................................................................................................................... 264
A-21 Probability of flooding (values in percent).................................................. 265
A-22 Probability of flooding—close-up area (values in percent)....................... 266
A-23 Average flood depth histogram showing the number of vertices on the TIN
     with different water depth values for simulation 3.................................................. 267
A-24 Probability histogram showing the number of vertices on the TIN with different probability values for simulation 3 .............................................................. 268
1 Introduction

Floodplain delineation is the process of determining the extent of a floodplain at a given recurrence interval using map and/or elevation data. Determining the extents of the floodplain requires approximate values for the hydrologic and hydraulic parameters influencing these extents. These factors include, but are not limited to, the following:

1. The storm precipitation total at the flood recurrence interval.
2. The percentage of water that flows overland, compared with the amount that evaporates or infiltrates into the subsurface.
3. The topography of the floodplain cross-sectional data.
4. Roughness coefficients at all typical locations in the floodplain.

Current methods exist for determining each of these parameters within reasonable ranges using experience and sound engineering principles. However, uncertainty prevents us from obtaining exact values for any of them. For example, you may determine the 100-year precipitation total for a 72-hour storm to be six inches. However, the actual value could be anywhere between five and eight inches. Depending on antecedent moisture conditions, the percentage of water infiltrating into the ground can vary from storm to storm. If a storm occurs following a relatively wet period, there would be only small rainfall losses, and most of the precipitation
converts to runoff. On the other hand, if a relatively dry period precedes the storm, the soils have more infiltration capacity and much of the initial rainfall infiltrates into the ground. Uncertainties also exist in measuring cross-section elevations and in determining Manning’s roughness coefficients along the floodplain.

![24-Hour Precipitation-Frequency Curve](image)

Figure 1-1: Precipitation-frequency curve with observed data for Laurinburg, NC

Consider the precipitation data shown in Figure 1-1. You can create an equation from this precipitation data that relates precipitation to recurrence interval. Even though the precipitation values computed from the precipitation-frequency equation fit closely to the observed data, there is still a difference between the equation and the observed data. This difference is greatest for recurrence intervals for which less data exists. The focus of this research is to develop methodologies that
account for knowledge uncertainty and natural variability in hydrologic and hydraulic modeling as well as the subsequent floodplain delineation.

*Natural variability* refers to the inherent variability of natural processes. Examples of natural variability include stream flow, precipitation, and soil properties. These characteristics vary in time and/or space.

*Knowledge uncertainty* refers to incomplete knowledge about the scientific process leading to flooding in a floodplain or incomplete data to model the rainfall-runoff or hydraulics of a floodplain correctly. Examples of knowledge uncertainty include uncertainties in peak discharges caused by simplifications in a hydrologic model, uncertainties in river stages caused by assumptions of a hydraulic model, and uncertainties in measurement of the hydrologic or hydraulic model parameters. The existence of uncertainties does not invalidate a model. You just need to account for these uncertainties somehow in the hydrologic/hydraulic modeling process.

If you could define a curve of flow vs. recurrence interval (a *flow-frequency* curve) from historical data in a watershed, you could eliminate the hydrologic model. You could use the flow-frequency curve directly to determine the discharge from a 100-year storm. However, even this value would be uncertain, just as the values for precipitation, rainfall losses, or any other parameter is uncertain.

The word “stochastic” is an adjective meaning “involving or containing a random variable or variables”. It can also mean “involving chance or probability”. It comes from two Greek words, *stokhazesthai*, meaning *to guess at*, and *stokhos*, meaning an *aim* or a *goal* (American Heritage Dictionary of the English Language,
Fourth Edition, 2000, Houghtin Mifflin Company). The goal of stochastic modeling is to guess at variable values to determine a possible range of solutions.

This research uses stochastic methods to perturb each of the floodplain input parameters, using a probability distribution for each parameter, to determine the extents of a floodplain that accounts for the uncertainty in all of these input conditions. By running several instances of a hydrologic, a hydraulic, and a floodplain delineation model, this research creates a map that shows the probability of flooding at any point in the floodplain model. You create this floodplain probability map for a single recurrence interval, such as the 100-year recurrence interval as shown in Figure 1-2.

![Figure 1-2: A flood probability map for the 100-year floodplain](image)

A method for developing a flood probability map is the first result of this research. The floodplain probability map is a useful tool for evaluating the probability of flooding for a 100-year storm. There is never 100% certainty in the boundary of a
floodplain in a hydrologic/hydraulic analysis, and this method of determining a floodplain probability map acknowledges that fact. Rather then defining a boundary as a “disputable” in or out boundary, this map defines the probability of flooding based on a range of reasonable model parameters. You can use this floodplain probability map to evaluate the uncertainty of the floodplain boundary based on the ranges of input parameters. The probability of flooding at any point in the floodplain model can be determined from this map.

However, engineers are still required to determine a single line showing the boundary of a floodplain for flood insurance and other floodplain studies. This is despite the fact that the input parameters to the models used to determine the floodplain are uncertain (from natural variability and knowledge uncertainty) and the models themselves include assumptions and uncertainty (from knowledge uncertainty). This makes the process of certifying flood maps difficult, and often leads disputing parties to develop floodplain maps that seemingly contradict accepted floodplain limits for a certain recurrence interval.

The second major objective of this research is to develop a method that incorporates the inherent uncertainty in hydrologic and hydraulic models to create a map showing the probability of flooding in any year and to determine a single “most probable” floodplain boundary from this map. This method extends the current methods used by the US Army Corps of Engineers (USACE) for determining an annual exceedance probability (AEP) to the spatial domain. The AEP is the probability of overtopping of a levee or other flood control structure in any year. Instead of computing a single AEP value for a section of a river, the AEP at any point
on the floodplain can be determined. For example, the contours of the AEP map in Figure 1-3 represent the probability of flooding in any given year.

The 0.01-probability contour represents the boundary of a floodplain that will flood in 1% of the years (once in 100 years). Since $RP = 1 / \text{probability}$ ($RP = \text{return period}$), this is the boundary of the 100-year floodplain. Therefore, you can approximate the 10, 50, 100, or any recurrence interval floodplain directly from the contour of the spatially distributed map of the AEP (by converting the desired probability to a return period as in Figure 1-4). These floodplains include
uncertainties inherent in the modeling process. In this way, you can define a single boundary that accounts for uncertainty in the floodplain modeling process.

![AEP map showing floodplain boundaries](image)

**Figure 1-4: An AEP map showing the floodplain boundaries for different recurrence intervals**

Thus, the two products of this research are the flood probability map for a specified return period and the annual exceedance probability (AEP) map. Currently, FEMA requires a single floodplain boundary. The AEP map approximates the probability of flooding at any point in the floodplain during any single year. You can delineate a floodplain boundary at any recurrence interval from this map. However, you can only delineate the uncertainty of the floodplain at a return period using a flood
probability map. The flood probability map considers the uncertainty in floodplain delineation at a single recurrence interval while the AEP map considers the uncertainty at all recurrence intervals. Figure 1-5 compares a 100-year floodplain boundary and the 50% probability contour on these two types of maps for a location in southern Utah.
Figure 1-5: A comparison between the 100-year floodplain boundary on the AEP map and the 100-year flood probability map (1000 simulations each)

This dissertation discusses how to quantify natural variability and knowledge uncertainty in floodplain delineation using hydrologic and hydraulic models to
produce flood probability and AEP maps. This research linked hydrologic, hydraulic, and floodplain delineation models together in an original, stochastic approach to provide the capability of creating these two types of maps.

Chapter 2 discusses the current methods used in floodplain mapping for FEMA projects. It then describes the current efforts by the USACE to incorporate risk analysis and uncertainty in flood damage reduction studies and in their levee certification process.

Chapter 3 outlines risk analysis in floodplain delineation—it defines probability, how to use probability distribution functions to quantify the natural variability and knowledge uncertainty for hydrologic and hydraulic variables, how these probability distributions are simulated using a Monte Carlo method, and the definition of annual exceedance probability. Chapter 3 also covers the process of creating a precipitation or discharge-frequency curve and defining the uncertainty of these curves to determine the annual exceedance probability.

Chapter 4 describes the process of linking hydrologic, hydraulic, and floodplain models to create floodplain maps. It also discusses methods of thinning large amounts of digital terrain data to obtain an accurate digital representation of the floodplain. These processes must be linked efficiently on typical desktop computers in order for this approach to be a reasonable option for practicing engineers.

Chapter 5 gives an overview of how this research combines risk analysis with the hydrologic, hydraulic, and floodplain models to create flood probability and annual exceedance probability maps.
Chapter 6 describes two case studies that show how flood probability and annual exceedance probability maps are created using the methods devised in this dissertation.

Chapter 7 includes the conclusions from this research and from the case studies. This chapter outlines the contributions to the field of floodplain mapping and presents ideas for future research.
2 Review of Current Methods

As stated in the introduction, the objective of this research is to create two maps. The first map is the flood probability map. The second map is the spatial annual exceedance probability (AEP) map. Creating these maps requires hundreds or thousands of floodplain boundary instances. This chapter describes the methods currently used to determine a single floodplain boundary. It then describes the methods used for obtaining some of the input parameters to the hydrologic and hydraulic models and the methods used for describing the uncertainty of these input parameters. Finally, it introduces current methods for risk analysis in flood studies.

Defining the boundary of a floodplain, or floodplain delineation, is a complex task that involves an interaction of variables and models to compute a floodplain boundary at a single recurrence interval. This study combines computer hydrologic, hydraulic, and water surface interpolation models to delineate the floodplain, as shown in Figure 2-1 (see FEMA, 2003).
Figure 2-1: Procedure for floodplain delineation

First, a hydrologic model determines the runoff volume in the floodplain.

Second, a hydraulic model computes the water levels (or stages) at several locations in the floodplain. Finally, a floodplain delineation model interpolates the extent of the floodplain from the water levels to a digital terrain model.

For a two-dimensional model, the water level is determined at each point in the hydraulic model. The extent of the floodplain for a two-dimensional model is where the water level is equal to the elevation (water depth is zero). When using one-dimensional models, engineers have traditionally determined the location where the water level intersects the ground surface in cross sections on a topographic map. They have then approximated the location of the floodplain boundary between cross sections. Recently, scientists have developed algorithms that interpolate the cross
section stages to determine the extent of the floodplain. Talbot (1993), DHI (1997), and Noman (2001) have devised algorithms that extrapolate stages over the entire floodplain.

The Federal Emergency Management Agency (FEMA, 1995 and 2003) and the US Army Corps of Engineers (USACE, 1996) give the most widely used guidelines and standards for flood studies. Most flood mapping projects in the United States use the FEMA guidelines (FEMA, 2003). A 1995 version of the guidelines (FEMA, 1995) preceded the current guidelines. Under the 2003 guidelines, the investigator determines the scope of the flood study and collects data for the study. The investigator then performs hydrologic and hydraulic analysis to delineate the floodplain. From the floodplain, he creates a flood insurance rate map (FIRM) and submits it with a report describing the modeling methods and important aspects of the flood study.

The USACE also has guidelines for performing flood damage reduction studies and for levee certification (see USACE, 1996 and National Research Council (NRC), 2000). The USACE has pioneered efforts over the last decade to incorporate risk analysis into their flood damage reduction studies.

2.1 Determining the Scope of the Flood Study

FEMA has specified two levels of flood insurance studies: approximate and detailed. The scope of the study depends on the following factors (FEMA, 2003, Volume 1):

1. Availability of data from previous flood insurance studies.
2. Floodplain development pressures from city planners and developers.

3. The amount of money available for the study.

If accurate study data are available from previous studies and there have been no significant changes in the floodplain, planners can still use these studies. If the development pressures from city planners and real estate developers are high, a detailed flood analysis is required, which necessitates field data surveys.

2.2 Data Collection

Data collection involves conducting a thorough search of the literature and data available from libraries and governments (local, state, and federal). After you have conducted this search, you obtain any additional required data through a field survey (FEMA, 2003, Volume 1).

Topographic data are required for any hydrologic or hydraulic study. Greenwood et al. (1994) obtained 4-foot contour data for their floodplain study. Methods of elevation surveys range from traditional methods to using differential global positioning system (GPS) technology (FEMA, 1995, Chapter 3) and light detection and ranging (LIDAR) technology (Marks and Bates, 2000 and Cobby et al., 2001). Bathymetric data are required for hydraulic modeling. This data can be obtained using standard survey methods or from boat-mounted sonar.

2.3 Hydrologic Analysis

You should conduct a detailed hydrologic analysis using one of the approved computer programs or methods for hydrologic analysis. According to FEMA (2003), if somebody has already performed a hydrologic analysis of the watershed feeding the
floodplain, no additional analysis is necessary (unless watershed conditions have changed since the original study). However, FEMA may require additional analyses to account for uncertainty in the original hydrologic analysis. As a minimum, the 100-year floodplain must be determined, but additional recurrence intervals, including the 10, 50, and 500-year events, are often modeled (FEMA, 2003, Volume 1). The 500-year floodplain boundary is often included on the FIRM.

For gaged streams, you can obtain flood flow frequency curves from the USGS (Water Resources of the United States, 2001). From these curves, you can determine the maximum flowrates at each recurrence interval. For ungaged streams, you can use the National Flood Frequency (NFF) method, developed by the USGS (2002), for obtaining peak flow data. If the NFF method does not adequately reflect the peak discharge for the upstream area of a floodplain, you can generate a detailed hydrologic model using HEC-1/HEC-HMS, TR-20, or other rainfall-runoff software (FEMA, 2003).

After you perform the hydrologic analysis, compare the discharges from the watershed with the discharges from previous studies or with observed discharges. If the discharges are within a confidence interval of the discharges from previous studies, they are acceptable. This assumes that the discharges from previous studies are “correct”. Sometimes, a plot of drainage area vs. peak discharge is made to determine any problems with the analysis. If the peak discharge does not correspond with the expected discharge for drainage areas of the study area’s size, a flaw could exist in the model, its input parameters, or the previous study (FEMA, 2003). Figure 2-2 shows a
flowchart showing the decision process in determining the type of hydrologic analysis to perform.

Figure 2-2: Flowchart for a FEMA hydrologic analysis

Two components of performing a detailed hydrologic analysis include determining precipitation values and rainfall/infiltration percentages (curve numbers) for a storm. Since the peak discharge from a watershed is most sensitive to these two parameters, this chapter discusses methods of obtaining values for these two parameters. In addition, since these parameters can vary over a wide range because of natural variability and model uncertainty, this chapter presents methods for defining their variability.
2.3.1 Precipitation

Precipitation is a primary parameter required for most hydrologic models. In determining the precipitation totals for a hydrologic analysis, you must first determine the precipitation total for a return period or a specific storm. Most hydrologic models only operate on a single precipitation value and do not account for uncertainty. However, you should consider uncertainty in determining storm precipitation totals.

2.3.1.1 Determining Precipitation

The first value that must be determined for a hydrologic analysis is the storm precipitation at a recurrence interval. The recurrence interval, or return period, is “the average interval, in years, between the occurrence of a flood of specified magnitude and an equal or larger flood” (Linsley et al., 1992). Since the extent of flooding is derived from the amount of precipitation and a hydrologic model, the recurrence interval for a storm precipitation value and for a flood are closely related.

FEMA guidelines require the extent of flooding at the 100-year recurrence interval. To determine the storm precipitation at the 100-year recurrence interval, tabulate and sort the highest rainfalls for all the years of record from highest to lowest. Given the table of yearly maximum storm precipitation totals, you can approximate the recurrence interval for each storm according to the following equation (Linsley et al., 1992):

\[
T_r = \frac{(N + 1)}{m}
\]  

(2-1)
Where:

\[ T_r = \text{The recurrence interval,} \]

\[ N = \text{The total number of years of data, and} \]

\[ m = \text{The rank of the precipitation value.} \]

You plot each storm on a semi log plot, creating a depth-duration-frequency curve (Smemoe, 1995). Figure 2-3 shows a depth-duration-frequency curve generated from storm data in Austin, Texas between 1970 and 1993.

![Depth-Duration-Frequency Curve](image)

**Figure 2-3:** A depth-duration-frequency curve for Austin, Texas (from Smemoe, 1995)

From the depth-duration-frequency curve, you can determine a log-linear fit (see Figure 2-4).
You determine the precipitation depth for a one hundred year storm by solving the log-linear fit equation for the depth. For Austin, Texas, the log-linear fit line is:

$$depth = 1.0097 \ln(T) + 1.5049$$ (Figure 2-4),

so the approximate precipitation depth for the one hundred year storm is 6.2 inches.

The accuracy of this method depends on the number of years of data and the quality of the log-linear fit. If you have less than 100 years of data, you extrapolate the precipitation totals for the 100-year storm. Even if 100 or more years of data were available, natural variability results in only an approximation of a 100-year event.
Statisticians define the uncertainty of a random variable such as the 100-year precipitation by the mean, standard deviation, and the coefficient of skewness. If you have data from several adjacent rain gages, you can compute these statistical parameters by determining a log-linear fit for each gage. Then, use the following standard equations to determine the mean, standard deviation, and coefficient of skewness (Mays and Tung, 1992):

**Mean:** \[ \mu_{100} = \frac{1}{n_g} \sum_{i=1}^{n} p_{100,i} \]  

**Standard Deviation:** \[ \sigma_{100} = \sqrt{\frac{1}{n_g-1} \sum_{i=1}^{n} (p_{100,i} - \mu_{100})^2} \]  

**Coefficient of Skewness:** \[ \gamma_{100} = \frac{n_g \sum_{i=1}^{n} (p_{100,i} - \mu_{100})^3}{(n_g-1)(n_g-2)\sigma_{100}^3} \]  

Where:

- \( \mu_{100} \) = The mean of the 100-year precipitation,
- \( n_g \) = The number of gages,
- \( p_{100,i} \) = The 100-year precipitation for gage i,
- \( \sigma_{100} \) = The standard deviation of the 100-year precipitation, and
- \( \gamma_{100} \) = The coefficient of skewness of the 100-year precipitation.
You can compute a normal probability distribution function from the mean and standard deviation using the following equation:

\[
f(p) = \frac{1}{\sigma_{100} \sqrt{2\pi}} \exp \left( -\frac{1}{2} \left( \frac{p - \mu_{100}}{\sigma_{100}} \right)^2 \right)
\]

(2-5)

Where:

\( p \) = The precipitation value and

\( f(p) \) = The probability that the precipitation \( p \) will occur, and all other values are as specified above.

Precipitation frequency estimates for western areas of the United States are defined using data from NOAA Atlas 14. Precipitation frequency estimates for eastern areas of the United States are defined using the NOAA Technical Paper 40 (National Weather Service, 2003). Additionally, NOAA Atlas 14 provides probable upper and lower confidence values for the precipitation frequency estimates in the western United States.

2.3.1.2 Precipitation Uncertainty

Mays and Tung (1992) state that

“Because of the lack of perfect hydrologic information about these processes or events, for example, infinitely long historical records, there exist informational uncertainties about the processes. These uncertainties are referred to as the parameter uncertainty and model uncertainty. There is seldom enough information available to
accurately evaluate the parameters or statistical characteristics of a
probability model.”

This research accounts for the uncertainty caused by variability in precipitation by using a range and distribution of precipitation values for the hydrologic model. This research samples precipitation values from this distribution and determines the effects of the precipitation uncertainty on flood maps.

2.3.2 Runoff/Infiltration Percentages

Hydrologic models determine the amount of rainfall converted to runoff. The relationship between the total precipitation and runoff can be a very simple one. Linsley et al. (1992) propose the following equation for determining the amount of runoff ($Q$) corresponding with the precipitation ($P$):

$$Q = kP$$  \hspace{1cm} (2-6)

Hydrologists measure both $Q$ and $P$ in units of length. The coefficient, $k$, called the runoff coefficient, represents the percentage of precipitation that runs off a watershed area. In some cases, hydrologists approximate this coefficient as a constant value. However, for most cases, $k$ varies with the amount of precipitation and with the soil moisture and properties. Since $k$ depends on so many factors, there is a high degree of uncertainty in determining its value. Several different methods exist for estimating the relationship between rainfall ($P$) and runoff ($Q$). These methods include Green and Ampt’s method (Green and Ampt, 1911), the initial-uniform method (USACE, 1998a), the exponential loss method (USACE, 1998a), the Holtan
method (Holtan et al, 1975), and the NRCS curve number method (Mockus, 1964, 1972, 1985). The NRCS method is one of the most widely used in hydrologic analysis for floodplain mapping and this section will focus on using this method for determining the $P$-$Q$ relationship.

2.3.2.1 Determining Runoff from Rainfall

One of the most widely used methods for determining the amount of runoff ($Q$) is the Natural Resource Conservation Service (NRCS) curve number (CN) method. Mockus (1964, 1972, 1985) discusses the theory behind the NRCS curve number method. Mockus examined cumulative curves of watershed rainfall, rainfall retention, and runoff to determine the relationships between a watershed’s rainfall, retention, and runoff. The NRCS approach hypothesizes that the proportion of rainfall storage to total possible storage in a watershed is equal to the proportion of total rainfall runoff to total rainfall in a watershed. This means that if the watershed is 75 percent saturated, 75 percent of the precipitation will become rainfall runoff. Moreover, if a watershed has reached its maximum potential saturation (100% saturation), there will be no infiltration and all the rainfall will contribute to runoff. Mockus uses this hypothesis to propose the following relationship for a watershed with no initial abstraction (initial abstraction is the amount of rainfall that accumulates in the watershed before runoff occurs):

$$\frac{F}{S} = \frac{Q}{P}$$  \hspace{1cm} (2-7)
Where:

\[ F = \text{Actual retention after runoff begins} \]
\[ S = \text{Potential maximum retention } (S \geq F) \]
\[ Q = \text{Actual runoff} \]
\[ P = \text{Rainfall } (P \geq Q) \]

Since the retention is the difference between rainfall and runoff \((F = P - Q)\) for a watershed, you can derive the following relationship for determining runoff where there is no initial abstraction:

\[ Q = \frac{P^2}{P + S} \quad (2-8) \]

Considering initial abstraction \((I_a)\), the rainfall available for runoff is \(P - I_a\).

This means that with initial abstraction, the above equation changes to:

\[ Q = \frac{(P - I_a)^2}{(P - I_a) + S} \quad (2-9) \]

According to the USDA NRCS TR-55 method (1986), \(I_a\) can be approximated with the following empirical equation: \(I_a = 0.2S\). Others (Woodward et al., 2002) suggest that the relationship \(I_a = 0.05S\) provides a better fit to observed data.

Substituting \(I_a = 0.2S\) into the equation above we obtain the following relationship between \(Q\), \(P\), and \(S\):
\[
Q = \frac{(P - 0.2S)^2}{(P + 0.8S)}
\]  

(2-10)

The rainfall \((P)\) value in the equation above is a known value or a value that hydrologists can look up on a map for a particular storm recurrence interval. Since \(S\) is difficult to determine, a value that is more easily determined, called the runoff curve number \((CN)\), is used to determine \(S\). The following relationship exists between the \(CN\) and \(S\):

\[
S = \frac{1000}{CN} - 10
\]  

(2-11)

2.3.2.2 Determining Curve Numbers

The best method for determining a watershed curve number is to back calculate curve numbers for various storms (Mockus, 1964, 1972, 1985), and then compute the average curve number for the watershed. Depending on whether the antecedent watershed conditions are dry, normal, or moist (antecedent conditions I, II, or III), the curve number would be lower, stay the same, or increased from the average for a particular watershed. There is one problem with this method of determining the \(CN\): obtaining sufficient rainfall-runoff data for a watershed study is rarely possible. Therefore, an empirical approach to computing the \(CN\) is necessary.

Another method for estimating \(CN\) values is from experimental data based on hydrologic soil group, land use type, land treatment type, hydrologic condition, and antecedent runoff condition (USDA NRCS, 1986). Tables exist for determining \(CN\)
values from various combinations of hydrologic soil groups, land use types, land treatment types, and hydrologic conditions (see USDA NRCS, 1986 and Mockus, 1964, 1972, 1985). These tables normally give $CN$ values for antecedent runoff condition II (normal). You can convert $CN$ values to other antecedent runoff conditions (dry or wet) using Figure 2-5.

![Figure 2-5: Antecedent runoff condition (ARC) adjustment for varying type II ARC curve numbers. Adapted from Mockus (1964, 1972, 1985).](image)

2.3.2.3 Curve Number Uncertainty

Because of the many inputs used to determine $CN$ values, and the variability of these inputs, the range of $CN$'s can be highly variable for a single watershed. Rainfall-
runoff relationships in a watershed can be used to establish an approximate watershed
CN, but even this method of estimating CN’s can only determine an average value
from several storms. The curve number for the storm being modeled could lie
anywhere in the range. In fact, Figure 2-5 shows that the curve number may vary
within a wide range of values based only on the antecedent moisture condition.
Because of the variability in CN values, you should run several hydrologic models
over a range of CN values to determine the sensitivity of discharge with respect to CN.

2.4 Hydraulic Analysis

After you complete a hydrologic analysis of the study area, you conduct a
hydraulic analysis of the area. The hydraulic analysis computes floodplain water
stages. You must calibrate final flood depths from the hydraulic model to actual,
observed flood depths from previous flood events within 0.5 feet (FEMA, 2003,
Appendix C).

Before beginning the hydraulic analysis, you should review existing studies of
the floodplain. According to FEMA (2003), if 100-year flood elevations already exist,
a new hydraulic model of the floodplain may not be required. The only drawback is
that FEMA requirements and current studies do not account for uncertainty.

One important parameter in the hydraulic analysis of the floodplain is the
roughness coefficient. An experienced modeler must estimate this coefficient based
on observations at each cross section in the floodplain. It is also important to obtain
accurate cross section data to conduct an accurate hydrologic analysis. Burnham and
Davis (1990) developed equations relating Manning’s roughness and geometry
uncertainty to mean and maximum water surface elevation errors in steady flow models. Their paper reports that engineers use a wide range of Manning’s roughness estimates. They also discuss the effects of various Manning’s roughness values on the water surface elevations. They found that a high uncertainty of Manning’s roughness values could result in greater errors than those caused by elevation error uncertainty.

2.4.1 Cross Section/Elevation Data

Multiple data sources exist for determining cross section data. Noman (2001) discusses how modelers obtain cross section data from surveys and from existing digital terrain data. The vertical accuracy of a cross section depends on how the data are obtained. Some survey-grade GPS equipment claim vertical accuracies within 10 mm of the actual value (see Trimble, 2001). On the other hand, some of the most accurate aerial surveys can only be accurate within ½ meter (see Intermap Technologies, 2004) and may include errors of several meters. If the elevation data are accurate within Δz, the data can vary anywhere between a minimum value \(z - Δz\) and a maximum value \(z + Δz\), as shown in Figure 2-6. Because inaccuracies in elevation data exist, modelers need to account for the uncertainty in cross section geometries in the modeling results.
Burnham and Davis (1990) studied the effects of various elevation data gathering techniques on steady flow profiles. They found mean errors in the water surface profiles of up to a foot and maximum errors of up to four feet exist in water surface elevations from hydraulic models created from aerial spot elevation surveys if the other parameters remain the same. For topographic maps, they calculated mean errors of up to four feet and maximum errors of up to nine feet.

2.4.2 Roughness Coefficient

The roughness coefficient is another hydraulic parameter that adds to uncertainty. The most common equation used in hydraulic modeling is Manning’s equation (Manning, 1890):
\[ V = \frac{1.49}{n} R_{h}^{\frac{2}{3}} S_{0}^{\frac{1}{2}} \]  

(2-12)

Where:

\( V \) = Mean velocity of the water in the stream (ft/s)

\( n \) = Manning’s coefficient of roughness

\( R_{h} \) = Hydraulic radius

\( S_{0} \) = Slope of energy grade line (dimensionless)

Manning’s equation includes a single parameter that corresponds with material properties of the channel: Manning’s coefficient of roughness. Table 2-1 shows minimum and maximum values for Manning’s coefficient, derived from test studies, for different materials. This table illustrates the high variability and resulting high uncertainty of Manning’s coefficient.

Table 2-1: Manning’s n-values for various channel surfaces (from Daugherty et al, 1985).

<table>
<thead>
<tr>
<th>Nature of Surface</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neat cement surface</td>
<td>0.010</td>
<td>0.013</td>
</tr>
<tr>
<td>Precast concrete</td>
<td>0.011</td>
<td>0.013</td>
</tr>
<tr>
<td>Brick with cement mortar</td>
<td>0.012</td>
<td>0.017</td>
</tr>
<tr>
<td>Cast iron—new</td>
<td>0.013</td>
<td>0.017</td>
</tr>
<tr>
<td>Corrugated metal pipe</td>
<td>0.021</td>
<td>0.025</td>
</tr>
<tr>
<td>Canals and ditches, smooth earth</td>
<td>0.017</td>
<td>0.025</td>
</tr>
<tr>
<td>Smooth canals, dredged in earth</td>
<td>0.025</td>
<td>0.033</td>
</tr>
<tr>
<td>Rough bedded canal with weeds on sides</td>
<td>0.025</td>
<td>0.040</td>
</tr>
<tr>
<td>Smooth natural stream</td>
<td>0.025</td>
<td>0.033</td>
</tr>
<tr>
<td>Roughest natural stream</td>
<td>0.045</td>
<td>0.060</td>
</tr>
<tr>
<td>Very weedy natural stream</td>
<td>0.075</td>
<td>0.150</td>
</tr>
</tbody>
</table>

Furthermore, the Manning’s roughness for a channel is not constant, but varies along the length and width of the study area. Manning’s roughness also varies with water
depth. Variability of values for Manning’s coefficient cause resulting variability for velocity and water depth. It is useful to determine how changes in values of Manning’s coefficient cause changes in water depths and in the extent of the floodplain.

The study of data errors on steady-flow profiles by Burnham and Davis (1990) found that variations in Manning’s coefficient impede model results, with the effect being that there is twice the error in water surface elevations than the error caused with elevation data obtained from both aerial surveys and topographic maps.

2.5 Determining Flood Elevations

You can apply several models for determining water surface elevations, including HEC-RAS, HEC-2, WSPRO, and WSP-2. You can use other hydraulic models, as long as they are “reviewed and accepted by a government agency responsible for the implementation of programs for flood control and/or the regulation of floodplain lands” (FEMA, 1995, Chapter 5).

2.6 History of Floodplain Delineation Algorithms

Floodplain delineation has evolved over the years from a tedious process done with hydraulic equations and paper maps to a process automated by digital data and computers. Today, engineers use computer-based hydrologic and hydraulic models, digital elevation data, and automated floodplain delineation methods to determine more numerically justified floodplain boundaries. Table 2-2 shows the history of floodplain delineation algorithms.
Table 2-2: History of floodplain delineation (from Bedient and Huber, 1988 and Noman, 2001).

<table>
<thead>
<tr>
<th>Date</th>
<th>Event</th>
</tr>
</thead>
<tbody>
<tr>
<td>1889</td>
<td>Manning’s equation developed</td>
</tr>
<tr>
<td>1900-1930</td>
<td>Empirical hydrologic equations developed</td>
</tr>
<tr>
<td>1922</td>
<td>International Association of Scientific Hydrology formed</td>
</tr>
<tr>
<td>1930-1950</td>
<td>Unit hydrograph, infiltration theories, and Gumbel's extreme value frequency analysis methods developed</td>
</tr>
<tr>
<td>1950-Present</td>
<td>Urbanization in the US required FEMA to establish guidelines for delineating floodplains. Computer methods were developed for hydrologic and hydraulic modeling for watersheds and floodplains.</td>
</tr>
<tr>
<td>1990-Present</td>
<td>Several floodplain delineation models were developed, such as Reinhards’s floodplain delineation using Arc/Info (1995), DHI’s Mike 11 GIS for ArcView (1997), HEC-RAS and HEC-GeoRAS (1999), and the Watershed Modeling System (1994)</td>
</tr>
</tbody>
</table>

2.7 Creating the (Digital) Flood Insurance Rate Map (FIRM/DFIRM)

Table 2-3 lists the flood insurance rate zones for both approximate and detailed flood studies.
Table 2-3: FEMA flood insurance rate zones for FIRMs (from FEMA, 1995, Chapter 8).

<table>
<thead>
<tr>
<th>Zone Identifier</th>
<th>Type of analysis</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zone A</td>
<td>Approximate</td>
<td>Area within the 100-year floodplain</td>
</tr>
<tr>
<td>Zone AE</td>
<td>Detailed</td>
<td>Area within the 100-year floodplain</td>
</tr>
<tr>
<td>Zone AH</td>
<td>Detailed</td>
<td>Areas of shallow flooding (1-3 feet) with a constant water surface elevation (areas of ponding) within the 100-year floodplain</td>
</tr>
<tr>
<td>Zone AO</td>
<td>Detailed</td>
<td>Areas of shallow flooding (1-3 feet) with a sloping water surface elevation within the 100-year floodplain, used for alluvial fan flood hazards</td>
</tr>
<tr>
<td>Zone A99</td>
<td>Approximate</td>
<td>Areas within the 100-year floodplain protected by a federal flood protection system</td>
</tr>
<tr>
<td>Zone AR</td>
<td>Approximate</td>
<td>Areas where a flood protection system has become de-certified and is being restored to provide a 100-year or greater level of flood protection</td>
</tr>
<tr>
<td>Zone V</td>
<td>Approximate</td>
<td>Areas within 100-year coastal floodplains that have additional hazards associated with storm waves—approximate analysis</td>
</tr>
<tr>
<td>Zone VE</td>
<td>Detailed</td>
<td>Areas within 100-year coastal floodplains that have additional hazards associated with storm waves—detailed analysis</td>
</tr>
<tr>
<td>Zone X</td>
<td>Approximate</td>
<td>Areas that meet one of the following criteria: 1. Outside 100-year floodplain 2. Inside 100-year floodplain with average depths less than 1 foot 3. Inside 100-year floodplain with contributing area less than 1 mi² 4. Areas protected from 100-year flood by levees</td>
</tr>
<tr>
<td>Zone D</td>
<td>N/A</td>
<td>Area that is not studied</td>
</tr>
</tbody>
</table>

According to FEMA (2003), the flood insurance rate map (FIRM) or digital flood insurance rate map (DFIRM) is the final product of a flood insurance study (FIS). Engineers create flood insurance rate maps from the output stages generated by the hydraulic model. The final product delivered by the study contractor consists of two maps: the community base map and the work map. The community base map includes the area surrounding the floodplain and contains infrastructure features such as corporate boundaries, roads and their names, parcels, and all other hydrologic and constructed features (roads, railroads, airports, large buildings, etc.) in the study area.
The community base map can be in either hardcopy or digital format. The work map is a draft of the FIRM, and contains the information on the community base map in addition to the floodplain and floodway boundaries. The FIRM labels flood insurance rate zones and displays contours of the water surface elevations if they are known.

In addition to the community base map and the draft of the FIRM, the study contractor for a flood insurance study is required to submit a report of all the items on the flood insurance study report data checklist. Appendix J of FEMA (2003) lists these items.

2.8 Risk Analysis in Floodplain Mapping and Flood Damage Studies

The remainder of this chapter discusses current methods for considering uncertainty in floodplain analysis. The process of modeling and mapping a floodplain is laden with uncertainty, but engineers are still required to determine a single line showing the boundary of a floodplain for flood insurance and other floodplain studies. This is despite the fact that the input parameters to the models used to determine the floodplain are uncertain and the models themselves include limiting simplifying assumptions. This makes the process of certifying flood maps arbitrary, and often leads disputing parties to develop contradictory floodplain maps.

While the FEMA guidelines for flood insurance studies say very little about uncertainty considerations in floodplain mapping, in recent years, the USACE has developed methods of using risk analysis in conducting flood damage reduction studies. Their approach subdivides the study area into “damage reaches”, which are cross sections or gage stations representing an entire river reach (USACE, 1998b).
This method determines the expected annual damage (EAD, or the amount of expected damage in a single year) by developing three curves for each damage reach in the study. To use this method, you must first develop a flow-frequency curve, which is a plot of discharge (linear scale) versus recurrence interval (log scale). You can develop this curve using the Log-Pearson III flow-frequency analysis procedures described in USGS Bulletin 17B (1982). Second, develop a stage-discharge curve using either measured data or computed water surface profiles. Third, develop a stage-damage curve as described by the USACE (1996). This curve shows a plot of damage costs at different stages at the index (gage or cross section) location on the damage reach. You can use a stream gage location or a cross section as an index location. From these three curves, flood damage analysis software (USACE, 1998b) develops a damage-frequency curve and determines the EAD for each damage reach. The algorithm aggregates the EAD from each damage reach over the entire model and determines the total model EAD.

The method proposed by the USACE is to compute the EAD with and without a proposed project. From these values, you compute an annual benefit of the project. The net annual benefit is the difference between the annual project cost and the annual benefits from the project. Floodplain managers then use the plan with the greatest net annual benefit for the National Economic Development (NED) plan. Another result of this analysis is the AEP for the proposed project. The AEP is the probability of overtopping of a levee or other flood control structure in any year. The USACE is currently using risk analysis to compute the AEP for damage reaches in flood damage reduction studies (USACE, 1998b).
2.9 Current Methods for Computing AEP

The USACE has devised two methods for computing the AEP—the annual flood sampling procedure and the function sampling procedure.

2.9.1 Computing AEP Using the Annual-Flood Sampling Procedure

The first method for computing the AEP of a damage reach is the Annual-flood sampling procedure. This algorithm requires a discharge-probability curve and a stage-discharge curve with ranges of uncertainty for each curve. The algorithm first determines a random probability between 0 and 100%. This number represents the probability of exceedance of a maximum discharge in a single year. From this probability, the algorithm obtains an annual maximum discharge, $Q_i^*$, from the discharge-probability curve and the error distribution of that curve (see Figure 2-7).

![Figure 2-7: Obtaining a discharge value from an exceedance probability and an error function](image)

From this discharge, the algorithm obtains a stage, $S_i^*$, from the stage-discharge curve and the error distribution of that curve (see Figure 2-8).
The algorithm increments the number of exceedances \((n_e)\) if the stage, \(S_i^*\), is greater than the capacity of the levee. This process is repeated for a user-defined number of samples \((n_s)\), and the AEP is the number of exceedances divided by the number of samples \((AEP = n_e/n_s)\).

### 2.9.2 Computing AEP Using the Function Sampling Procedure

The function sampling procedure uses single instances of the entire discharge-probability and the stage-discharge curves to compute the AEP. From these two curves, this algorithm creates a stage-probability curve by sampling the discharge-probability (see Figure 2-9) and the stage-discharge (see Figure 2-10) curves at probability intervals of 0.001, 0.002, 0.005, 0.01, 0.02, 0.1, 0.2, 0.5, and 1.0 \((p_1, p_2, p_3, \ldots)\). This procedure develops the resulting stage-probability curve as shown in Figure 2-9 to Figure 2-11. The probability of exceedance \((p_e)\) for a single sampling of functions is found by determining the probability associated with the stage that will exceed the elevation of the flood control structure \((S_e)\) (see Figure 2-11).
Figure 2-9: Finding discharge values from an instance of the discharge-probability curve

Figure 2-10: Finding stage values from an instance of the stage-discharge curve

Figure 2-11: Creating the stage-probability curve and finding the exceedance probability
The function sampling procedure repeats this process of generating instances of the discharge-probability, the stage-discharge, and the stage-probability curves, and of determining the exceedance probability a user-defined number of times. The average exceedance probability from all these runs is the AEP.

2.9.3 Geotechnical Uncertainty

Even though a simulation does not exceed the height of the levee, a levee or flood control structure could still be breached and undergo geotechnical failure from cracks or seepage through the levee. The USACE procedures for computing the AEP have methods for including this geotechnical uncertainty of the levee in the AEP calculation (see National Research Council, 2000 and US Army Corps of Engineers, 1996). The USACE includes a relationship between water depth and the probability of levee failure in the AEP calculation. The USACE factors this depth-probability curve into the two methods described above for determining the AEP.

2.10 Quantifying Uncertainty in Floodplain Delineation

This dissertation has already described the current approach to floodplain delineation prescribed by FEMA. First, engineers obtain water levels from a hydraulic model. Then, floodplain delineation models use these levels to determine the extent of the floodplain.

Before recent computer methods were developed, engineers used the water level at each cross section to determine the floodplain elevation using a paper topographic map and engineer’s judgment. Newer numerical methods determine the
extent of the floodplain by extrapolating stage values and intersecting the numerical water surface with a digital ground surface (this eliminates the need for paper maps).

Although these methods have less arbitrary judgment involved than manual methods, they still do not account for uncertainty in the hydrologic or hydraulic modeling parameters.

The USACE has pioneered efforts over the last decade to incorporate risk analysis into their flood damage reduction studies. They have a method of computing the AEP and EAD for damage reaches on a floodplain. Though worthwhile, the NRC created a report (2000) describing weaknesses which indicate more work is needed. One of the most important shortcomings this report described was that the USACE computes all the analysis parameters for a single point in a damage reach. The USACE needs to extend their risk analysis methods to compute risk as a spatially distributed system instead of at a single point. This research provides a method for computing spatially distributed flood risk.

2.11 Research Objectives

There are several limitations of current approaches to floodplain delineation. First, delineating a floodplain provides only one solution (you are either in or out of the floodplain). However, when considering uncertainty in modeling parameters, multiple solutions to a floodplain exist; in other words, there is some probability associated with being in or out of the floodplain for a given modeling scenario. These multiple solutions are due to the following factors:

1. The probability of different rainfall depths and durations.
2. Inaccuracies in hydrologic loss parameters.

3. Inaccuracies in hydraulic roughness coefficients.

4. Inaccuracy in elevation measurement.

5. Other inaccuracies and model assumptions (knowledge uncertainty).

A single 100-year floodplain boundary always contains uncertainty. Recent studies have shown that floods occur more frequently than originally thought. For example, a geological and historical study of the Mississippi river floodplain showed that three “500-year” flood events have occurred along this floodplain between 700 and 500 years ago. In addition, hydrologists thought the great Mississippi flood of 1993 was an extremely rare occurrence. But historical records show that at least six floods with at least this magnitude have occurred in the Mississippi river floodplain since 1780 (Knox, 1997).

Some uncertainty stems from the model itself. Brunner and Piper (1994) compared the hydraulic models HEC-2 and HEC-RAS. They found that differences in water surface elevations as high as 2.75 feet existed at one cross section, though most cross sections had water surface elevations within ½ foot of the elevation computed by HEC-2.

With all the uncertainty and limited data in hydrologic modeling, you usually know a probable range of hydrologic values. Even in a seemingly simple case of asphalt or concrete pavement, between 70 and 95 percent of the water from a storm may run off the lot (Wanielista, 1990). If there are many cracks in the pavement, the value may be closer to 70 and may never actually reach 95.
However, if you can define a range of values, you can determine a range of floodplain extents based on these values and determine the probability that the 100-year floodplain will flood a certain location. This is a more “honest” approach from an engineering standpoint. Instead of determining a single floodplain boundary, engineers can incorporate this uncertainty into the hydrologic and hydraulic modeling process that is used to determine a 100-year floodplain boundary. One focus of this research is to create a flood probability map by defining ranges and distributions of input parameters to hydrologic and/or hydraulic models.

The other focus of this research is to expand the USACE’s method that computes an AEP value for a damage reach. This research uses their method to determine an AEP map in a floodplain. You can then use this spatially distributed AEP to find a floodplain boundary for a given recurrence interval that inherently considers the uncertainty associated with the modeling parameters.

This spatial approach to flood damage risk analysis allows engineers to not only evaluate the uncertainty in a floodplain boundary at a single recurrence interval (from the flood probability map), but it also allows them to define a single, 100-year floodplain boundary that considers all the variability (from the AEP map). Also, instead of computing flood risk parameters at a single point in a damage reach, as is currently done in the USACE, a map of these parameters can be computed as a spatially distributed system.

Elevation data are an important consideration in this research. This research uses accurate, dense floodplain elevation data sets for determining cross section elevations and for determining floodplain extents from water surface elevations.
Large elevation datasets (such as LIDAR data) are now available for floodplain
delineation. However, these datasets require substantial model processing time unless
the final model uses fewer elevation values. For example, Marks and Bates (2000)
had 250,000 measurements from a LIDAR survey of a river floodplain in England,
but, because of computational limitations, they could only use only 6,049 points in
their model. Engineers must either thin or interpolate high-density elevation datasets
to a lower-density model before delineating the floodplain. This dissertation will
provide an overview of some of these methods of filtering data points to retain the
necessary points for accurate floodplain delineation. Omer et al. (2003) used the
normal angle method (described in chapter 4) to filter elevation data. This dissertation
uses the results from Omer et al’s research to filter elevation datasets for floodplain
delineation.
3 Risk Analysis in Floodplain Studies

Creating a flood probability map requires a distribution of input parameters and a method of sampling values from that distribution. For example, you cannot determine the exact curve number for a sub-basin. However, you can guess at the range of possible values for the curve number. You can assume the middle of this range as the “average”, and you can use this curve number distribution and the distribution of other input parameters (such as precipitation or Manning’s roughness) to create a flood probability map. You can use the distribution and uncertainty of rainfall depths or watershed discharges at different return periods to create an annual exceedance probability (AEP) map.

This chapter discusses risk analysis in floodplain studies. It defines probability, how this research uses probability density functions to define the natural variability and knowledge uncertainty for hydrologic and hydraulic variables, how this research simulates these probability distributions using a Monte Carlo method, and the definition of AEP. This chapter also covers the process of creating a precipitation or discharge-probability curve and of sampling the uncertainty of these curves to determine the AEP. Finally, this chapter explains methods for future research in stochastic floodway delineation using ineffective flow zone boundaries as the stochastic parameter.
Stochastic modeling techniques described in this chapter determine the input values for hundreds or thousands of model runs (see Figure 3-1).

![Figure 3-1: Stochastic modeling procedure](image)

### 3.1 Probability

The traditional method for determining whether a building requires flood insurance is to look on a flood insurance rate map. If the building location is outside of the boundary of the 100-year floodplain, flood insurance is not required. If the location is inside the boundary of the 100-year floodplain, flood insurance is required.

However, natural variability and knowledge uncertainty exists in hydrologic and hydraulic model input parameters. Because of these uncertainties, the exact location of the 100-year floodplain boundary is an uncertain boundary.

#### 3.1.1 What is Probability?

From a single set of input parameters, you create a single floodplain boundary. This research creates a floodplain probability map by defining a distribution of input parameters to hydrologic and/or hydraulic models. This “fuzzy” floodplain boundary is created by adjusting the input parameters inside an acceptable range.
Probability is defined as “the likelihood that a specific event will occur” (American Heritage Dictionary of the English Language, 4th Edition, 2000). For a flood at a certain recurrence interval, the probability of flooding at a single point in the floodplain is the ratio of the number of times that point was flooded to the total number of floods. Therefore, if a building in a floodplain floods 70 out of 100 occurrences of a 100-year flood, it has a 70% probability of flooding in a 100-year flood.

3.1.2 Natural Variability and Knowledge Uncertainty

The National Research Council (NRC, 2000) recommended that the Corps of engineers should be “clear about which variables it treats as natural variability, which it treats as knowledge uncertainty, and why and how it makes this distinction.” The NRC illustrated the importance of distinguishing these uncertainties with the following example: “Variations in stream flow, treated as natural variability, average out in a calculation from one year to the next (high flows in one year balance against low flows in another). In contrast, uncertainty in the mean annual flow parameter, treated as knowledge uncertainty, introduces a systematic effect into a calculation. If the mean flow is overestimated in one year, it is overestimated in every year of the calculation (NRC, 2000).”

The USGS (1982) illustrates how to distinguish natural variability and knowledge uncertainty from each other in their approach for generating a discharge-probability curve and its uncertainty. The discharge-probability curve represents
natural variability, while the uncertainty of this curve at each probability represents knowledge uncertainty (see Figure 3-2).

**Figure 3-2: Natural variability and knowledge uncertainty represented on a discharge-probability curve**

3.2 **Probability Density Functions**

The *probability density function* (PDF) of a continuous random variable shows the frequency of occurrence of any value of that variable. For example, a sub-basin’s curve number (CN) for different storms might range anywhere between 50 and 80, with an average value of 65. The PDF for this CN might look like the bell-shaped curve shown in Figure 3-3, with the most probable values centered close to 65. Values approaching 50 or 80 may be less likely for this CN. The probability that the CN lies between two values, $a$ and $b$, is the area under the curve between those values. The total area under the curve is 1.0, meaning that there is a 100% probability that the CN will fall within the ranges defined by the bell-shaped curve.
Statisticians have developed several mathematical models to model the distribution of values for a variable. Some common distributions used in this research include:

1. Normal
2. Linear (Uniform)
3. Lognormal
4. Loglinear

The following sections describe each of these distributions.
3.2.1 Normal Distribution

Many naturally variable phenomena follow a normal distribution. The normal, or Gaussian, distribution has the following probability density function (Hayter, 1995):

\[
f(x) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}
\]

(3-1)

Where \( \sigma \) is the standard deviation and \( \mu \) is the mean. You can approximate these values using the equations below, where \( N \) is the number of known data values and \( x_i \) is a sample data value:

\[
\sigma = \left[ \frac{\sum_{i=0}^{N} (x_i - \mu)^2}{N - 1} \right]^{1/2}
\]

(3-2)

\[
\mu = \frac{\sum_{i=0}^{N} x_i}{N}
\]

(3-3)

Figure 3-4 shows an example of a normal probability density function (100-year precipitation probability, for example) with a mean of 5.0 and a standard deviation of 2.0.
Figure 3-4: A normal distribution curve with $\mu = 5.0$ and $\sigma = 2.0$

3.2.2 Linear Distribution

The linear, or uniform, distribution has a constant probability density function between its minimum value and maximum value. This function has the following value for $\min \leq x \leq \max$ (Hayter, 1995):

$$f(x) = \frac{1}{\max - \min}$$  \hspace{1cm} (3-4)

Everywhere else, $f(x) = 0$. The linear probability density function is simple to conceive. Figure 3-5 shows an example of a linear probability density function for a 100-year precipitation with a minimum value of 3.0 and a maximum value of 7.0.
3.2.3 Lognormal Distribution

The lognormal distribution gives a normal distribution of the logarithm of the modeled variable. It has the following probability density function (Hayter, 1995):

\[
f(x) = \frac{1}{\sqrt{2\pi} \sigma x} e^{-\frac{(\ln(x) - \mu)^2}{2\sigma^2}}
\]  

(3-5)

This function is valid for \( x \geq 0 \). Elsewhere, \( f(x) = 0 \). \( \sigma \) is the standard deviation of the natural logarithms of the variable values and \( \mu \) is the mean of the natural logarithms of the variable values. You can approximate these values using the
The equations below, where \( N \) is the number of known data values and \( x_i \) is a sample data value:

\[
\sigma = \sqrt{\frac{\sum_{i=1}^{N} (\ln x_i - \mu)^2}{N-1}}
\]  

\( \mu = \frac{\sum_{i=1}^{N} \ln x_i}{N} \)  

(3-6)

(3-7)

Figure 3-6 shows an example of a lognormal probability density function (yearly peak discharges, for example) with a mean of logs of 5.3 and a standard deviation of logs of 0.6.
Figure 3-6: A lognormal distribution curve with $\mu_{(\text{of logs})} = 5.3$ and $\sigma_{(\text{of logs})} = 0.6$

3.2.4 Loglinear Distribution

A uniform distribution in a log scale between the log of its minimum value and the log of its maximum value defines the loglinear, or loguniform, distribution. Its probability density function has the following value for $\min \leq x \leq \max$:

$$f(x) = \frac{1}{x(\ln \max - \ln \min)}$$  \hspace{1cm} (3-8)

Everywhere else, $f(x) = \text{zero}$. You can use a loglinear distribution when a uniform distribution of values exists over several orders of magnitude. Figure 3-7 shows an example of a loglinear probability density function with a minimum value of 3.0 and a maximum value of 300.0.
3.3 Stochastic Analysis Methods

This research uses a stochastic approach to determine the parameters for models used in developing a floodplain. The basic approach is to use a standard Monte Carlo simulation (Parkinson, 2001). You can use the Latin Hypercube method, an optimized form of a Monte Carlo simulation, to obtain a wider range of results with fewer simulations (Smith and Goodrich, 2000 and McKay et al, 1979).

3.3.1 Monte Carlo Simulation

A Monte Carlo simulation, in which each specified input variable is randomly perturbed within a specified minimum and maximum value a predetermined number
of times, can be used in determining the probability that floodplain boundaries would extend to all locations based on a 100-year storm (Figure 3-8).

![Figure 3-8: Determining the probabilities of a floodplain reaching certain extents](image)

Figure 3-8: Determining the probabilities of a floodplain reaching certain extents

This research utilizes a Monte Carlo simulation, in which you might specify the total 24-hour, 100-year storm rainfall as a variable to be randomly perturbed. The flow rate, $Q$, is a function of precipitation, $P$ ($Q=f(P)$). Therefore, perturbing $P$ affects $Q$. Furthermore, the water surface elevations, $E_{ws}$, are a function of $Q$ ($E_{ws}=f(Q)$). The floodplain extents are determined from the water surface elevations. Therefore, the floodplain extent is a function of the precipitation.

For example, consider a case where the mean value of rainfall to a 24-hour storm with a recurrence interval of 100 years is determined to be between 6 and 8 inches. If you use a uniform probability distribution, the probability that 6 inches of precipitation occurs would equal the probability that 7 or 8 inches occurs. The extents
of the floodplain could then fall anywhere between the extents determined from a precipitation of 6 inches and a precipitation of 8 inches, as shown in Figure 3-9.

Figure 3-9: Range of floodplain extents for 6-8 inches of precipitation in a 24-hour, 100-year recurrence interval

Figure 3-10 shows a uniform probability distribution for precipitation between 6 and 8 inches. For each precipitation value, the probability of an instance of that precipitation value occurring is equal to the probability of any other precipitation value occurring.

Figure 3-10: A uniform probability distribution
If a PDF such as the normal distribution shown in Figure 3-11 is used, a Monte Carlo simulation samples many values close to the mean and fewer values close to the minimum and maximum precipitation values.

![Normal Probability Distribution](image)

**Figure 3-11: A normal probability distribution**

Other probability distributions include the Poisson, lognormal, gamma (Pearson type III), log Pearson type III, and Gumbel distributions (See Bedient and Huber, 1988, Linsley et al., 1992, and Mays and Tung, 1992).

For each of $N$ precipitation values, the algorithm used in this research performs separate runs of hydrologic and hydraulic models and computes a floodplain extent. A floodplain probability map is determined from the floodplain extent maps by determining the number of times, $n$, each point on a grid or mesh is inundated as the result of the combined hydrologic, hydraulic, and floodplain delineation. The probability (in percent) of a point becoming inundated is then equal to $\frac{n}{N} \times 100$, where $n$ is the number of times the point is inundated and $N$ is the total number of
simulations. This flood probability map is a two-dimensional cumulative distribution function for flooding.

3.3.2 Latin Hypercube Simulation

For a Monte Carlo simulation with a uniform probability distribution, each precipitation value would have equal probability. This means if you run five simulations using the Monte Carlo method, the precipitation values could be located anywhere between the minimum and maximum value. While it is possible that they would be evenly distributed, as shown in Figure 3-12 it is highly improbable.

![Figure 3-12: A Monte Carlo simulation with an even distribution of values](image)

Figure 3-12: A Monte Carlo simulation with an even distribution of values

Figure 3-13 shows a likely situation, where the random values are not evenly distributed, but are grouped together. The only way to prevent this with a standard Monte Carlo simulation is to run enough simulations to insure that the simulations explore the entire range of precipitation values.
Figure 3-13: A Monte Carlo simulation with an uneven distribution of values

You can get around this problem of encountering random values that are grouped together by running a Latin hypercube simulation (Smith and Goodrich, 2000). Latin hypercube simulations allow modelers to explore the full range of possible input parameters with far fewer runs of the model than are required for standard Monte Carlo simulations. The Latin hypercube method divides the probability distribution curve into equal areas. This method then numbers each area of the curve, as in Figure 3-14.
Figure 3-14: The Latin Hypercube method

For a constant linear distribution, the distribution would look like Figure 3-14(b). This method maintains equal area probabilities for each segment of the input parameter.

In the Latin Hypercube method, each of the runs generates a random number until a number is found that falls in the segment. After this method finds a number falling within the segment, it uses this number as the precipitation value for the run. If multiple parameters are being perturbed (for example, precipitation and curve number), equal-area probability distributions are determined for each parameter. The total number of simulations run is the product of the number of segments for each parameter. Therefore, if precipitation has $A$ segments and curve number has $B$ segments, the total number of segments is $A \times B$. For each of the $A$ precipitation segments, each of the curve number segments $B$ is run.
The Latin Hypercube method overcomes the problem of uneven distributions of values between the maximum and minimum by forcing the values to fall within each segment under the probability distribution curve.

### 3.4 Determining Variable Values for Each Run

With the given distributions, determining values that fit the distribution for each run is straightforward. The algorithm generates a random number between $\rho$ between zero and one that fits into the specified probability distribution. For example, a linear distribution generates input parameters using the following equation:

$$x = \min + \rho (\max - \min)$$  \hspace{1cm} (3-9)

A standard Monte Carlo simulation generates input parameters using a single execution of the above equation. A Latin Hypercube simulation generates values until it finds a value found within the minimum and maximum value for the current segment in the distribution function.

### 3.5 Annual Exceedance Probability (AEP)

The AEP is the probability of overtopping of a levee or other flood control structure in any year. As discussed in the previous chapter, the USACE has two methods for computing the AEP at a point in a damage reach. In the annual flood sampling procedure, a random probability value, $p_i$, is determined. From this probability value, a corresponding discharge value $Q_i^*$ is determined from the discharge-probability curve and its uncertainty [Figure 3-15].
From $Q_i^*$, the annual flood sampling procedure determines a stage value $S_i$ from the stage and its uncertainty (Figure 3-16). If this stage is greater than the elevation of the levee, the levee fails for that simulation. This simulation is repeated until the AEP, which is the number of levee failures divided by the total number of simulations, stops changing.
The function sampling procedure uses instances of the discharge-probability and the stage-discharge curves to generate a stage-probability curve (Figure 3-17). The probability associated with the height of the levee on the stage-probability curve (Figure 3-17(c)) is the AEP for the current simulation. This probability is determined from instances of the discharge-probability, stage-discharge, and stage-probability curves until the average probability is unchanging, and this average probability is the AEP.

![Figure 3-17: Function sampling procedure](image)

This research uses the annual flood sampling procedure to compute a spatial map of AEP for an entire floodplain. A single discharge value, $Q_i^*$, for a sub-basin is randomly generated using a discharge-probability curve and its uncertainty distribution with the annual flood sampling procedure (Figure 3-15). You define the discharge-probability curve and its uncertainty by defining the minimum, mean, maximum, and standard deviation of discharge values at probability values between 0.0 and 1.0. Table 3-1 shows an example of the data requirements.
Table 3-1: Discharge-probability curve and uncertainty input data

<table>
<thead>
<tr>
<th>Probability</th>
<th>Mean [m³/s]</th>
<th>Minimum [m³/s]</th>
<th>Maximum [m³/s]</th>
<th>Standard Deviation [m³/s]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>42.5</td>
<td>11.9</td>
<td>73.1</td>
<td>15.3</td>
</tr>
<tr>
<td>0.5</td>
<td>72.9</td>
<td>20.4</td>
<td>125.4</td>
<td>26.2</td>
</tr>
<tr>
<td>0.2</td>
<td>137.9</td>
<td>52.4</td>
<td>223.4</td>
<td>42.7</td>
</tr>
<tr>
<td>0.1</td>
<td>189.6</td>
<td>81.5</td>
<td>297.7</td>
<td>54.0</td>
</tr>
<tr>
<td>0.04</td>
<td>272.9</td>
<td>125.6</td>
<td>420.3</td>
<td>73.7</td>
</tr>
<tr>
<td>0.02</td>
<td>346.8</td>
<td>163.0</td>
<td>530.6</td>
<td>91.9</td>
</tr>
<tr>
<td>0.01</td>
<td>421.1</td>
<td>197.9</td>
<td>644.3</td>
<td>111.6</td>
</tr>
<tr>
<td>0.002</td>
<td>646.4</td>
<td>303.8</td>
<td>989.0</td>
<td>171.3</td>
</tr>
</tbody>
</table>

The AEP algorithm uses $Q_i^*$ as input to a hydraulic model, which computes stages at each cross section in the floodplain. The algorithm delineates the floodplain from these stages. This process is repeated several times. The AEP is the number of times each floodplain point is flooded divided by the total number of floods.
Figure 3-18 shows how the AEP algorithm determines each discharge value, $Q_i^*$, from a discharge-probability curve and its uncertainty.

In the left side of step (1) of Figure 3-18, a random probability value between 0.0 and 1.0 is determined. Since $RP = 1 / \text{probability}$ ($RP =$ return period), this random probability value of 0.3 represents a return period of 3.3 years. The algorithm
determines the minimum, mean, maximum, and standard deviation of the discharge-probability curve at this return period by linear interpolation from the closest known values. These values define the PDF for the return period (the right side of step (1) of Figure 3-18). From this PDF, a random discharge, $Q^*$, of 92.0 is determined. Using this same method, $Q^*$ is determined for each simulation, as shown in steps (2) and (3) of Figure 3-18.

3.6 Stochastic Floodway Delineation

The *floodway* is the area reserved to pass the 100-year flood. No development can occur in this area, and you cannot insure property in a floodway against flooding.

The floodway is defined as “the channel of a river or other watercourse and the adjacent land areas that must be reserved in order to discharge the base flood without cumulatively increasing the water-surface elevation by more than a designated height” (FEMA, 1995). Most often, modelers use the 100-year flood for the base flood and one foot as the designated height. Figure 3-19 illustrates how to determine a floodway’s extents. When determining a floodway, the flux, or conveyance, on each side of the floodway must be equal.

![Figure 3-19: Determining the floodway](image_url)
Currently, most engineers determine the extents of the floodway using one of a few one-dimensional floodway modeling tools. The most popular of these is HEC-RAS (USACE, 2001a), which provides several options for automatically determining floodway extents.

One of the most important variables in determining a floodway is defining the extents of ineffective flow zones. An ineffective flow zone is an area along the bank of a floodplain where essentially no flow occurs. In ineffective flow zones, the flow just stagnates or flows in circular motions as shown in Figure 3-20.

![Figure 3-20: The ineffective flow zone along the banks of a floodplain](image)

Normally, an engineer determines the location of the ineffective flow zones by estimating its location (Zundel, 2001). The engineer then runs the hydraulic model to determine the new extents of the floodway based on the estimated ineffective flow zone boundary. However, this approach is highly inaccurate at best, since the location
of this ineffective flow zone boundary greatly affects the floodway extents (Figure 3-21).

Figure 3-21: Effect of the ineffective flow zone size on floodway extents

Figure 3-22 shows a cross sectional view of the effect of the ineffective flow zone on the width of the floodway. As the ineffective flow zone becomes longer along one side of the cross section, the width of the floodway decreases and the water level rises. The conveyance loss on each side of the floodway must be equal while the water level rises due to the ineffective flow zone. Therefore, the floodway moves further in on the side of the stream with ineffective flow as the ineffective flow zone increases in length. On the other side of the stream, the floodway approaches the bank since the water depth increases.
One way to discover the effect the ineffective flow zone has on a floodway’s extents is to run a stochastic analysis. The methods in this research vary precipitation and/or Manning’s roughness values between minimum and maximum values in hydrologic or hydraulic models to determine probabilities of different floodplain extents. In the same manner, the ineffective flow zone boundaries can be varied between minimum and maximum values to determine the probabilities of different floodway extents, as shown in Figure 3-23.
This stochastic approach allows us to quantify and visualize the possible extents of the floodway based on the ineffective flow zone ranges. If a point is in the floodway for 100 percent of the ineffective flow zone possibilities, that area is in the floodway.

The only correct method of solving the ineffective flow zone problem is to use velocity data from a two-dimensional hydraulic model to determine the effective ineffective flow zone. An approach for determining the floodway based on a two-dimensional model would solve the ineffective flow zone problem since you can compute the flow rates between any two points in a two-dimensional model based on the velocities and water depths between these points. If there is no flow between two points, this can be determined from the velocity vectors and water depths between the points.
This section described methods for computing a map of floodway probabilities. This dissertation did not implement the methods described in this section. However, future research should explore the methods for stochastic floodway analysis described in this section.

3.7 Chapter Summary

This chapter has shown how this research uses Monte Carlo or Latin Hypercube techniques with the variable distributions to create a flood probability map. It has also shown techniques for determining annual discharge values from a discharge-probability curve and its uncertainty. Finally, this chapter has explained methods for stochastic floodway delineation using ineffective flow zone boundaries as the stochastic parameter. This research uses the probability techniques described in this chapter with the hydrologic, hydraulic, and floodplain-modeling techniques described in the next chapter to create a flood probability map and an AEP map.
4 Model Implementation

This research combines the current methods for delineating a floodplain with the risk analysis methods implemented by the USACE to create two maps: a flood probability map and an annual exceedance probability (AEP) map. Doing this requires a coupling of hydrologic, hydraulic, and floodplain delineation models in an automated manner so that these models can be run repeatedly without user interaction. This chapter describes the integration of hydrologic, hydraulic, and floodplain delineation models into a single interface to create flood probability and AEP maps.

As described in Chapter 2, the first step in delineating a floodplain is to obtain a stream discharge value for the floodplain under consideration. A river gage with sufficient historical data may exist in the floodplain. Engineers can compute the discharge value at the desired recurrence interval from these gage data. It is more likely that insufficient stream gage data will exist for the floodplain under consideration. In this case, an engineer utilizes a hydrologic model. The engineer uses the peak discharge computed by the hydrologic model as input to a hydraulic model that calculates river stages at each cross section. Then, the floodplain delineation model uses these stages to compute the floodplain boundary (Figure 4-1).
This research applies HEC-1 (US Army Corps of Engineers, 1998a) as the hydrologic model, HEC-RAS (US Army Corps of Engineers, 2001a) as the hydraulic model, and the Watershed Modeling System (WMS) (Noman, 2001 and Talbot, 1993) as the floodplain delineation model. The modeling process is flexible, so that if you measure or compute stream flow values or water surface elevations using another method, you can use these values as input to the hydraulic or floodplain delineation models.

This chapter describes these models and the geospatial data processing methods used to delineate a floodplain. An important part of modeling is preparing accurate, manageable elevation datasets. This chapter also discusses tools and procedures used to manage these elevation datasets.

4.1 HEC-1

HEC-1 is a lumped parameter watershed model that “simulates the surface runoff response of a river basin to precipitation by representing the basin as an interconnected system of hydrologic and hydraulic components” (US Army Corps of Engineers, 1998a). These components can represent a sub-basin, a sub-basin confluence (or outlet) point, or a reservoir within the river basin. You
define a set of parameters for each sub-area, outlet point, or reservoir. Based on these parameters, HEC-1 computes a hydrograph for each component of the river basin.

![HEC-1 components diagram](figure-4-2)

**Figure 4-2: HEC-1 components**

4.1.1 HEC-1 Basin Data

HEC-1 requires geometric and hydrologic data to compute a hydrograph at specified outlets in a model. HEC-1 divides its basin data into 4 categories: general basin data, precipitation data, loss data, and unit hydrograph data (see Figure 4-3).

General basin data includes basin area and baseflow. Precipitation data include the storm total precipitation and a time distribution of that precipitation. If several rain gages are located within a basin, you can assign a weight to the precipitation totals from each gage to determine the precipitation total for the basin. Basin loss data include the basin curve number, Green-Ampt parameters, or data for any of the other available loss methods. Unit hydrograph data include the sub-basin unit hydrograph (derived or synthetic) and lag time or time of concentration.
Automated delineation and watershed characterization algorithms compute geometric parameters such as area and average slope from watershed boundaries and elevation data (Environmental Modeling Research Laboratory, 2003c). Other algorithms compute hydrologic parameters (such as lag time, precipitation, and curve number) from additional user input. Some equations use geometric parameters, such as the basin slope and stream length, to approximate each sub-basin’s time of concentration and/or lag time. The time of concentration is the time it takes for a particle of water to travel from the hydraulically most distant point in a sub-basin to the outlet point. A basin’s lag time is the amount of time between the center of mass of the rainfall event to the time of peak runoff for the hydrograph (Wanielista, 1990).

4.1.2 HEC-1 Routing Data

Another important component of the HEC-1 model is the ability to compute the changes in a hydrograph between sub-basin confluence points or in a reservoir (hydrograph routing). You can use two methods of routing. One set of routing methods use storage routing to route a hydrograph. These methods require the storage
characteristics of the reach or reservoir. The other set of routing methods use channel hydraulic or hydrologic characteristics to route the hydrograph.

### 4.2 HEC-RAS

HEC-RAS is the Hydrologic Engineering Center’s river analysis system (US Army Corps of Engineers, 2001a). HEC-RAS models both steady and unsteady flow in river reaches. This research focuses on using the HEC-RAS steady flow model, SNET. For a steady flow model, you assign a single flow value to reaches of a hydraulic model. Using a standard step method, HEC-RAS computes the river stage at each cross section of the model. HEC-RAS requires geometric and hydraulic data as input (see Figure 4-4).

![Figure 4-4: HEC-RAS input and output](image)

The geometric data input for HEC-RAS include the location, geometry, and slopes for each cross section. The hydraulic data input for HEC-RAS include the hydraulic coefficients, flow rate, and a boundary control point.
4.2.1 Using HEC-1 Output for HEC-RAS Modeling

The primary result of running an HEC-1 simulation is a flow hydrograph for each sub-basin and confluence point. For a steady state simulation, HEC-RAS requires a single flow rate for each reach as a boundary condition. If confluence points in the HEC-1 model coincide with cross section locations of an HEC-RAS reach, then HEC-RAS can obtain these flow values from the HEC-1 flow hydrographs. After running the HEC-1 simulation, the methods in this research obtain the peak flow from each flow hydrograph. This peak flow value is then used as input into the HEC-RAS model, as shown in Figure 4-5.
HEC-RAS determines the stage values at each cross section in the hydraulic model. These stage values drive the floodplain delineation model.

4.3 The WMS Floodplain Delineation Model

Noman (2001) describes the WMS floodplain delineation model. The input data include a digital terrain model of the floodplain, water levels at different locations.
in the floodplain, and a floodplain barrier coverage. Using these data, the floodplain
delineation model uses a two-step approach to compute the flood depths for the digital
terrain model of the floodplain.

4.3.1 Floodplain Delineation Model Input

You can obtain the digital terrain model (DTM) of the floodplain from a
survey, from georeferenced cross-section geometry, or from existing floodplain
elevation data. The floodplain delineation model uses digital terrain data represented
in a file as XYZ data, as a grid of points, or as contours. You can obtain water levels
at locations in the floodplain from a hydraulic model. The floodplain barrier coverage
is an optional input parameter for the floodplain delineation model. The floodplain
barrier coverage is a layer of polylines that define proposed levees, high points,
structures, or other flow barriers in the floodplain.

4.3.2 Interpolating Water Surface Elevations

HEC-RAS determines a single water surface elevation for the entire length of a
cross section. The floodplain delineation algorithm stores the water surface elevation
at the intersection of the stream and the cross section. The algorithm then interpolates
the water surface elevations to the elevation locations in the DTM. The accuracy of a
floodplain delineation increases as the quantity of known water surface elevation
points in the floodplain increases. Therefore, to delineate a floodplain, you must
distribute the results from the HEC-RAS model along each cross section and river
reach before interpolating (Figure 4-6).
For example, consider using the closest few water surface elevation points to determine the floodplain water depth at the computation point shown in Figure 4-6. In part (a) of Figure 4-6, only the computed water surface elevation points are used. Since there are very few computed points, most of the water surface points are far away from the floodplain computation point. The water elevations at these distant points may not have an effect on the floodplain at the floodplain computation point. Alternatively, in part (b) of Figure 4-6, the user has interpolated additional water surface elevations along the reach and along each cross section. Computing a stage at the floodplain computation points from the marked water surface elevations results in a more accurate representation of conditions near the floodplain computation point.

![Figure 4-6](image)

**Figure 4-6:** Using computed versus interpolated water surface elevations to delineate a floodplain
This approach uses two assumptions to justify the interpolation of computed water surface elevation output and to create additional solution points along each cross section and river reach. The first assumption is that the water level is constant along the cross section. Figure 4-7 illustrates this assumption.

![Figure 4-7: Interpolating the HEC-RAS solution along a cross section](image)

The second assumption is that the water level varies linearly along the river reach between cross sections (if this is violated, or not within acceptable tolerances then additional cross sections should be included in the model). Figure 4-8 shows how water surface elevation points are interpolated using this assumption.

![Figure 4-8: Interpolating the HEC-RAS solution between two cross sections](image)
Often, a junction point occurs in hydraulic modeling, where two river reaches converge into a single river reach (Figure 4-9). If this occurs, interpolation between solution points can be difficult.

One method that can be used to create points between known solution points at a junction is to interpolate water surface elevations along the main stem on the stream first, and then interpolate elevations between the water surface elevation on the secondary branch and the main stem (see Figure 4-10).

Figure 4-9: A junction with three water surface solution points to interpolate

Figure 4-10: Diagram showing the interpolation method.
Normally, the main stem is the branch that intersects the lower branch at an angle closest to 180 degrees (see Figure 4-11). In other words, the main stem is the stem where the angle of entrance into the junction is about the same as the angle of exit from the junction.
4.3.3 Determining the Floodplain Boundary

Noman (2001) uses a two-step approach for determining the water depth at each point in the digital terrain model of the floodplain. First, he determines water surface elevation points to use for interpolation at each digital terrain model point based on a set of three criteria. Second, he interpolates the water surface elevation value to the current point in the floodplain. If the water surface elevation interpolated at that point is greater than the actual elevation, the point is flooded.

The first step determines the set of water surface elevation points to use for interpolation based on three criteria. Figure 4-12 illustrates these criteria.
Figure 4-12: Water surface elevation point selection criteria

The first criterion searches for points within a given radius of the digital terrain model elevation point. If there are any points inside this radius, the model retains these points for further consideration. The second step breaks the search area into four quadrants and retains up to the allowable number of points in each quadrant. In Figure 4-12, the allowable number of points was set to two. The final criterion is the flow distance/flood barrier criterion. This criterion draws a flow path to each of the water surface elevation points. If the flow path cannot reach a water surface elevation point within a minimum specified distance, the model discards that point. In Figure 4-12, a
flood barrier obstructs one of the points (this may be a structure or a levee). The algorithm discards this point and does not use it for interpolation. The application of these criteria results in six points for interpolation.

The second step interpolates the water surface elevation to the point under consideration on the digital terrain model. The water surface elevation is interpolated using inverse distance weighted interpolation. This interpolation method assigns a weight to each point based on its distance to the interpolation point. This method uses the following equation to determine the water surface elevation ($wse_p$) at the digital terrain model point from the water surface interpolation points:

\[ wse_p = \sum_{i=1}^{n} w_i f_i \]  

(4-1)

Where $n$ is the number of water surface interpolation points, $f_i$ is the water surface elevation at each point, and $w_i$ is a weighting function defined by the following equation:

\[ w_i = \frac{\left[ \frac{R - h_i}{Rh_i} \right]^2}{\sum_{j=1}^{n} \left[ \frac{R - h_j}{Rh_j} \right]^2} \]  

(4-2)

Where $R$ is the distance from the point on the digital terrain model to the furthest water surface interpolation point and $h_i$ is the distance to each water surface
interpolation point. If specified, the algorithm uses a flowpath distance instead of the straight-line distance.

4.4 Combining HEC-1, HEC-RAS, and Floodplain Delineation

The purpose of this study is to create a flood probability map or an AEP map using risk analysis methods. To do this, the algorithm linked the hydrology of HEC-1, the hydraulics of HEC-RAS, and floodplain delineation of WMS to delineate a large number of floodplains without the requirement of human intervention.

Each model run uses a different set of input values, resulting in a different floodplain boundary for each combined model run. This procedure stochastically modifies input values to HEC-1 or HEC-RAS to find the effect of uncertainty in the modeling parameters on the probabilistic floodplain boundary.

Linking HEC-1, HEC-RAS, and the WMS floodplain delineation model requires an understanding of data formats of the three models. This section discusses how WMS uses the output from HEC-1 as input to HEC-RAS and how it uses output from HEC-RAS as input to the WMS floodplain delineation model.

4.4.1 Linking HEC-1 and HEC-RAS

The result of HEC-1 is a hydrograph for each basin, as illustrated in Figure 4-13.
Figure 4-13: A hydrograph generated from HEC-1

A hydrograph consists of an XY series of data of flow (Y) at various times (X) in a storm event (see Table 4-1). The maximum flow can be determined from the table of data (in the example below the peak flow would be 2129 CFS). WMS then assigns this value as a flow value in HEC-RAS.
Table 4-1: Flow hydrograph generated from HEC-1 (with the peak flow highlighted)

<table>
<thead>
<tr>
<th>Time (minutes)</th>
<th>Flow (CFS)</th>
</tr>
</thead>
<tbody>
<tr>
<td>420</td>
<td>0.001</td>
</tr>
<tr>
<td>435</td>
<td>0.021</td>
</tr>
<tr>
<td>450</td>
<td>0.11</td>
</tr>
<tr>
<td>465</td>
<td>0.343</td>
</tr>
<tr>
<td>480</td>
<td>0.826</td>
</tr>
<tr>
<td>495</td>
<td>1.712</td>
</tr>
<tr>
<td>510</td>
<td>3.198</td>
</tr>
<tr>
<td>525</td>
<td>5.505</td>
</tr>
<tr>
<td>540</td>
<td>8.855</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>810</td>
<td>1581.784</td>
</tr>
<tr>
<td>825</td>
<td>1822.7</td>
</tr>
<tr>
<td>840</td>
<td>1993.886</td>
</tr>
<tr>
<td>855</td>
<td>2093.605</td>
</tr>
<tr>
<td>870</td>
<td>2128.819</td>
</tr>
<tr>
<td>885</td>
<td>2106.389</td>
</tr>
<tr>
<td>900</td>
<td>2037.403</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>

Two methods exist for entering the peak flow value in HEC-RAS. HEC-RAS steady flow data includes information for stages at the upstream and downstream locations of the model and flow values for each river reach. One method of entering the value in HEC-RAS is to enter the value in the field shown in Figure 4-14 manually.

Figure 4-14: Entering the hydrograph peak flow value in HEC-RAS
When performing hundreds of stochastic runs, determining these peak flow values and entering them for each river reach can be an onerous task. Therefore, WMS automates this task. A robust method of entering the peak flow value for a cross section on a river reach is through a Visual Basic (VB) interface to HEC-RAS, provided as part of HEC-RAS. Using this interface, a flow value can be set for a specific river, reach on the river, or portion of a reach.

This research added the capability to WMS of linking together the HEC-1, HEC-RAS, and the floodplain delineation models. Using a mapping of hydrographs to river reaches and their cross sections, WMS writes a “HEC-RAS steady flow linkage” file that it uses to set the flow boundary conditions for river reaches. You can automatically map hydrographs at outlet points to the corresponding cross sections in HEC-RAS using a tool that finds the cross sections closest to outlets and assigns the outlet hydrographs to those cross sections. Here is a sample file created by WMS for setting a peak flow value:

```plaintext
"setflow"
"Leith River", "Upper Branch", "2648.528", 1
2128.8
```

WMS then launches the VB interface to HEC-RAS, which reads this “HEC-RAS steady flow linkage” file and assigns the flow value to the specified river, reach, and cross section. Each hydrograph peak flow is set in the same manner. After all the steady flow boundary conditions are set, WMS launches HEC-RAS to run the simulation.
4.4.2 Linking HEC-RAS and the Floodplain Delineation Model

Using the same VB interface to HEC-RAS that WMS uses to set the flow boundary conditions and to run HEC-RAS, it extracts the solution from the HEC-RAS simulation. The VB interface writes an HEC-RAS stage output file in the following format (comments are shown with brackets—<>):

```
"xsecs"
"newreach","7","Leith River","Upper Branch" <"7" is the number of cross sections on the river and reach>
... ... ... <more reaches and rivers>
"newvar","W.S. Elev","PFL" <PFL is the name of the profile>
"71.357","7" <Cross section "W.S. Elev", followed by an index used to determine the cross section in WMS>
"70.943","6"
... ... ... ...
```

Each stage from HEC-RAS is stored as a water surface elevation point in Noman’s (2001) floodplain delineation model described in section 4.3. Interpolating the water depths along cross sections and river reach centerlines, and using the floodplain delineation model, the water depths at each point in the floodplain can be determined. From these water depths, the floodplain boundary is determined.

Figure 4-15 diagrams the entire process of running the HEC-1 model, assigning HEC-RAS boundary conditions, reading the HEC-RAS solution, assigning the water depths from HEC-RAS to the floodplain delineation model, and running the floodplain delineation model. WMS allows for direct input of peak discharge if you obtain the discharge in a way other than from the HEC-1 hydrologic model.
4.5 High Resolution Elevation Data

The floodplain and hydraulic modeling processes described in this chapter require accurate elevation data. High-resolution elevation and river channel bathymetry data are becoming more accurate and affordable. If the resolution of the data is too fine, however, the data may be unusable for normal floodplain delineation.
because of large memory, storage, and computer processing requirements. Often high resolution is only necessary to capture important points, even though many of the points are redundant (lie within the same plane) and unnecessary to accurately model the terrain surface. These redundant points can significantly increase the required computer resources. Therefore, you should reduce these high-resolution data to include only those points that are necessary for accurate delineation of the floodplain. You should consider three issues when thinning high-density elevation points for use in floodplain delineation:

1. Which algorithm is most effective for removing the most points while still maintaining an accurate floodplain boundary?
2. How many points can be deleted while maintaining an accurate floodplain boundary?
3. What are the ideal input values to these algorithms to insure the floodplain boundary is accurately determined?

Researchers have proposed several methods for reducing the number of elevation points in a digital elevation model (Zundel, 2001 and Southard, 1991). One method determines distances between adjacent points. This method sorts these distances, and combines vertices closer than a given radius into a single vertex. Another method removes a point if the minimum dot product between the angles of the normal vectors of the point’s adjacent triangles is greater than the cosine of a specified angle. An alternative of this method is to remove a point if the difference between the current z-value and the interpolated z-value when the point is removed is within a specified tolerance. A final method of removing unneeded points is to use a
Laplacian filter to determine the flat areas of the digital elevation model. If these flat areas are removed, interpolating between adjacent vertices gives approximately the same elevation model as if the points remained in the model.

4.5.1 XY Distance Method

The XY distance method visits each point in a digital elevation model. The distance between each point and each of its neighbors within a specified distance is determined (see Figure 4-16).

![Figure 4-16: The XY distance method of removing points](image)

This algorithm determines the point-to-point distances for each set of points within the specified distance. The algorithm records all the distances and their corresponding vertex IDs in a list, and then they are sorted from lowest to highest distance. Table 4-2 shows an example for one node (node 1 in Figure 4-16).
Table 4-2: Distance table for a single vertex.

<table>
<thead>
<tr>
<th>Node 1 ID</th>
<th>Node 2 ID</th>
<th>Distance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6</td>
<td>d_{16}</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>d_{12}</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
<td>d_{13}</td>
</tr>
<tr>
<td>1</td>
<td>5</td>
<td>d_{15}</td>
</tr>
<tr>
<td>1</td>
<td>4</td>
<td>d_{14}</td>
</tr>
</tbody>
</table>

The vertices that are closest together can be merged into a single vertex using one of several methods. One such method of merging two vertices into one is to delete one of the vertices...either randomly or using some kind of test (for example, keep the vertex whose z-value differs most from the surrounding vertex z-values). Another method of merging two vertices is to average the X, Y, and Z values between the two vertices to create a new vertex (see Figure 4-17).

\[
\left( \frac{x_1 + x_2}{2}, \frac{y_1 + y_2}{2}, \frac{z_1 + z_2}{2} \right)
\]

![Figure 4-17: Merging two vertices by averaging their values](image)

The XY distance method is good for removing duplicate points or points that are too close together to have much effect on the model. However, since it does not consider the Z-coordinate when determining whether to keep a point, it is not very effective for thinning points in large, flat areas. Researchers have devised other methods for removing unnecessary points in flat areas or in areas of constant slope.
4.5.2 Normal Angle and Z-Distance Methods

Zundel (2001) proposed two methods for removing redundant data points in flat areas or in areas of constant slope. The first of these methods is the normal angle method. This algorithm determines the unit (magnitude = 1.0) normal to each triangle in the digital elevation model. Then, it visits each vertex in the digital elevation model. For each vertex, the dot product is determined from the normals of each triangle surrounding that vertex, as shown in Figure 4-18.

\[
\forall i, j \neq j \Rightarrow \left( \vec{N}_i \cdot \vec{N}_j \right) > \cos(\theta_{\text{max}})
\]  

(4-3)

Where:

\( i \) and \( j \) are counters that go from 1 to the number of triangles,
\( N_i = \) The unit normal vector for triangle \( i \),

\( N_j = \) The unit normal vector for triangle \( j \), and

\( \theta_{\text{max}} = \) The maximum angle between any two triangle normals adjacent to the vertex for that vertex to be removed.

In other words, this equation says that if the normals of all the triangles are pointing in the same direction, the area around the vertex is essentially a planar surface and that vertex is removed.

The second method proposed by Zundel (2001) to remove redundant vertices from an elevation model is called the Z-distance method. This method visits each vertex in the digital elevation model. The algorithm removes that vertex from the model and the triangles near that vertex are re-built, ignoring the vertex in the new triangulation (see Figure 4-19).

![Figure 4-19: Step 1 of the Z-distance method](image)

This algorithm determines the difference between the original vertex Z-value and the interpolated vertex Z-value with the new triangulation by linear interpolation, as shown in Figure 4-20.
Removing the vertex creates different values of the interpolated Z-value for different triangulation schemes. Therefore, the algorithm swaps each edge in the triangulation to determine the other interpolated Z-values, as shown in Figure 4-21.

If the minimum difference between the original and interpolated vertex Z-values ($\Delta Z_{\text{min}}$) is less than a tolerance $\delta$, the algorithm removes the vertex and maintains the triangulation producing that minimum difference. If $\Delta Z_{\text{min}}$ is greater than the tolerance $\delta$, the algorithm restores the vertex and maintains the original triangulation.
You can use both the normal angle and Z-distance methods to filter out unneeded vertices in large flat areas or over large areas of constant slope. Omer et al (2003) used the normal angle method with good results in filtering over large areas. Nobody has used the Z-distance method, but a comparison between these two methods with digital terrain models would be a good research topic. Perhaps the best method is a combination of the normal angle and Z-distance methods. This algorithm could use the normal angle method to determine whether a vertex is a candidate for removal. Then, it could use the Z-distance method to determine the triangulation giving results closest to the original dataset after removing the vertex. Using a combination of the normal angle and Z-distance methods would ensure that the dataset is thinned as much as possible and that interpolated Z-values remain as close as possible to the original dataset.

Omer et al. (2003) used the normal angle method to thin data obtained using light detection and ranging (LIDAR). They concluded that you should use a filter angle of 4 degrees to filter the LIDAR data without producing a significant change in hydraulic or floodplain model results. This study used a filter angle of 4 degrees to thin the elevation data. Using a filter angle of 4 degrees reduced the number of elevation points in one dataset from 171,705 to 65,956 points, reducing the total number of points to 38.4% of the original dataset.

4.5.3 Laplacian Filter Method

The final method is a mathematical approach to removing vertices in flat areas and in areas of constant slope. Southard (1991) proposed the Laplacian filter method.
This method is designed to preserve changes in slope that occur along peaks, ridges, valleys, passes, inflection points, and in pits. As in the normal angle and Z-distance methods, this method removes vertices in flat or constant slope areas and maintains vertices along changes in slope.

The method discussed in this section assumes the elevations are arranged in a grid, but this method can be extended to a triangulated irregular network of points. The first step of the Laplacian filter method smoothes the elevations by convolving the elevations, $F$, with a filter matrix, $H$. One example of the filter matrix would be the following (Southard, 1991):

$$H = \frac{1}{16} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix} \quad (4-4)$$

The second step determines the curvature at each point. This is determined using a second derivative operator. In two dimensions, this is the Laplacian operator:

$$\nabla^2 = \frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2} \quad (4-5)$$

Digitally, you perform the Laplacian operator on a dataset by using a second-difference operator at each point. For two-dimensional datasets, the second-difference operator is determined by convolving the elevations, $F$, with the second difference
operator matrix, $G$. Many digital forms of the Laplacian operator exist, and the following matrices show some examples of digital versions of the Laplacian:

$$
G = \begin{bmatrix}
0 & -1 & 0 \\
-1 & 4 & -1 \\
0 & -1 & 0
\end{bmatrix}
$$

(4-6)

$$
G = \begin{bmatrix}
-1 & -1 & -1 \\
-1 & 8 & -1 \\
-1 & -1 & -1
\end{bmatrix}
$$

(4-7)

$$
G = \begin{bmatrix}
1 & -2 & 1 \\
-2 & 4 & -2 \\
1 & -2 & 1
\end{bmatrix}
$$

(4-8)

If an area is flat, convolving the elevations with any of the digital Laplacians results in a value of zero for the Laplacian. However, if curvature exists, the Laplacian is non-zero.

A traditional approach is to assign a cutoff value for the absolute value of the Laplacian at each point. This approach deletes all points with Laplacians below this value. Southard (1991), however, found this approach to work well only in areas of high relief. Therefore, he devised a neighborhood ranking method to determine which vertices should be kept and which should be deleted. After determining the Laplacian at each point, this algorithm ranks the Laplacians at each point according to their
surrounding neighbors. The algorithm takes the absolute value of the Laplacians in a neighborhood around each point. This neighborhood can be any size. The algorithm then sorts the Laplacians lowest to highest, and determines the ranking of the current point in its neighborhood and assigns it to that point, as shown in Figure 4-22 for a neighborhood of 3 points.

\[
\begin{array}{ccc}
1 & -1 & -4 \\
0 & -2 & 0 \\
3 & 1 & 1 \\
\end{array}
\]

Figure 4-22: Neighborhood ranking in Southard's method (1991)

The algorithm then assigns a cutoff for the entire grid. It removes points with rankings below the cutoff from the digital elevation model and retains points with rankings above the cutoff. Southard (1991) showed that this method is a good approach that you can use to remove flat areas or areas of constant slope on a digital elevation model effectively.

4.5.4 Modifying Elevation Data

Sometimes, there are too much elevation data. You can filter these data using one of the methods described above. Other times, too little elevation data exists or the elevation data are inaccurate. In these cases, you can stamp missing features into the elevation data to make it more accurate. Three types of elevation features can exist: point features, linear features, and polygonal features.
4.5.4.1 *Point Features*

Point features are single point elevation data that you can add to digital elevation models for greater accuracy. Suppose, for example, rough, sparse digital elevation data exists for a certain area. A carefully conducted survey of the area gives very accurate elevations for a few points in the study area.

There are two approaches for adding these points to the digital elevation model. The first approach adds these points to the elevation model or interpolates the points into the existing elevation data. The second approach determines the difference between each point and the interpolated elevation value on the digital elevation model at that point. These differences are stored as a surface (see Figure 4-23).

![Figure 4-23: Interpolating point features to elevation data](image)

Then, the surface containing the differences is interpolated (using linear interpolation or any other interpolation scheme) to the existing digital elevation data. The result should be a more accurate representation of the topography.
4.5.4.2  Linear Features

Linear features represent linear elevation data that you want to use to update a digital elevation model. Examples of linear features are roads, levees, pathways, streambed elevations, and any other type of linear data. You can add a linear feature to an elevation dataset by interpolating the elevation properties of the linear feature to the elevation dataset, as shown in Figure 4-24.

Figure 4-24: Interpolating linear features to elevation data

4.5.4.3  Polygonal Features

Polygonal features represent areas where you have collected more accurate elevation data. This elevation data may come from survey points, depressions, hills, valleys, or ridges that a digital elevation model does not adequately represent. You can create a polygon around the area to “cut out” of the original elevation dataset. You can then derive the elevations inside the polygon from a separate set of elevation data.
Having accurate elevation data is one of the most important parts of developing good hydrologic, hydraulic, and floodplain delineation models. The methods described in this section provide useful approaches for thinning and modifying elevation data. Many times, you need to thin or modify elevation data for use in floodplain, hydraulic, and hydrologic studies.

You can repeat this process of running the HEC-1 model, assigning HEC-RAS boundary conditions, running HEC-RAS and reading the HEC-RAS solution, assigning the water depths from HEC-RAS to the floodplain delineation model, and running the floodplain delineation model with stochastic input parameters to define a flood probability or an AEP map.
5 Stochastic Modeling Applications

This probabilistic approach executes multiple instances of linked hydrologic, hydraulic, and floodplain delineation models with a range of input parameters. From the multiple floodplain delineations, a flood probability map or an annual exceedance probability (AEP) map is created.

This chapter will show how this research uses the coupled modeling tools with the risk analysis methods described in Chapter 3 to modify the modeling parameters for each run of the hydrologic, hydraulic, and/or floodplain delineation model. The algorithm modifies the parameters using the Monte Carlo or Latin Hypercube methods described in Chapter 3. First, this chapter discusses the available stochastic variables. The stochastic methods developed through this research extend the risk analysis methods currently used by the US Army Corps of Engineers (USACE). The spatial approach to developing a probability map enhances and improves upon the standard risk analysis methods used by the USACE. It solves several of the problems with the USACE’s current approach to risk analysis described in National Research Council (2000) and opens up entire new areas of research and risk-based flood damage analysis methods in the spatial domain.
5.1 Variables Modeled

The objective of this risk-based approach to floodplain modeling is to run a hydrologic model, use its results (peak flows) as input to a hydraulic model, and then use its results (water surface elevations) as input to a floodplain delineation model. To account for uncertainty, we repeat this process with different hydrologic/hydraulic model input values.

Figure 5-1 shows some HEC-1 sub-basin input parameters. Figure 5-2 shows HEC-RAS input parameters.
Not all these variables can or should be modeled as stochastic variables. The variables chosen for stochastic modeling in this research include:

1. Average basin precipitation in HEC-1 and TR-20.
2. Sub-basin curve numbers (amount of rainfall converted to runoff) in HEC-1 and TR-20.
3. HEC-RAS Manning’s coefficient.
4. HEC-RAS flow rates at cross section flow change locations.

These variables cause a large amount of uncertainty in hydrologic and hydraulic models. Sub-basin discharge is very sensitive to precipitation and curve number values, while the Manning’s coefficient has an effect on the water surface elevations of a river reach. Other variables that could be modeled in the future include sub-basin lag time or time of concentration, baseflow parameters, and cross-section geometric (elevation) data.

The procedure for defining a variable as a stochastic parameter as implemented in the WMS for this project is shown in Figure 5-3. A key value is a negative number that links a stochastic variable to a hydrologic or hydraulic model. For each stochastic variable, the minimum, maximum, mean, standard deviation, and PDF for the variable define the distribution of the variable. To define a stochastic variable, you create the variable with a key value and distribution in the Stochastic Run Parameters dialog. Then, this key value is entered in the model dialog (such as the HEC-1 Precipitation dialog) corresponding to the data type.
Figure 5-3: Defining a stochastic variable in the WMS

When the algorithm runs an instance of the model with the stochastic variable, it replaces the negative key value with a random value based on the mean, minimum, and maximum values and the distribution type for that stochastic variable.

5.2 Computing a Flood Probability Map

The algorithm then uses the risk analysis methods described in Chapter 3 to perturb each of the floodplain input parameters, using a probability distribution for each parameter, to determine the extents of a floodplain that accounts for the uncertainty in the input conditions. Running $N$ instances of the hydrologic, hydraulic, and floodplain delineation model results in $N$ floodplain extent maps. Using these $N$ maps, the probability of flooding at any point in the floodplain is the number of times, $n$, each point on the floodplain is inundated divided by the number of runs $N$. This method creates a floodplain probability map for a single recurrence interval, such as
the 100-year recurrence interval. The method described here assumes any levees or flood control structures in the floodplain do not fail. Figure 5-4 shows a floodplain probability map showing the location of the 50% probability contour.

Figure 5-4: Floodplain probability map showing the location of the 50% probability contour

The floodplain probability map can be a useful tool for evaluating the probability of flooding for a 100-year storm. Rather than defining a boundary as a “disputable” in or out boundary, this map defines the probability of flooding based on reasonable model parameters. There is never 100% certainty in the exact boundary of a floodplain in a hydrologic/hydraulic analysis, and this method of determining a floodplain probability map acknowledges that fact. You use this floodplain probability map to evaluate the uncertainty of the floodplain boundary based on the
ranges of input parameters. You can determine the probability of flooding at any point in the floodplain from this map.

The probability map is based on a single recurrence interval. Normally, this represents guesses at a 100-year storm. The 100-year storm itself is a probabilistic term. An AEP map combines the flood probability at all recurrence intervals to create a map showing the probability of flooding in any single year.

5.3  \textit{Computing the Spatial Distribution of the Annual Exceedance Probability (AEP)}

The USACE is currently using risk analysis to compute the AEP for damage reaches in flood damage reduction studies. It is possible to compute the spatial distribution of the AEP on a floodplain using the risk analysis capabilities and the integrated hydrologic, hydraulic, and floodplain delineation models in WMS (see \textbf{Figure 5-5}). The input requirements are the same as for a flood probability map except it requires a precipitation-probability or a discharge-probability curve and their associated uncertainties.
This method of computing the AEP, discussed in chapter 3, assumes that any levees or other structures represented by the elevations in the floodplain do not fail. The AEP algorithm randomly samples the discharge-probability curve and uses the discharge value as input into the HEC-RAS model. The algorithm first determines a random probability between. This number represents the probability of exceedance for the current simulation. From this probability, the algorithm interpolates the mean, min, max, and standard deviation from the closest known values, creating a PDF. The
algorithm then uses these values and the distribution at this probability to determine a random discharge from the PDF. The algorithm runs the HEC-RAS model repeatedly, using different discharges as flow boundary conditions for each run until it canvasses the entire range of discharge probabilities. If performing a Monte Carlo simulation, the number of simulations is user-specified, if a Latin Hypercube simulation, it is the product of the number of segments of all the stochastic variables.

An alternative to using a discharge-probability curve is to use a precipitation-probability curve as input into the HEC-1 hydrologic model. The peak discharge computed at each outlet point in the HEC-1 model can then be used as flow values at cross sections in the HEC-RAS model. This approach also considers “uncertainty” in the hydrologic modeling parameters such as CN, as well as the primary driving input of rainfall. This study tests both approaches and generates the resulting AEP maps.

You can compare this procedure of computing the AEP for a floodplain with the existing methods used by the USACE. It is most similar to the annual-flood sampling procedure (see Chapter 2). You define a discharge-probability curve (see Figure 5-6) with a minimum, maximum, mean, and standard deviation value for probability values on the curve. You also define a distribution type (linear, loglinear, normal, or lognormal) to determine the discharge uncertainty at each probability value along the curve.
Figure 5-6: A discharge-probability curve with uncertainty

Table 5-1 shows an example of the data required to generate a discharge-probability curve with uncertainty.

Table 5-1: Discharge-probability curve input data

<table>
<thead>
<tr>
<th>Probability</th>
<th>Mean [m³/s]</th>
<th>Minimum [m³/s]</th>
<th>Maximum [m³/s]</th>
<th>Standard Deviation [m³/s]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>42.5</td>
<td>11.9</td>
<td>73.1</td>
<td>15.3</td>
</tr>
<tr>
<td>0.5</td>
<td>72.9</td>
<td>20.4</td>
<td>125.4</td>
<td>26.2</td>
</tr>
<tr>
<td>0.2</td>
<td>137.9</td>
<td>52.4</td>
<td>223.4</td>
<td>42.7</td>
</tr>
<tr>
<td>0.1</td>
<td>189.6</td>
<td>81.5</td>
<td>297.7</td>
<td>54.0</td>
</tr>
<tr>
<td>0.04</td>
<td>272.9</td>
<td>125.6</td>
<td>420.3</td>
<td>73.7</td>
</tr>
<tr>
<td>0.02</td>
<td>346.8</td>
<td>163.0</td>
<td>530.6</td>
<td>91.9</td>
</tr>
<tr>
<td>0.01</td>
<td>421.1</td>
<td>197.9</td>
<td>644.3</td>
<td>111.6</td>
</tr>
<tr>
<td>0.002</td>
<td>646.4</td>
<td>303.8</td>
<td>989.0</td>
<td>171.3</td>
</tr>
</tbody>
</table>

HEC-RAS has the ability to compute water surface elevations at cross sections in a river model. This algorithm stochastically models the HEC-RAS input parameters to determine the range of stages for each discharge value.
Using the water surface elevations computed from HEC-RAS, the WMS floodplain delineation model determines the extent of the flood for each HEC-RAS simulation. In a sense, HEC-RAS outputs a spatially distributed stage-discharge curve (see Figure 5-7). You define the uncertainty of this spatially distributed curve by identifying stochastic variables, such as Manning’s roughness, as input values to HEC-RAS and using randomly distributed values for each of the HEC-RAS runs. You define the number of HEC-1, HEC-RAS, and floodplain simulations run. At the end of these simulations, the algorithm determines the probability of flooding at each point. This probability is the AEP—it is the number of times each point is flooded divided by the total number of simulations.

5.4 Determining Precise Floodplain Extents at Any Recurrence Interval from the AEP Map

The contours of this AEP map represent the probability of flooding in any given year. Therefore, you contour the 10, 50, 100, or any recurrence interval floodplain directly from the spatially distributed map of the AEP by converting the
desired return period to a probability (Probability = 1 / Return Period). This floodplain contour includes uncertainties inherent in the modeling process. This contour determines a single, definite boundary for which uncertainties have been accounted. An example of an AEP map showing the floodplain boundaries for different recurrence intervals is shown in Figure 5-8.
Computing Expected Annual Damage (EAD) from an AEP Simulation

Using risk analysis and integrated hydrologic modeling, hydraulic modeling, and floodplain delineation, you can compute EAD for a floodplain. The input requirements are essentially the same as is used to compute the AEP. They include a calibrated hydrologic model or discharge-probability data, a calibrated hydraulic model, precise elevation data for the floodplain, and the uncertainty parameters for a discharge-probability or precipitation-probability curve. In addition, the algorithm requires a point layer (coverage) that represents the locations of buildings in the floodplain. Computing the EAD requires a stage-damage curve for each point (building) in this layer. This algorithm computes the EAD using a procedure similar to the annual flood sampling procedure:

1. Randomly sample the discharge-probability or precipitation-probability curve to determine a discharge or precipitation according to the methods used in computing the spatial distribution of the AEP.
2. Run the HEC-RAS model to determine the water surface elevations on the floodplain.
3. Use these water surface elevations to delineate the floodplain and to determine the water depths in the floodplain.
4. Use these water depths in conjunction with the layer of points with stage-damage curves to compute the total damage for the current simulation.
5. Repeat steps 1-4, keeping track of the average damage from all simulations, until the average of the simulation damages stabilizes. The average of the damages is the expected annual damage.
5.6 Solutions for Some Recommendations by the National Research Council (NRC)

The government enacted a mandate in 1996 that required a committee sponsored by the USACE to study the current procedures used in “risk-based analysis for the evaluation of hydrology, hydraulics, and economics in flood damage reduction studies” (NRC, 2000). In 2000, the National Research Council published their recommendations for improving the current methods of performing risk analysis in flood damage reduction studies. This section discusses these recommendations and the complete or partial solutions provided by this research.

1. **Recommendation:** “The Corps [USACE] should be clear about which variables it treats as natural variability, which it treats as knowledge uncertainty, and why and how it makes this distinction.” (p. 42-43).

   **Solution:** Though the method developed in this research does not distinguish between natural variability and knowledge uncertainty, it provides a framework within the WMS which models all these uncertainties.

2. **Recommendation:** “The flood hydrology and hydraulics should be randomized at the scale of the river reach rather than at the damage reach…This concept would also allow quantification of uncertainty in the spatial extent of the floodplain boundary.” (p. 135)

   **Solution:** It is now possible to define a spatial watershed model and a model of the entire floodplain. The floodplain does not need to be broken up into damage reaches…the entire floodplain can be modeled as one
complete unit. Since an interface for stochastic modeling links these models together, you can quantify the uncertainty in the location of the floodplain boundary. The floodplain probability map and the annual exceedance probability maps quantify this uncertainty.

3. **Recommendation:** “The committee…recommends that the Corps use *annual exceedance probability* as the performance measure of engineering risk.” (p. 161-162)

**Solution:** This research has focused on creating a map of annual exceedance probabilities for an entire floodplain. The annual exceedance probability map supersedes other measures of engineering risk.

4. **Recommendation:** “The committee recommends that the Corps’s risk analysis method evaluate the performance of a levee as a spatially distributed system.” (p. 162)

**Solution:** Currently, the USACE “treats a levee within each damage reach as independent and distinct from one reach to the next. Further, within a reach, the analysis focuses on the portion of each levee that is most likely to fail (p. 162-163).” If this procedure incorporates geotechnical levee performance, the performance of a levee could be considered as a spatially distributed system. This method would consider the entire length of the reach and all aspects of levee failure “at any point along the levee” in a floodplain study.

5. **Recommendation:** “The committee recommends that the Corps calculate the risks associated with flooding, and the benefits of a flood damage
reduction project, structure by structure, rather than conducting risk analysis on damage aggregated over groups of structures in damage reaches.” (p. 164)

**Solution:** Section 5.5 proposes how to accomplish this task using the computed AEP map.

6. **Recommendation:** “The committee recommends that the federal levee certification program focus not upon some level of assurance of passing the 100-year flood, but rather upon *annual exceedance probability*…This annual exceedance probability of flooding should include uncertainties derived from both natural variability and knowledge uncertainty.” (p. 165)

**Solution:** This research computes a map of annual exceedance probability for an entire floodplain. This map displays the AEP at any point in the floodplain, including the AEP of areas protected by levee systems. The stochastic approach to floodplain delineation used by this research considers natural variability and knowledge uncertainty.

If a method for modeling the geotechnical uncertainty of levees were created, the AEP map would represent the AEP of levee exceedance over the entire floodplain. This method of developing an AEP map is a significant step forward in solving the problems set forth by the National Research Council Committee on Risk-Based Analyses for Flood Damage Reduction.

The methods described in this chapter are extremely useful in flood insurance studies. The FEMA guidelines for creating a FIRM or a DFIRM currently specify that the floodplain boundary is a single line, where structures are inside or outside of the
floodplain boundary. If a structure is inside, the owner of that structure pays flood
insurance. If a structure is outside, the owner does not pay insurance. The flood
probability map presents an improved method for determining flood insurance
premiums. If a structure has a probability of flooding, but the probability is low, the
insurance premium for that structure should be lower than a structure with a 100%
probability of flooding in a 100-year flood. However, FEMA guidelines still require a
single, most probable in-or-out boundary. The AEP map provides this single in-or-out
boundary. This boundary (for a 100-year floodplain) is located along the 0.01-
exceedance probability contour on the AEP map. This single 100-year flood boundary
includes all the uncertainty inherent in hydrologic and hydraulic modeling (neglecting
geotechnical uncertainty).

These appear to be simple solutions, but future research is still required. This
entire approach of computing a flood probability map and an AEP map calls for an
unsteady flow hydraulic simulation. Floodplain extents do not only vary spatially, but
they also vary temporally. The peak discharges do not all occur at the same time at
each point in a floodplain, but they rather occur at different times (see Figure 5-9). An
unsteady flow simulation effectively models these varying peaks.
Furthermore, an unsteady hydraulic model best models the effects of geotechnical uncertainty and levee breaches. You could create an algorithm to model a levee with a steady state model, using the water depth and a depth-probability of failure curve at the levee to determine the probability of levee failure. Then, the algorithm could use a random number to determine whether each section of a levee fails, and if the number is less than the probability of failure, the algorithm could remove that section of the levee from the hydraulic and/or floodplain model. However, a levee break is not a steady state problem—it is like a dam break. An unsteady model best models a levee break.
6 Case Studies

Two case studies were performed to test, validate, and analyze the procedures set forth in this research. The first study is located in North Carolina. The second study is located in southern Utah.

The first case study utilized four stochastic simulations to determine the flood probability maps by varying different input parameters. Another simulation used a precipitation-probability curve to determine the AEP map for the North Carolina model. This case study compared the results of the flood probability maps with the AEP map and its floodplain boundary. The location of the floodplain boundary from a floodplain database, the location of the 50% probability contour on the flood probability map, and the 100-year floodplain boundary from the AEP map all turned out to be about the same. The North Carolina case used real world data and contained all the data to comprise a complete test case. However, because of the geometry of the North Carolina floodplain, there was not much variability in the floodplain boundary with different values as input.

The second model—the southern Utah model—illustrates a flat, wide floodplain geometry. AEP maps and 100-year floodplain probability maps were created for this model. In this model, small variations in input parameters resulted in large variations in the floodplain boundary. This model shows how a discharge-
probability curve is used to create an AEP map instead of a precipitation-probability curve. The model also demonstrates the effects of running additional simulations on the AEP and floodplain probability maps. This case study compared the location of the 100-year floodplain boundary on the AEP map with the 50% probability contour on the flood probability map. These two maps gave about the same location for the delineation of the 100-year floodplain boundary. The 100-year floodplain boundary on the AEP map considers much of the natural variability and knowledge uncertainty that can occur in hydrologic and hydraulic models and gives a single boundary that FEMA can use to determine whether a building is in or out of the floodplain.

6.1 The Leith Creek Model

Figure 6-1 shows the Leith Creek watershed near Laurinburg, North Carolina, on the North Carolina-South Carolina border.
Figure 6-1: Location of Laurinburg, North Carolina and the Leith Creek model

Figure 6-2 shows the approximate boundary of the watershed and the floodplain model areas. This case study used detailed elevations of the floodplain to extract floodplain cross-sections for the HEC-RAS model and to delineate the floodplain.
This case study created four 100-year floodplain probability maps and an AEP map for this floodplain. The kinds of questions that a stochastic simulation such as this is capable of answering include:

1. What effect do precipitation values have on the hydrographs and on the floodplain boundary/floodplain probabilities? How sensitive is the floodplain boundary/probability to Curve Number and the river Manning’s n-values?
2. What is the effect of randomizing all three variables (precipitation, CN, and Manning’s n) on the floodplain boundaries? What does the probability map look like?

The setup of the stochastic floodplain delineation required the creation of three types of models: A hydrologic model using HEC-1, a hydraulic model using HEC-
RAS, and a floodplain delineation model using WMS. Figure 6-3 shows the data required for each of the three models and the required data for a stochastic simulation.

<table>
<thead>
<tr>
<th>Watershed Model (HEC-1)</th>
<th>Hydraulic Model (HEC-RAS)</th>
<th>Floodplain Model (WMS)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Required Data:</td>
<td>Required Data:</td>
<td>Required Data:</td>
</tr>
<tr>
<td>1. Watershed elevation</td>
<td>1. Elevation data (for</td>
<td>1. Floodplain elevation data</td>
</tr>
<tr>
<td>data (for watershed</td>
<td>cross section geometry)</td>
<td>2. Water surface elevation</td>
</tr>
<tr>
<td>delineation, basin area</td>
<td>2. Cross section hydraulic</td>
<td>values at closely-spaced points</td>
</tr>
<tr>
<td>and other geometric</td>
<td>coefficients (Manning's</td>
<td>along the floodplain</td>
</tr>
<tr>
<td>parameters, and for</td>
<td>n-values)</td>
<td></td>
</tr>
<tr>
<td>computing basin lag</td>
<td>3. Location and orientation</td>
<td></td>
</tr>
<tr>
<td>time/time of</td>
<td>of cross sections, river</td>
<td></td>
</tr>
<tr>
<td>concentration)</td>
<td>reaches, and junction</td>
<td></td>
</tr>
<tr>
<td>2. Precipitation data &amp;</td>
<td>points</td>
<td></td>
</tr>
<tr>
<td>distribution</td>
<td>4. Flow along each river</td>
<td></td>
</tr>
<tr>
<td>3. Land use and soil</td>
<td>reach</td>
<td></td>
</tr>
<tr>
<td>type data for computing</td>
<td>(from watershed model)</td>
<td></td>
</tr>
<tr>
<td>curve numbers</td>
<td>5. The slope, stage, or a</td>
<td></td>
</tr>
<tr>
<td></td>
<td>rating curve at each</td>
<td></td>
</tr>
<tr>
<td></td>
<td>model boundary location</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Figure 6-3: Data requirements for the watershed, hydraulic, floodplain, and the stochastic models**

The Geospatial Data Acquisition (GSDA) web site (Environmental Modeling Research Laboratory, 2003a) provided links to most of the data for setting up models. After obtaining the data, the models were created using procedures described in Environmental Modeling Research Laboratory’s Watershed Modeling System tutorials (2003c). One important part of setting up the stochastic model is determining the
distribution, minimum, maximum, mean, and standard deviation for each random variable. An important part of setting up data for the AEP map was to determine the precipitation-probability curve and its uncertainty distribution.

6.1.1 Developing the Hydrologic Model

There are many different ways to develop hydrologic models. Traditional methods used contour maps to delineate watersheds and extract key hydrologic modeling parameters such as area, slope, and runoff distances. With the development of digital data sources for contours (elevations), land use, soils, and the use of GIS, it is possible to automate many of the steps required for hydrologic modeling.

6.1.1.1 Elevation Data

The first step in creating the hydrologic model is to obtain elevation data. Elevation data are necessary for delineating the watershed and computing the watershed geometric parameters (such as area and slope). You can obtain seamless elevation data for anywhere in the United States from the USGS (2003), but the elevation data for the watershed model in this research was obtained from the Geo Community web site (2003). Two 30-meter resolution digital elevation models (DEMs) in Spatial Data Transfer Standard (SDTS) format were obtained from the USGS—the Laurinburg, NC and the Gibson, NC-SC DEMs. One important consideration when using elevation or any other type of data is the coordinates and units of the data. The elevation data, background image, soil and land use data, and all other data used in the model must be in the same Cartesian coordinate system. In
addition, the X, Y, and Z units must be the same (feet or meters). For this study, all
the data used were converted to a specific UTM zone, with the X, Y, and Z (elevation)
values in meters.

6.1.1.2 Soil/Land Use Data

This study required soil and land use data to develop an estimate of curve
number for the watershed. The EPA, through the BASINS program initiative, has
made soils data from the NRCS and land use data from the USGS available in a single
location. The EPA’s “Surf Your Watershed” web site (2003a) allows you to locate a
Hydrologic Unit Code (HUC) for any watershed in the United States. Knowing this
HUC allows you to obtain soil and land use data from the EPA BASINS download
site (2003b).

Two types of soil data exist—statewide and countywide data. “STATSGO”
(State Soil Geographic Database) data is statewide soils data. Since no countywide
data were available for Scotland county and the Leith Creek watershed, the STATSGO
data were used. Both the soil and land use data were in geographic
(latitude/longitude) coordinates, and so they were converted to the specific UTM zone
used in the watershed model. After obtaining this data, WMS combined the land use
types, the soil types, and a table relating land use and soil types to compute the
composite curve number for each sub-basin.
6.1.1.3 Precipitation Data

Precipitation is a primary input of any deterministic hydrologic model. Modelers commonly use the 100-year event for delineating a floodplain (FEMA, 1995, Chapter 4). The precipitation data were obtained from the National Climactic Data Center’s climactic data web site (2003).

6.1.1.4 Generating the Hydrologic Model

To delineate the sub-basin boundaries, the DEM elevation data were first read into WMS and converted to the correct coordinates. The next step was to run TOPAZ, software developed by Garbrecht and Martz (1999) that computes flow directions and flow accumulations for a digital elevation model set to a grid. The primary results from running a TOPAZ simulation are two grids: one grid containing the flow direction at each cell of the DEM and another grid with a value for flow accumulation at each cell of the DEM. Cells with high flow accumulation values are more likely to contain streams, and algorithms derive the flow accumulation grid from the flow direction grid. [Figure 6-4] shows a contoured DEM of the Leith Creek study area with arrows of flow directions and with filled cells having an accumulation of 0.1 square miles or greater.
After computing the flow directions and flow accumulations using TOPAZ, you select a confluence (outlet) point for the watershed model. WMS uses the flow directions and flow accumulations to determine the location of the stream automatically and to delineate the watershed boundary from this outlet point. WMS converts the streams and watershed boundaries to vector data to establish connections between the streams and watershed boundaries and to more efficiently compute and store sub-basin data. You define one or more outlet locations, and delineate sub-basins from each of the outlet locations. You should place outlet points at key locations that link to the river reaches of the hydraulic model. Figure 6-5 shows the stream and sub-basin definitions of the Leith Creek watershed model.
Figure 6-5: Stream and sub-basin definitions for the Leith Creek watershed model with basin names and hydrograph combine names

After defining the streams and sub-basins, WMS computes the geometric parameters of each sub-basin. The program uses this computed geometric data to generate parameters such as sub-basin areas and lag times for the HEC-1 hydrologic model.

One of the most important input parameters to the hydrologic model is the storm precipitation value. The procedure described in section 2.3.1 was used to determine the mean and standard deviation of the 100-year, 24-hour storm precipitation. The 100-year storm was determined for two precipitation gages—one in Laurinburg, NC and the other in Moore County, NC. Figure 6-6 and Figure 6-7 show
the plots used to determine the 100-year storm precipitation totals for these two gage stations.

Figure 6-6: Precipitation versus recurrence interval for 24-hour storms for Laurinburg, NC
Figure 6-7: Precipitation versus recurrence interval for 24-hour storms for Moore County, NC

From the equation cited in Figure 6-6, the 100-year precipitation for Laurinburg is $30.023 \ln(100) + 48.152 = 186 \text{ mm (7.3 inches)}$. From the equation cited in Figure 6-7, the 100-year precipitation for Moore County is $35.908 \ln(100) + 45.872 = 211 \text{ mm (8.3 inches)}$. The NRCS Technical Release 55 (TR-55) manual (USDA NRCS, 1986) also has plots of 100-year, 24-hour precipitation values for the eastern United States. From the plot shown in Figure 6-8, the 100-year, 24-hour precipitation for Laurinburg is about 8.2 inches (208 mm).
From these three precipitation values (186 mm, 211 mm, and 208 mm), the following statistics can be determined for precipitation in Laurinburg:

**Table 6-1: Statistics for 100-year, 24-hour precipitation in Laurinburg, NC**

<table>
<thead>
<tr>
<th>100-year, 24-hour precipitation—Laurinburg, NC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
</tr>
<tr>
<td>Standard Deviation</td>
</tr>
<tr>
<td>Maximum</td>
</tr>
<tr>
<td>Minimum</td>
</tr>
</tbody>
</table>

The HEC-1 model used the mean value of 201.7 mm (7.9 inches) and the other statistical parameters in Table 6-1 for setting up the stochastic model. The model used

After determining the precipitation values, the curve numbers for the model were determined. WMS used Table 6-2 to determine the composite sub-basin curve numbers from the land use and soil type data.
Table 6-2: Curve number table used for computing sub-basin composite curve numbers from soil and land use data, antecedent moisture condition II

<table>
<thead>
<tr>
<th>ID</th>
<th>Description</th>
<th>CN A</th>
<th>CN B</th>
<th>CN C</th>
<th>CN D</th>
</tr>
</thead>
<tbody>
<tr>
<td>11</td>
<td>Residential</td>
<td>57</td>
<td>72</td>
<td>81</td>
<td>86</td>
</tr>
<tr>
<td>12</td>
<td>Commercial and Services</td>
<td>89</td>
<td>92</td>
<td>94</td>
<td>95</td>
</tr>
<tr>
<td>13</td>
<td>Industrial</td>
<td>81</td>
<td>88</td>
<td>91</td>
<td>93</td>
</tr>
<tr>
<td>14</td>
<td>Transportation, Communications, and Utilities</td>
<td>83</td>
<td>89</td>
<td>92</td>
<td>93</td>
</tr>
<tr>
<td>15</td>
<td>Industrial and Commercial Complexes</td>
<td>84</td>
<td>90</td>
<td>92</td>
<td>94</td>
</tr>
<tr>
<td>16</td>
<td>Mixed Urban or Built-up Land</td>
<td>81</td>
<td>88</td>
<td>91</td>
<td>93</td>
</tr>
<tr>
<td>17</td>
<td>Other Urban or Built-up Land</td>
<td>63</td>
<td>77</td>
<td>85</td>
<td>88</td>
</tr>
<tr>
<td>21</td>
<td>Cropland and Pasture</td>
<td>49</td>
<td>69</td>
<td>79</td>
<td>84</td>
</tr>
<tr>
<td>22</td>
<td>Orchards, Groves, Vineyards, Nurseries, and Ornamental Horticultural Areas</td>
<td>45</td>
<td>66</td>
<td>77</td>
<td>83</td>
</tr>
<tr>
<td>23</td>
<td>Confined Feeding Operations</td>
<td>68</td>
<td>79</td>
<td>86</td>
<td>89</td>
</tr>
<tr>
<td>24</td>
<td>Other Agricultural Land</td>
<td>59</td>
<td>74</td>
<td>82</td>
<td>86</td>
</tr>
<tr>
<td>31</td>
<td>Herbaceous Rangeland</td>
<td>49</td>
<td>69</td>
<td>79</td>
<td>84</td>
</tr>
<tr>
<td>32</td>
<td>Shrub and Brush Rangeland</td>
<td>35</td>
<td>56</td>
<td>70</td>
<td>77</td>
</tr>
<tr>
<td>33</td>
<td>Mixed Rangeland</td>
<td>35</td>
<td>56</td>
<td>70</td>
<td>77</td>
</tr>
<tr>
<td>41</td>
<td>Deciduous Forest Land</td>
<td>36</td>
<td>60</td>
<td>73</td>
<td>79</td>
</tr>
<tr>
<td>42</td>
<td>Evergreen Forest Land</td>
<td>36</td>
<td>60</td>
<td>73</td>
<td>79</td>
</tr>
<tr>
<td>43</td>
<td>Mixed Forest Land</td>
<td>36</td>
<td>60</td>
<td>73</td>
<td>79</td>
</tr>
<tr>
<td>51</td>
<td>Streams and Canals</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>52</td>
<td>Lakes</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>53</td>
<td>Reservoirs</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>54</td>
<td>Bays and Estuaries</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>61</td>
<td>Forested Wetland</td>
<td>30</td>
<td>55</td>
<td>70</td>
<td>77</td>
</tr>
<tr>
<td>62</td>
<td>Nonforested Wetland</td>
<td>30</td>
<td>58</td>
<td>71</td>
<td>78</td>
</tr>
<tr>
<td>71</td>
<td>Dry Salt Flats</td>
<td>74</td>
<td>84</td>
<td>90</td>
<td>92</td>
</tr>
<tr>
<td>72</td>
<td>Beaches</td>
<td>50</td>
<td>50</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>73</td>
<td>Sandy Areas other than Beaches</td>
<td>63</td>
<td>77</td>
<td>85</td>
<td>88</td>
</tr>
<tr>
<td>74</td>
<td>Bare Exposed Rock</td>
<td>98</td>
<td>98</td>
<td>98</td>
<td>98</td>
</tr>
<tr>
<td>75</td>
<td>Strip Mines, Quarries, and Gravel Pits</td>
<td>77</td>
<td>86</td>
<td>91</td>
<td>94</td>
</tr>
<tr>
<td>76</td>
<td>Transitional Areas</td>
<td>77</td>
<td>86</td>
<td>91</td>
<td>94</td>
</tr>
<tr>
<td>77</td>
<td>Mixed Barren Land</td>
<td>77</td>
<td>86</td>
<td>91</td>
<td>94</td>
</tr>
<tr>
<td>81</td>
<td>Shrub and Brush Tundra</td>
<td>48</td>
<td>67</td>
<td>77</td>
<td>83</td>
</tr>
<tr>
<td>82</td>
<td>Herbaceous Tundra</td>
<td>68</td>
<td>79</td>
<td>86</td>
<td>89</td>
</tr>
<tr>
<td>83</td>
<td>Bare Ground Tundra</td>
<td>77</td>
<td>86</td>
<td>91</td>
<td>94</td>
</tr>
<tr>
<td>84</td>
<td>Wet Tundra</td>
<td>35</td>
<td>56</td>
<td>70</td>
<td>77</td>
</tr>
<tr>
<td>85</td>
<td>Mixed Tundra</td>
<td>35</td>
<td>56</td>
<td>70</td>
<td>77</td>
</tr>
<tr>
<td>91</td>
<td>Perennial Snowfields</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>92</td>
<td>Glaciers</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
As discussed in section 2.3.2, curve numbers are variable based on antecedent moisture conditions and the condition of the soil. Table 6-2 assumes antecedent moisture condition II. Therefore, a range of curve numbers from antecedent moisture conditions I, II, and III should be used for each of the sub-basins. The composite curve number for each sub-basin was determined from the land use and soil data. Then, the possible minimum and maximum values for each curve number were obtained from Figure 6-9.

![CN Adjustment for Different Runoff Conditions](image)

**Figure 6-9**: Antecedent runoff condition (ARC) adjustment for varying type II ARC curve numbers. Adapted from Mockus (1964, 1972, 1985)

Table 6-3 shows the curve numbers with the approximate minimum and maximum values for each sub-basin.
Table 6-3: Curve numbers with their minimum and maximum values for each sub-basin

<table>
<thead>
<tr>
<th>Basin Name</th>
<th>Curve Number</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>1B</td>
<td>68.5</td>
<td>49.2</td>
<td>84.1</td>
</tr>
<tr>
<td>2B</td>
<td>66.2</td>
<td>46.4</td>
<td>82.7</td>
</tr>
<tr>
<td>3B</td>
<td>65.4</td>
<td>45.5</td>
<td>82.3</td>
</tr>
<tr>
<td>4B</td>
<td>65.1</td>
<td>45.1</td>
<td>82.1</td>
</tr>
<tr>
<td>5B</td>
<td>66.6</td>
<td>46.9</td>
<td>83.0</td>
</tr>
<tr>
<td>6B</td>
<td>65.8</td>
<td>46.2</td>
<td>82.5</td>
</tr>
<tr>
<td>7B</td>
<td>69.4</td>
<td>50.3</td>
<td>84.6</td>
</tr>
</tbody>
</table>

The next step was to compute the lag times for each sub-basin. Since this model used the SCS dimensionless unit hydrograph method in HEC-1, the lag time was all that was required. While the variability of lag time results for an individual sub-basin would make lag time a good candidate for consideration as a stochastic variable, this study did not consider lag times as stochastic variables. Because of the rural nature of the Leith Creek watershed, this model used the Tulsa rural equation (Claborn et al, 1992) to compute the lag times for each sub-basin. This equation is:

\[ T_l = C_t \left( \frac{L \times L_{ca}}{\sqrt{S}} \right)^m \quad (6-1) \]

Where \( T_l \) is the lag time in hours, \( C_t \) is a coefficient (equal to 1.42 for the Tulsa rural method), \( L \) is the watershed length (in miles), \( L_{ca} \) is the length (in miles) along the main channel from the outlet to the centroid, \( S \) is the slope of the maximum flow distance in the watershed (in feet per mile), and \( m \) is a power coefficient (equal to 0.39 for the Tulsa rural method). Table 6-4 contains a list of the sub-basins and the lag time for each sub-basin.
Table 6-4: Lag times for each sub-basin

<table>
<thead>
<tr>
<th>Basin Name</th>
<th>Lag Time (hours)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1B</td>
<td>0.56</td>
</tr>
<tr>
<td>2B</td>
<td>0.99</td>
</tr>
<tr>
<td>3B</td>
<td>0.62</td>
</tr>
<tr>
<td>4B</td>
<td>1.98</td>
</tr>
<tr>
<td>5B</td>
<td>0.85</td>
</tr>
<tr>
<td>6B</td>
<td>0.42</td>
</tr>
<tr>
<td>7B</td>
<td>0.59</td>
</tr>
</tbody>
</table>

With the watershed and sub-basins delineated, the areas computed, and the precipitation values, curve numbers, and lag times determined for each sub-basin, the HEC-1 model is ready to run. You could also define routing for river reaches in the watershed, but this study did not define routing. This was a conservative approach since routing the hydrographs would create lower hydrograph peak flows, resulting in lower water depths and a smaller floodplain. Using the mean values for all the watershed parameters, the model was run and the hydrographs were determined for each sub-basin and hydrograph combine location. Figure 6-10 shows the HEC-1 hydrographs for this “mean value” simulation.
Next, a hydraulic model was created and linked to the hydrograph peak flows in the hydrologic model.

### 6.1.2 Developing the Hydraulic Model

The HEC-RAS hydraulic model for Leith Creek required definition of geometry and Manning’s roughness values. This section will discuss the process of collecting the data and setting up the hydraulic model.

#### 6.1.2.1 Elevation Data

The first step in acquiring data for the hydraulic model (and floodplain delineation) is to obtain elevation data. Digital elevation models (DEMs) from the
USGS have a resolution of about 10 or 30 meters between each elevation point (set to a rectangular grid). However, these data sets may not include bathymetry and may miss hydraulic details.

Researchers have developed new methods of collecting data, including light detection and ranging (LIDAR). This method of collecting data provides data at a very high resolution. One problem with LIDAR surveys is that they collect more points than are required, even for hydraulic modeling or floodplain delineation. Therefore, this research used the data filtering technique described in Chapter 4 of this dissertation and in Omer et al. (2003) to filter the LIDAR data.

Omer et al. (2003) concluded that a filter angle of 4 degrees could be used to filter the LIDAR data without affecting hydraulic or floodplain model results. Therefore, this research used a filter angle of 4 degrees to thin the LIDAR elevation data for this study. Using a filter angle of 4 degrees reduced the number of elevation points from 171,705 to 65,956 points, reducing the total number of points to 38.4% of the original dataset. Figure 6-11 shows a section of the final contoured, triangulated LIDAR dataset.
As you can see in Figure 6-11 areas with abrupt changes in elevation maintain the high resolution of data points (and triangles). On the other hand, flat areas or areas with gradually sloping elevations have a low resolution of data points. From this geometry, WMS “cuts” cross sections for hydraulic models and delineates floodplains.
6.1.2.2  Manning’s n-values

This model used a combination of the land use polygons obtained in section 6.1.1.2 and the river reach and bank locations in the hydraulic model to find the land uses and estimate the roughness along each of the cross sections. Then, the model used a table of Manning’s n-values for different land use/channel types (see Table 6-5) to estimate the minimum, average, and maximum Manning’s n value for each land use polygon.

Table 6-5: Manning's n-values for land uses (adapted from US Army Corps of Engineers, 2001b and Omer et al., 2003)

<table>
<thead>
<tr>
<th>Land use type</th>
<th>Minimum n-value</th>
<th>Normal n-value</th>
<th>Maximum n-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cropland and Pasture</td>
<td>0.030</td>
<td>0.040</td>
<td>0.050</td>
</tr>
<tr>
<td>Deciduous Forest Land</td>
<td>0.100</td>
<td>0.120</td>
<td>0.160</td>
</tr>
<tr>
<td>Commercial and Services</td>
<td>0.055</td>
<td>0.070</td>
<td>0.085</td>
</tr>
<tr>
<td>Residential</td>
<td>0.065</td>
<td>0.080</td>
<td>0.095</td>
</tr>
<tr>
<td>Other Urban or Built-up</td>
<td>0.055</td>
<td>0.070</td>
<td>0.085</td>
</tr>
<tr>
<td>River</td>
<td>0.030</td>
<td>0.035</td>
<td>0.040</td>
</tr>
</tbody>
</table>

6.1.2.3  Cross Section, River Reach, and Junction Point Locations

WMS defines the river reach and junction point locations using the automatically generated stream arc locations from running TOPAZ during creation of the watershed model. Then, you can use the elevation contours on the TIN to determine the approximate bank locations. The only junction point in the model was at the tributary branch and Leith Creek.
The HEC-RAS hydraulic reference manual (US Army Corps of Engineers, 2001b) recommends that cross sections should “extend across the entire floodplain and should be perpendicular to the anticipated flow lines” (p. 3-5). It further states that locations where abrupt changes occur in the channel geometry require more closely spaced cross sections, while uniform rivers with a low slope require fewer cross sections (p. 3-6). Additional cross sections were placed based on the need to create more points in the floodplain and to more accurately determine the floodplain boundaries. The high density of cross sections was possible because of the high-density elevation data available and the computer tools to extract cross sections from this elevation data. Figure 6-12 shows the completed hydraulic model geometry with cross sections and river reaches.
6.1.2.4 Peak Flows and Boundary Conditions

After defining the hydraulic model geometry, you can define the peak flows along each river reach and the boundary conditions at each end of the model. The peak river flows at flow change locations of the hydraulic model come from the HEC-
Table 6-6 shows the resulting peak flows using mean values for the hydrologic parameters.

<table>
<thead>
<tr>
<th>HEC-1 Hydrograph Location</th>
<th>River Name</th>
<th>Reach Name</th>
<th>Cross Section River Station (meters)</th>
<th>Flow Value (m3/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2B</td>
<td>Branch</td>
<td>Left</td>
<td>2122.94</td>
<td>26.1</td>
</tr>
<tr>
<td>4C</td>
<td>Branch</td>
<td>Left</td>
<td>1200.33</td>
<td>38.3</td>
</tr>
<tr>
<td>4B</td>
<td>Leith</td>
<td>Upper</td>
<td>3814.80</td>
<td>59.1</td>
</tr>
<tr>
<td>6C</td>
<td>Leith</td>
<td>Upper</td>
<td>2896.40</td>
<td>70.3</td>
</tr>
<tr>
<td>7C</td>
<td>Leith</td>
<td>Upper</td>
<td>2095.34</td>
<td>74.3</td>
</tr>
<tr>
<td>8C</td>
<td>Leith</td>
<td>Lower</td>
<td>1000.15</td>
<td>136.9</td>
</tr>
<tr>
<td>2C</td>
<td>Leith</td>
<td>Lower</td>
<td>61.78</td>
<td>158.8</td>
</tr>
</tbody>
</table>

WMS replaces the peak flows listed in Table 6-6 with the values generated by the HEC-1 model for each stochastic simulation.

The model used a normal water surface boundary condition at the extent of each river reach in the model. Normal water surface boundary conditions require the energy slope at the boundary of each river reach. HEC-RAS then uses Manning’s Equation to compute the normal water depth at the boundary. WMS computed the energy slope using the average slope of the channel at the location of each boundary (see US Army Corps of Engineers, 2001b for more information on entering boundary conditions in HEC-RAS). Table 6-7 lists these slopes at the boundaries.
<table>
<thead>
<tr>
<th>River Name</th>
<th>Reach Name</th>
<th>Boundary Location</th>
<th>Slope</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leith</td>
<td>Upper</td>
<td>Upstream</td>
<td>0.0041</td>
</tr>
<tr>
<td>Leith</td>
<td>Lower</td>
<td>Downstream</td>
<td>0.0019</td>
</tr>
<tr>
<td>Branch</td>
<td>Left</td>
<td>Upstream</td>
<td>0.0027</td>
</tr>
</tbody>
</table>

6.1.2.5 Generating the HEC-RAS Hydraulic Model

WMS extracts cross section stations and their elevations from the elevation data by intersecting each cross section line with the TIN, as shown in Figure 6-13. WMS exports the reach and cross section data and the Manning’s n values to HEC-RAS. You manually enter the flow and boundary condition values in HEC-RAS.
WMS extracts the material properties along the cross sections from the land use data. You define Manning’s n values for each of the material properties, allowing Manning’s n values to be defined along the length of each of the cross sections. WMS generates the topology (connectivity) of the river reaches and cross sections from the cross sections and river centerlines. After the HEC-RAS model is set up and running to completion, you can use the output from HEC-RAS to determine the floodplain boundary.

6.1.3 Determining the Floodplain Boundary

Determination of the water depths and stages in the floodplain uses the methods developed by Noman (2001). Chapter 4 describes Noman’s method. The
model used the same LIDAR elevation data for defining the hydraulic model to
delineate the floodplain.

WMS interpolated the water depths from the HEC-RAS solution along the
river centerline and cross sections at an 85 meter spacing to be close enough to create
a sufficient number of solution points, but far enough apart to delineate the floodplain
in a reasonable amount of time. Similarly, the search radius for the floodplain
delineation was specified as 800 meters to be far enough to capture all the significant
water depth points influencing the floodplain at each TIN vertex, but close enough so
insignificant water depth points are not considered.

The floodplain was delineated using the following parameters: Quadrant
option: ON, Number of stages in a quadrant: 3, Flow path option: OFF. Figure 6-14
shows a contour map of water depths in the floodplain (with a background image of
the Leith Creek floodplain).
Tables 6-8 to 6-10 give a summary of the results from running the HEC-1, HEC-RAS, and Floodplain delineation models with mean values for curve number, precipitation, and Manning’s N.

Table 6-8: Peak flow values for selected locations in the hydrologic model

<table>
<thead>
<tr>
<th>Peak flow at 4B (m$^3$/s)</th>
<th>Peak flow at 2B (m$^3$/s)</th>
<th>Peak flow at 2C–Primary Outlet (m$^3$/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>59.088</td>
<td>26.101</td>
<td>158.654</td>
</tr>
</tbody>
</table>
Table 6-9: Minimum, maximum, and mean water surface elevations from the hydraulic model

<table>
<thead>
<tr>
<th>Minimum Water Elevation (m)</th>
<th>Maximum Water Elevation (m)</th>
<th>Mean Water Elevation (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>64.035</td>
<td>71.754</td>
<td>67.31427</td>
</tr>
</tbody>
</table>

Table 6-10: Maximum and mean flood depths and floodplain area from the floodplain model

<table>
<thead>
<tr>
<th>Maximum Flood Water Depth (m)</th>
<th>Mean Flood Water Depth (m)</th>
<th>Floodplain Area (m²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.947096</td>
<td>0.848804</td>
<td>631521.8</td>
</tr>
</tbody>
</table>

6.1.4 Running the Stochastic Simulations

This research ran four stochastic simulations using the Leith Creek watershed-hydraulic-floodplain model. Each run used different sets of model parameters as stochastic variables. The four simulations included:

1. A Latin Hypercube (LH) simulation with five segments for average precipitation using a linear (uniform) probability distribution with the stochastic parameters defined in Table 6-1.

2. An LH simulation with three segments for each basin curve number. This simulation grouped the curve numbers for basins with similar curve numbers into a single stochastic parameter. This simulation combined the curve numbers in Table 6-3 into three stochastic parameters with mean, minimum, and maximum values defined in Table 6-11. A Gaussian (normal) distribution was used with a standard deviation of 18.0 for all the
curve numbers. Since there were three stochastic parameters, this required a total of $3^3 = 27$ model runs.

Table 6-11: Stochastic curve number values for each sub-basin

<table>
<thead>
<tr>
<th>Basin Name</th>
<th>Curve Number</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>1B, 7B</td>
<td>68.95</td>
<td>49.75</td>
<td>84.35</td>
</tr>
<tr>
<td>2B, 5B</td>
<td>66.4</td>
<td>46.65</td>
<td>82.85</td>
</tr>
<tr>
<td>3B, 4B, 6B</td>
<td>65.43</td>
<td>45.6</td>
<td>82.3</td>
</tr>
</tbody>
</table>

3. An LH simulation with three segments for each land use’s roughness value. The Mannings n-values for three land use types were considered as stochastic parameters. This results in $3^3 = 27$ model runs. As illustrated in Figure 6-15, the majority of the floodplain overlays one of the following three land uses: “River”, “Cropland and Pasture”, or “Deciduous Forest Land”. Using Table 6-12, the Manning’s n-values for these three land uses were defined as stochastic parameters with normal probability distributions.

Table 6-12: Stochastic Manning’s roughness parameters for selected land uses (adapted from US Army Corps of Engineers, 2001b and Omer et al., 2003)

<table>
<thead>
<tr>
<th>Land use type</th>
<th>Mean n-value</th>
<th>Minimum n-value</th>
<th>Maximum n-value</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cropland and Pasture</td>
<td>0.040</td>
<td>0.030</td>
<td>0.050</td>
<td>0.010</td>
</tr>
<tr>
<td>Deciduous Forest Land</td>
<td>0.120</td>
<td>0.100</td>
<td>0.160</td>
<td>0.020</td>
</tr>
<tr>
<td>River</td>
<td>0.035</td>
<td>0.030</td>
<td>0.040</td>
<td>0.005</td>
</tr>
</tbody>
</table>
4. An LH simulation with all three of the above variables—precipitation, curve number, and Manning’s coefficient—as stochastic variables. An area-weighted curve number was determined for the entire watershed using the formula \( CN = \frac{\sum (C_{Ni} \times A_i)}{\sum A_i} \) (Equation 6-2), where \( CN \) is the composite watershed curve number, \( C_{Ni} \) is the curve number for each sub-basin, and \( A_i \) is the area of each sub-basin. This model defined the River Manning’s coefficient as a stochastic parameter using the stochastic parameters defined for the Manning’s coefficient in Table 6-12. Table 6-13 shows parameters used for stochastic modeling in this simulation.
Table 6-13: Stochastic parameters for simulation 4—All parameters stochastic

<table>
<thead>
<tr>
<th>Value</th>
<th>Key</th>
<th>Mean</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Standard Deviation</th>
<th>Number of Segments</th>
</tr>
</thead>
<tbody>
<tr>
<td>CN—All Basins</td>
<td>-1</td>
<td>66.19</td>
<td>46.43</td>
<td>82.72</td>
<td>18</td>
<td>3</td>
</tr>
<tr>
<td>Precipitation-All Basins</td>
<td>-2</td>
<td>201.7</td>
<td>186.0</td>
<td>211.0</td>
<td>13.65</td>
<td>3</td>
</tr>
<tr>
<td>River Manning’s Coefficient</td>
<td>-3</td>
<td>0.035</td>
<td>0.030</td>
<td>0.040</td>
<td>0.005</td>
<td>3</td>
</tr>
</tbody>
</table>

For each of the four simulations, the following input and output data were determined:

1. The input value for each stochastic parameter for each model run.
2. The peak flows for selected hydrograph locations for each HEC-1 model run.
3. For each hydraulic (HEC-RAS) model run, the maximum, minimum, range, mean, median, and standard deviation of water surface elevation values.
4. For each floodplain delineation, the maximum, minimum, range, mean, and standard deviation of flood depth and water surface elevation values.
5. For each stochastic simulation, histograms of the average flood depth of all model runs and of probability values for all model runs were determined.
6. The following maps: The floodplain probability contours and the minimum, maximum, and average water depth (flood extent) contour maps.
7. The areas of the minimum and maximum flood extents.
6.1.5  Results and Analysis

This research analyzed the results of each of the stochastic models to determine their validity and interesting features from each stochastic model. The first three model runs showed the effects of varying single parameters on the flood extents. Appendix A shows the results from these simulations. These models showed that high curve number and precipitation values give high flow rates, water depths, and larger floodplain areas. Moreover, high Manning’s coefficients give low water depths and smaller floodplain areas. One expects these results since flow increases as curve number and precipitation increase and flow (water velocity) decreases as Manning’s coefficient increases.

Simulation 4, described above, was the most comprehensive. This simulation included all three variables (precipitation, curve number, and Manning’s coefficient) as stochastic parameters. In this simulation, the interactions of these three variables on the floodplain boundary and a comprehensive 100-year floodplain probability map could be determined. The following section gives the results from this final simulation.

6.1.5.1  100-Year Floodplain Probability Map from a Latin Hypercube Simulation

The first three simulations were similar in nature since they used a single variable as a stochastic parameter. This section will present in detail the results of the fourth, or most comprehensive, model. This simulation included precipitation, curve number, and Manning’s coefficients as stochastic variables. You can find details for
the other three models in Appendix A. The purpose of these simulations was to test the stochastic modeling interface and to create initial floodplain probability maps.

6.1.5.1.1 Input Values

Each sub-basin’s precipitation, curve number, and the river’s roughness coefficient were all assigned three segments. This model ran 27 simulations to search through all the possible LH segment combinations. Figure 6-16, Figure 6-17, and Figure 6-18 show the segment input values for each of the parameters.
Figure 6-16: Precipitation values used for each segment

Figure 6-17: Curve number values used for each segment
Figure 6-18: Manning's coefficient values used for each segment

6.1.5.1.2 Peak Flow Values

Table 6-14 lists the peak flow values for basins 4B, 2B, and outlet 2C for each HEC-1 model run. It shows the percent change for the peak flow at outlet 2C.
Table 6-14: Peak flow values and percent changes for each HEC-1 model run

<table>
<thead>
<tr>
<th>Run Number</th>
<th>Precipitation - All Basins</th>
<th>Curve Number - All Basins</th>
<th>Manning’s Coefficient - River</th>
<th>Peak flow at 4B (m^3/s)</th>
<th>Peak flow at 2B (m^3/s)</th>
<th>Peak flow at 2C—Primary Outlet (m^3/s)</th>
<th>Change (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original</td>
<td>201.700</td>
<td>(66.19)</td>
<td>0.035</td>
<td>59.088</td>
<td>26.101</td>
<td>158.654</td>
<td>None</td>
</tr>
<tr>
<td>1</td>
<td>194.56</td>
<td>50.46</td>
<td>0.0306</td>
<td>28.522</td>
<td>12.114</td>
<td>70.07</td>
<td>-55.83</td>
</tr>
<tr>
<td>2</td>
<td>190.95</td>
<td>60.90</td>
<td>0.0304</td>
<td>45.695</td>
<td>19.619</td>
<td>114.515</td>
<td>-27.82</td>
</tr>
<tr>
<td>3</td>
<td>186.44</td>
<td>76.85</td>
<td>0.0317</td>
<td>72.821</td>
<td>30.863</td>
<td>188.025</td>
<td>18.51</td>
</tr>
<tr>
<td>4</td>
<td>197.21</td>
<td>59.72</td>
<td>0.0325</td>
<td>46.412</td>
<td>19.932</td>
<td>116.276</td>
<td>-26.71</td>
</tr>
<tr>
<td>5</td>
<td>203.16</td>
<td>61.69</td>
<td>0.0301</td>
<td>53.074</td>
<td>22.752</td>
<td>133.228</td>
<td>-16.03</td>
</tr>
<tr>
<td>6</td>
<td>199.86</td>
<td>82.50</td>
<td>0.0328</td>
<td>90.399</td>
<td>38.062</td>
<td>235.91</td>
<td>48.69</td>
</tr>
<tr>
<td>7</td>
<td>206.71</td>
<td>58.56</td>
<td>0.0315</td>
<td>48.597</td>
<td>20.871</td>
<td>121.748</td>
<td>-23.26</td>
</tr>
<tr>
<td>8</td>
<td>207.34</td>
<td>68.06</td>
<td>0.0323</td>
<td>67.755</td>
<td>28.886</td>
<td>172.716</td>
<td>8.86</td>
</tr>
<tr>
<td>9</td>
<td>204.46</td>
<td>70.62</td>
<td>0.0314</td>
<td>71.2</td>
<td>30.297</td>
<td>182.332</td>
<td>14.92</td>
</tr>
<tr>
<td>10</td>
<td>190.21</td>
<td>59.48</td>
<td>0.0362</td>
<td>42.719</td>
<td>18.358</td>
<td>106.932</td>
<td>-32.60</td>
</tr>
<tr>
<td>11</td>
<td>192.19</td>
<td>63.02</td>
<td>0.0346</td>
<td>50.258</td>
<td>21.544</td>
<td>126.163</td>
<td>-20.48</td>
</tr>
<tr>
<td>12</td>
<td>189.14</td>
<td>82.32</td>
<td>0.0339</td>
<td>83.929</td>
<td>35.373</td>
<td>218.718</td>
<td>37.86</td>
</tr>
<tr>
<td>13</td>
<td>202.45</td>
<td>46.69</td>
<td>0.0363</td>
<td>24.87</td>
<td>10.434</td>
<td>60.359</td>
<td>-61.96</td>
</tr>
<tr>
<td>14</td>
<td>197.64</td>
<td>63.86</td>
<td>0.0347</td>
<td>54.554</td>
<td>23.359</td>
<td>137.343</td>
<td>-13.43</td>
</tr>
<tr>
<td>15</td>
<td>202.99</td>
<td>78.88</td>
<td>0.0349</td>
<td>85.857</td>
<td>36.269</td>
<td>222.958</td>
<td>40.53</td>
</tr>
<tr>
<td>16</td>
<td>210.19</td>
<td>54.51</td>
<td>0.0349</td>
<td>42.133</td>
<td>18.123</td>
<td>105.243</td>
<td>-33.67</td>
</tr>
<tr>
<td>17</td>
<td>205.51</td>
<td>68.94</td>
<td>0.0337</td>
<td>68.506</td>
<td>29.189</td>
<td>174.881</td>
<td>10.23</td>
</tr>
<tr>
<td>18</td>
<td>209.57</td>
<td>76.28</td>
<td>0.0356</td>
<td>84.823</td>
<td>35.9</td>
<td>219.576</td>
<td>38.40</td>
</tr>
<tr>
<td>19</td>
<td>189.22</td>
<td>48.68</td>
<td>0.0382</td>
<td>23.728</td>
<td>9.971</td>
<td>57.673</td>
<td>-63.65</td>
</tr>
<tr>
<td>20</td>
<td>186.19</td>
<td>62.83</td>
<td>0.0378</td>
<td>46.99</td>
<td>20.157</td>
<td>117.879</td>
<td>-25.70</td>
</tr>
<tr>
<td>21</td>
<td>188.98</td>
<td>79.06</td>
<td>0.0386</td>
<td>78.192</td>
<td>33.063</td>
<td>202.732</td>
<td>27.78</td>
</tr>
<tr>
<td>22</td>
<td>199.00</td>
<td>49.02</td>
<td>0.0381</td>
<td>27.658</td>
<td>11.707</td>
<td>67.711</td>
<td>-57.32</td>
</tr>
<tr>
<td>23</td>
<td>196.55</td>
<td>61.32</td>
<td>0.0366</td>
<td>49.152</td>
<td>21.088</td>
<td>123.282</td>
<td>-22.30</td>
</tr>
<tr>
<td>24</td>
<td>198.89</td>
<td>74.30</td>
<td>0.0375</td>
<td>75.125</td>
<td>31.879</td>
<td>193.508</td>
<td>21.97</td>
</tr>
<tr>
<td>25</td>
<td>205.63</td>
<td>56.52</td>
<td>0.0381</td>
<td>44.084</td>
<td>18.954</td>
<td>110.254</td>
<td>-30.51</td>
</tr>
<tr>
<td>26</td>
<td>206.57</td>
<td>66.28</td>
<td>0.0376</td>
<td>63.845</td>
<td>27.262</td>
<td>162.09</td>
<td>2.17</td>
</tr>
<tr>
<td>27</td>
<td>204.19</td>
<td>75.45</td>
<td>0.0380</td>
<td>80.241</td>
<td>34</td>
<td>207.274</td>
<td>30.65</td>
</tr>
</tbody>
</table>

Table 6-14 shows how sensitive the peak flow values at outlet 2C are to changes in sub-basin precipitation and curve numbers. The percent change from the peak flow value in the original run range from a decrease of 63.65% for simulation 19 to an increase of 48.69% for simulation 6.
6.1.5.1.3 **Hydraulic Model Results**

Table 6-15 shows the minimum, maximum, and mean water surface elevations from each run of the stochastic model. It also lists the percent changes in the mean water surface elevation from the original water surface elevations. The change in mean water surface elevations was significant, with a maximum decrease of 0.38 meters (1.25 feet) and a maximum increase of 0.19 meters (0.63 feet). This compares to a maximum decrease of 0.24 meters (0.80 feet) and a maximum increase of 0.16 meters (0.53 feet) when only the curve number was used as a stochastic parameter.
Table 6-15: Hydraulic model water surface elevations and percent changes for each HEC-RAS model run

<table>
<thead>
<tr>
<th>Run Number</th>
<th>Precipitation-All Basins</th>
<th>Curve Number-All Basins</th>
<th>Manning's Coefficient-River</th>
<th>Minimum Water Elevation (m)</th>
<th>Maximum Water Elevation (m)</th>
<th>Mean Water Elevation (m)</th>
<th>Mean Water Elevation Change (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original</td>
<td>201.700</td>
<td>(66.19)</td>
<td>0.035</td>
<td>64.035</td>
<td>71.754</td>
<td>67.31427</td>
<td>None</td>
</tr>
<tr>
<td>1</td>
<td>194.56</td>
<td>50.46</td>
<td>0.0306</td>
<td>63.531</td>
<td>71.511</td>
<td>66.95087</td>
<td>-0.540</td>
</tr>
<tr>
<td>2</td>
<td>190.95</td>
<td>60.90</td>
<td>0.0304</td>
<td>63.764</td>
<td>71.631</td>
<td>67.13194</td>
<td>-0.271</td>
</tr>
<tr>
<td>3</td>
<td>186.44</td>
<td>76.85</td>
<td>0.0317</td>
<td>64.08</td>
<td>71.822</td>
<td>67.3705</td>
<td>0.084</td>
</tr>
<tr>
<td>4</td>
<td>197.21</td>
<td>59.72</td>
<td>0.0325</td>
<td>63.817</td>
<td>71.636</td>
<td>67.15987</td>
<td>-0.229</td>
</tr>
<tr>
<td>5</td>
<td>203.16</td>
<td>61.69</td>
<td>0.0301</td>
<td>63.852</td>
<td>71.692</td>
<td>67.19691</td>
<td>-0.174</td>
</tr>
<tr>
<td>6</td>
<td>199.86</td>
<td>82.50</td>
<td>0.0328</td>
<td>64.257</td>
<td>71.914</td>
<td>67.50545</td>
<td>0.284</td>
</tr>
<tr>
<td>7</td>
<td>206.71</td>
<td>58.56</td>
<td>0.0315</td>
<td>63.826</td>
<td>71.655</td>
<td>67.17004</td>
<td>-0.214</td>
</tr>
<tr>
<td>8</td>
<td>207.34</td>
<td>68.06</td>
<td>0.0323</td>
<td>64.038</td>
<td>71.795</td>
<td>67.33712</td>
<td>0.034</td>
</tr>
<tr>
<td>9</td>
<td>204.46</td>
<td>70.62</td>
<td>0.0314</td>
<td>64.055</td>
<td>71.815</td>
<td>67.35416</td>
<td>0.059</td>
</tr>
<tr>
<td>10</td>
<td>190.21</td>
<td>59.48</td>
<td>0.0362</td>
<td>63.831</td>
<td>71.612</td>
<td>67.15404</td>
<td>-0.238</td>
</tr>
<tr>
<td>11</td>
<td>192.19</td>
<td>63.02</td>
<td>0.0346</td>
<td>63.897</td>
<td>71.671</td>
<td>67.21387</td>
<td>-0.149</td>
</tr>
<tr>
<td>12</td>
<td>189.14</td>
<td>82.32</td>
<td>0.0339</td>
<td>64.226</td>
<td>71.885</td>
<td>67.47629</td>
<td>0.241</td>
</tr>
<tr>
<td>13</td>
<td>202.45</td>
<td>46.69</td>
<td>0.0363</td>
<td>63.54</td>
<td>71.473</td>
<td>66.93875</td>
<td>-0.558</td>
</tr>
<tr>
<td>14</td>
<td>197.64</td>
<td>63.86</td>
<td>0.0347</td>
<td>63.945</td>
<td>71.705</td>
<td>67.25313</td>
<td>-0.091</td>
</tr>
<tr>
<td>15</td>
<td>202.99</td>
<td>78.88</td>
<td>0.0349</td>
<td>64.26</td>
<td>71.898</td>
<td>67.50014</td>
<td>0.276</td>
</tr>
<tr>
<td>16</td>
<td>210.19</td>
<td>54.51</td>
<td>0.0349</td>
<td>63.798</td>
<td>71.607</td>
<td>67.13684</td>
<td>-0.264</td>
</tr>
<tr>
<td>17</td>
<td>205.51</td>
<td>68.94</td>
<td>0.0337</td>
<td>64.072</td>
<td>71.8</td>
<td>67.35921</td>
<td>0.067</td>
</tr>
<tr>
<td>18</td>
<td>209.57</td>
<td>76.28</td>
<td>0.0356</td>
<td>64.263</td>
<td>71.895</td>
<td>67.50034</td>
<td>0.276</td>
</tr>
<tr>
<td>19</td>
<td>189.22</td>
<td>48.68</td>
<td>0.0382</td>
<td>63.542</td>
<td>71.461</td>
<td>66.93436</td>
<td>-0.564</td>
</tr>
<tr>
<td>20</td>
<td>186.19</td>
<td>62.83</td>
<td>0.0378</td>
<td>63.907</td>
<td>71.651</td>
<td>67.20933</td>
<td>-0.156</td>
</tr>
<tr>
<td>21</td>
<td>188.98</td>
<td>79.06</td>
<td>0.0386</td>
<td>64.262</td>
<td>71.868</td>
<td>67.48474</td>
<td>0.253</td>
</tr>
<tr>
<td>22</td>
<td>199.00</td>
<td>49.02</td>
<td>0.0381</td>
<td>63.613</td>
<td>71.5</td>
<td>66.98785</td>
<td>-0.485</td>
</tr>
<tr>
<td>23</td>
<td>196.55</td>
<td>61.32</td>
<td>0.0366</td>
<td>63.914</td>
<td>71.666</td>
<td>67.22027</td>
<td>-0.140</td>
</tr>
<tr>
<td>24</td>
<td>198.89</td>
<td>74.30</td>
<td>0.0375</td>
<td>64.21</td>
<td>71.848</td>
<td>67.44894</td>
<td>0.200</td>
</tr>
<tr>
<td>25</td>
<td>205.63</td>
<td>56.52</td>
<td>0.0381</td>
<td>63.876</td>
<td>71.626</td>
<td>67.18268</td>
<td>-0.195</td>
</tr>
<tr>
<td>26</td>
<td>206.57</td>
<td>66.28</td>
<td>0.0376</td>
<td>64.093</td>
<td>71.778</td>
<td>67.35907</td>
<td>0.067</td>
</tr>
<tr>
<td>27</td>
<td>204.19</td>
<td>75.45</td>
<td>0.0380</td>
<td>64.268</td>
<td>71.878</td>
<td>67.49323</td>
<td>0.266</td>
</tr>
</tbody>
</table>
### 6.1.5.1.4 Floodplain Delineation Results

Table 6-16 shows the effects of the precipitation, curve number, and Manning’s coefficient input values on the maximum and mean floodwater depths and on the floodplain areas.

**Table 6-16: Floodplain water depths, areas, and percent changes**

<table>
<thead>
<tr>
<th>Run Number</th>
<th>Precipitation-All Basins</th>
<th>Curve Number-All Basins</th>
<th>Manning’s Coefficient-River</th>
<th>Maximum Flood Water Depth (m)</th>
<th>Mean Flood Water Depth (m)</th>
<th>Floodplain Area (m²)</th>
<th>Area Change (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original</td>
<td>201.700</td>
<td>Different values for each basin (66.19)</td>
<td>0.035</td>
<td>2.947096</td>
<td>0.848804</td>
<td>631521.8</td>
<td>None</td>
</tr>
<tr>
<td>1</td>
<td>194.56</td>
<td>50.46</td>
<td>0.0306</td>
<td>2.420473</td>
<td>0.639545</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>190.95</td>
<td>60.90</td>
<td>0.0304</td>
<td>2.67285</td>
<td>0.743594</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>186.44</td>
<td>76.85</td>
<td>0.0317</td>
<td>3.002439</td>
<td>0.885539</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>197.21</td>
<td>59.72</td>
<td>0.0325</td>
<td>2.720675</td>
<td>0.76101</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>203.16</td>
<td>61.69</td>
<td>0.0310</td>
<td>2.764166</td>
<td>0.783258</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>199.86</td>
<td>82.50</td>
<td>0.0328</td>
<td>3.182422</td>
<td>0.961195</td>
<td>679479</td>
<td>7.59</td>
</tr>
<tr>
<td>7</td>
<td>206.71</td>
<td>58.56</td>
<td>0.0315</td>
<td>2.733037</td>
<td>0.766219</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>207.34</td>
<td>68.06</td>
<td>0.0323</td>
<td>2.956795</td>
<td>0.85017</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>204.46</td>
<td>70.62</td>
<td>0.0314</td>
<td>2.977054</td>
<td>0.875014</td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>190.21</td>
<td>59.48</td>
<td>0.0362</td>
<td>2.727102</td>
<td>0.756551</td>
<td></td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>192.19</td>
<td>63.02</td>
<td>0.0346</td>
<td>2.799961</td>
<td>0.793001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>189.14</td>
<td>82.32</td>
<td>0.0339</td>
<td>3.147392</td>
<td>0.942037</td>
<td></td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>202.45</td>
<td>46.69</td>
<td>0.0363</td>
<td>2.418538</td>
<td>0.631793</td>
<td></td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>197.64</td>
<td>63.86</td>
<td>0.0347</td>
<td>2.851275</td>
<td>0.816455</td>
<td></td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>202.99</td>
<td>78.88</td>
<td>0.0349</td>
<td>3.179328</td>
<td>0.957221</td>
<td></td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>210.19</td>
<td>54.51</td>
<td>0.0349</td>
<td>2.696017</td>
<td>0.746858</td>
<td></td>
<td></td>
</tr>
<tr>
<td>17</td>
<td>205.51</td>
<td>68.94</td>
<td>0.0337</td>
<td>2.988778</td>
<td>0.877225</td>
<td></td>
<td></td>
</tr>
<tr>
<td>18</td>
<td>209.57</td>
<td>76.28</td>
<td>0.0356</td>
<td>3.181132</td>
<td>0.956632</td>
<td></td>
<td></td>
</tr>
<tr>
<td>19</td>
<td>189.22</td>
<td>48.68</td>
<td>0.0382</td>
<td>2.418091</td>
<td>0.629581</td>
<td>535983.2</td>
<td>-15.13</td>
</tr>
<tr>
<td>20</td>
<td>186.19</td>
<td>62.83</td>
<td>0.0378</td>
<td>2.804785</td>
<td>0.789215</td>
<td></td>
<td></td>
</tr>
<tr>
<td>21</td>
<td>188.98</td>
<td>79.06</td>
<td>0.0386</td>
<td>3.173372</td>
<td>0.945783</td>
<td></td>
<td></td>
</tr>
<tr>
<td>22</td>
<td>199.00</td>
<td>49.02</td>
<td>0.0381</td>
<td>2.494467</td>
<td>0.65899</td>
<td></td>
<td></td>
</tr>
<tr>
<td>23</td>
<td>196.55</td>
<td>61.32</td>
<td>0.0366</td>
<td>2.81423</td>
<td>0.797039</td>
<td></td>
<td></td>
</tr>
<tr>
<td>24</td>
<td>198.89</td>
<td>74.30</td>
<td>0.0375</td>
<td>3.122085</td>
<td>0.926872</td>
<td></td>
<td></td>
</tr>
<tr>
<td>25</td>
<td>205.63</td>
<td>56.52</td>
<td>0.0381</td>
<td>2.770571</td>
<td>0.773079</td>
<td></td>
<td></td>
</tr>
<tr>
<td>26</td>
<td>206.57</td>
<td>66.28</td>
<td>0.0376</td>
<td>3.000959</td>
<td>0.876612</td>
<td></td>
<td></td>
</tr>
<tr>
<td>27</td>
<td>204.19</td>
<td>75.45</td>
<td>0.0380</td>
<td>3.180137</td>
<td>0.951143</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
There was a significant change in the maximum and mean floodwater depths from the original simulation. The maximum increase in mean flood depth was 0.11 meters (0.37 feet) in model run 6 and the maximum decrease in mean flood depth was 0.22 meters (0.72 feet) in model run 19. The floodplain area maximum and minimum changes were 7.59% and -15.13%, respectively. Figure 6-19 shows the contours of water depth at the floodplain’s minimum extents for the stochastic simulation. This model did not model any bridges or other structures. In addition, some discharges were not high enough to create significant water depth along the branch. These problems created “gaps” in some of the water depth contour maps.
Figure 6-19: Minimum water depth contours (all values in meters)

Figure 6-20 shows the contours of water depth at the floodplain’s maximum extents in this stochastic simulation.
The average water depth map for this stochastic simulation is shown in Figure 6-21. Some small, noticeable differences exist between the minimum, maximum, and average water depth contour maps in this stochastic simulation. These differences will be more noticeable in the flood probability map.
Figure 6-21: Averaged water depth contours from all floodplain delineations (all values in meters)

Figure 6-22 shows the flood probability map for this simulation.
Figure 6-22: Probability of flooding (values in percent)

Figure 6-22 illustrates significant variations in probabilities from this stochastic simulation. Figure 6-23 shows the close-up area of the lower portion of the probability map.
Figure 6-23: Probability of flooding—close-up area (values in percent)

Figure 6-24 and Figure 6-25 show histograms containing numerical values from the images in Figure 6-21 to Figure 6-23. Figure 6-24 shows the frequency distribution of flood depths in the floodplain. Most flood depths are in the 0-1.5 meter range, with some flood depths reaching up to 2.75 meters.
Figure 6-24: Average flood depth histogram showing the number of vertices on the TIN with different water depth values for simulation 4.

Figure 6-25 shows the probability values of the points in the model. The majority of points are 0 or 100%, meaning they are inside or outside of the floodplain.
Figure 6-25: Probability histogram showing the number of vertices on the TIN with different probability values for simulation 4

6.1.5.2 Comparison to North Carolina Flood Database 100-Year Floodplain Data

To test the validity of the 100-year flood probability map, this study made a comparison between the current 100-year floodplain maps for North Carolina and the floodplain probability map generated in simulation 4. Figure 6-26 shows the floodplain probability map with the current 100-year floodplain boundary from the North Carolina database and the location of the 50% probability contour.
Figure 6-26: A comparison of the 100-year floodplain boundary from the North Carolina database with the flood probability contours generated for simulation 4

Figure 6-27 shows a close-up of one section of the floodplain. This image shows that there is a close match between most areas of the floodplain boundary from the North Carolina flood database and the flood probability contours generated for simulation 4. The results of the zoomed section were consistent with the rest of the modeling area. However, the model did not consider an area including a bridge. The stochastic simulation produced qualitatively plausible results.
Figure 6-27: A close-up of the comparison of the 100-year floodplain boundary from the North Carolina database with the flood probability contours

6.1.5.3 Creating the AEP Map and Comparison to 100-Year Floodplain Probability Map

The AEP map for Leith Creek was created by defining a precipitation-probability curve for the entire watershed. This curve was created by fitting the precipitation dataset at Laurinburg to a log Pearson Type III distribution using the method described in Linsley et al. (1992), substituting precipitation values for flow
values. Table 6-17 shows the precipitation-probability curve parameters used to generate the AEP map.

Table 6-17: Precipitation-probability curve parameters used to create the AEP map of Leith Creek floodplain

<table>
<thead>
<tr>
<th>Probability</th>
<th>Mean Precipitation (mm)</th>
<th>Minimum (mm)</th>
<th>Maximum (mm)</th>
<th>Standard Deviation (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>35.00</td>
<td>20.00</td>
<td>60.20</td>
<td>12.60</td>
</tr>
<tr>
<td>0.5</td>
<td>72.20</td>
<td>20.22</td>
<td>124.18</td>
<td>25.99</td>
</tr>
<tr>
<td>0.1</td>
<td>112.83</td>
<td>48.52</td>
<td>177.14</td>
<td>32.16</td>
</tr>
<tr>
<td>0.04</td>
<td>134.48</td>
<td>61.86</td>
<td>207.10</td>
<td>36.31</td>
</tr>
<tr>
<td>0.02</td>
<td>151.17</td>
<td>71.05</td>
<td>231.28</td>
<td>40.06</td>
</tr>
<tr>
<td>0.01</td>
<td>168.32</td>
<td>79.11</td>
<td>257.52</td>
<td>44.60</td>
</tr>
<tr>
<td>0.005</td>
<td>186.09</td>
<td>87.46</td>
<td>284.72</td>
<td>49.31</td>
</tr>
</tbody>
</table>

Figure 6-28 shows the generated histogram of precipitation input values.
The AEP model also varied the Curve Numbers and Manning’s coefficients using the parameters specified in the 100-year floodplain probability simulation (simulation 4). Figure 6-29 shows a comparison between the AEP map generated using 180 simulations and the 100-year floodplain probability map for simulation 4.
Figure 6-29: Comparison between the AEP map and the 100-year floodplain probability map for simulation 4

It is difficult to determine differences between the two images in Figure 6-29. Therefore, Figure 6-30 shows a close-up view of the floodplain displaying the contour of the 1% (100-year) floodplain on the AEP map, the contour of the 50% probability on the 100-year floodplain probability map, and the location of the 100-year floodplain from the North Carolina database.
Figure 6-30: Comparison between the locations of the contour of the 1% (100-year) floodplain on the AEP map, the contour of the 50% probability on the 100-year floodplain probability map, and the 100-year floodplain from the North Carolina database.
As can be seen, the 100-year floodplain on the AEP map and the 50% probability on the 100-year floodplain probability map are in slightly different locations. However, both contour lines are close to each other, and the 100-year floodplain from the North Carolina database shows that any of the results could be used as the actual location of the floodplain. Theoretically, however, the 100-year floodplain from the AEP map shows the true location of the 100-year floodplain considering much of the inherent uncertainty.

6.2 Virgin River

A second model was created to demonstrate the process of creating a spatial map of annual exceedance probabilities. This model used floodplain elevation data from a section of the Virgin River in southern Utah. It was important to develop this second model because the floodplain of the North Carolina model was so well defined that the simulations did not result in much overtopping of the banks. In the North Carolina model, there was little change on the floodplain boundary with changes in input parameter values. However, the Virgin River floodplain is relatively flat. Therefore, the floodplain width is sensitive to small changes in computed water surface elevations. This study validated that the method of computing the AEP map from discharge-probability data is reliable.

Another purpose of this case study was to determine the number of simulations required to generate maps of annual exceedance probabilities and flood probabilities that do not change significantly with additional simulations. The final purpose of this
study was to compare the 100-year floodplain boundary obtained from the AEP map with the floodplain probability map for the 100-year storm.

6.2.1 Location

The outlet of the model is located near a small town named Virgin in southern Utah. The model is along the Virgin River between Zion National Park and St. George (see Figure 6-31).

Figure 6-31: Location of the Virgin River model

The watershed for this outlet point is very large (2200 km²) and takes up most of Zion National Park and its surrounding areas. The hydraulic/floodplain model was
created at the outlet point of the watershed. Figure 6-32 shows the watershed and the hydraulic model location.

![Figure 6-32: Watershed model boundary with location of the hydraulic and floodplain models](image)

6.2.2 Hydrologic Data

Peak yearly flow records are available from a gage station at the outlet location since 1910. An NFF model was created for the watershed and the results were
compared with the peak flows at different intervals from the gage values. The entire model region was in the Utah “Four Corners Region—Region 8” (USGS, 2002). The only input requirements to obtain a listing of peak flows at different intervals for this region are the watershed area and the mean watershed elevation. The peak flows at different intervals from the gage results were within the range of error provided by the peak flows from the NFF simulation. Table 6-18 shows the results from the NFF simulation.

Table 6-18: NFF and gage peak flow data at the Virgin River at different recurrence intervals

<table>
<thead>
<tr>
<th>Recurrence [years]</th>
<th>NFF Peak [m³/s]</th>
<th>Gage Peak [m³/s]</th>
<th>Error [%]</th>
<th>Minimum [m³/s]</th>
<th>Maximum [m³/s]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>42.5</td>
<td>72</td>
<td>11.9</td>
<td>73.1</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>72.9</td>
<td>72</td>
<td>20.4</td>
<td>125.4</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>137.9</td>
<td>62</td>
<td>52.4</td>
<td>223.4</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>189.6</td>
<td>270.1</td>
<td>57</td>
<td>297.7</td>
<td></td>
</tr>
<tr>
<td>25</td>
<td>272.9</td>
<td>54</td>
<td>125.6</td>
<td>420.3</td>
<td></td>
</tr>
<tr>
<td>50</td>
<td>346.8</td>
<td>53</td>
<td>163.0</td>
<td>530.6</td>
<td></td>
</tr>
<tr>
<td>100</td>
<td>421.1</td>
<td>53</td>
<td>197.9</td>
<td>644.3</td>
<td></td>
</tr>
<tr>
<td>500</td>
<td>646.4</td>
<td>53</td>
<td>303.8</td>
<td>989.0</td>
<td></td>
</tr>
</tbody>
</table>

The peak flow values at different recurrence intervals could also be determined using the recorded gage data and a log Pearson Type III distribution (Linsley et al., 1992). The first step in doing this is to tabulate the yearly instantaneous peak flow values and to compute the following data from the peak flows, where \( X \) represents each flow value:

1. The mean of the logs of all flows, \( \bar{\log X} \).

2. \( \sum (\log X - \bar{\log X})^2 \)
3. $\sum (\log X - \log \bar{X})^3$

Next, the standard deviation of the logs ($\sigma_{\log X}$) and skew coefficient ($g$) are determined from the following equations, where $N$ is the number of years of instantaneous peak flow data:

\[
\sigma_{\log X} = \left[ \frac{\sum (\log X - \log \bar{X})^2}{N - 1} \right]^{1/2} \quad (6-3)
\]

\[
g = \frac{N \sum (\log X - \log \bar{X})^3}{(N - 1)(N - 2)(\sigma_{\log X})^3} \quad (6-4)
\]

Spreadsheet functions also exist for computing the standard deviation and skew coefficient. If you compute and tabulate the logs of each value, you can compute the standard deviation and skew coefficient of the logs using these spreadsheet functions. Finally, the peak flow values of $X$ for different return periods can be determined from the following equation, where $K$ is obtained from a table that uses the skew coefficient ($g$) and the return period to be computed (see table A-5 in Linsley et al., 1992):

\[
\log X = \log \bar{X} + K \sigma_{\log X} \quad (6-5)
\]
These peak flow values are used with the minimum and maximum values and a standard deviation of \((Q_{\text{max}}-Q_{\text{min}})/4\) to create a flow-probability curve with a probability distribution at each recurrence probability, as illustrated in Figure 6-33.

![Probability Discharge Curve](image)

**Figure 6-33: A discharge-probability curve with uncertainty**

The stochastic model used this discharge-probability curve with uncertainty to generate discharge values and create the AEP map. The model uses the 100-year peak flow value with its minimum, maximum, and standard deviation values to create the 100-year flood probability map.

6.2.3 Developing the Hydraulic Model

The HEC-RAS hydraulic model was created using the same methods described in the previous section. First, you identify the river centerline and bank locations. Then, WMS uses elevation and area property data to extract cross sections and to determine the Manning's coefficient values along each cross section (see Figure 6-34).
Table 6-19 lists the Manning’s values for the different land use types in the floodplain. WMS assigns these values to the cross sections from the area property coverage.

Table 6-19: Manning's n-values used in the Virgin River model (adapted from US Army Corps of Engineers, 2001b)

<table>
<thead>
<tr>
<th>Land Use Type</th>
<th>Manning’s n value</th>
</tr>
</thead>
<tbody>
<tr>
<td>River Bed</td>
<td>0.035</td>
</tr>
<tr>
<td>Shrubs and Brush</td>
<td>0.06</td>
</tr>
<tr>
<td>Range and Cropland</td>
<td>0.04</td>
</tr>
</tbody>
</table>
After extracting the cross sections, you export the model to HEC-RAS and assign the peak discharge and boundary conditions to the model. Initially, the 100-year peak discharge from NFF (421.1 m³/s) was assigned to the model.

6.2.4 Generating the Annual Exceedance Probability (AEP) Map

Generating an AEP map requires flow-probability curve data with mean, minimum, maximum, and standard deviation values at each point along the flow-probability curve.

When running the simulations, a random probability (p_i) between 0.0 and 1.0 is first determined for each simulation (see Figure 6-35). This number represents the probability of exceedance for that simulation. From this probability, the mean (Q_{i(mean)}), minimum (Q_{i(min)}), maximum (Q_{i(max)}), and standard deviation (\sigma_i) are linearly interpolated from the closest known values. The discharge (Q_i^*) is determined from Q_{i(mean)}, Q_{i(min)}, Q_{i(max)}, \sigma_i, and the probability distribution function.
Figure 6-35: Determining a discharge value from discharge-probability curve data

WMS computed the data for the flow-probability curve using an NFF simulation, as described previously. The stochastic model used this data to compute a flow value for each HEC-RAS simulation. Table 6-20 shows the data used for the flow-probability curve.

Table 6-20: Discharge-probability curve input data

<table>
<thead>
<tr>
<th>Probability</th>
<th>Mean [m³/s]</th>
<th>Minimum [m³/s]</th>
<th>Maximum [m³/s]</th>
<th>Standard Deviation [m³/s]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>42.5</td>
<td>11.9</td>
<td>73.1</td>
<td>15.3</td>
</tr>
<tr>
<td>0.5</td>
<td>72.9</td>
<td>20.4</td>
<td>125.4</td>
<td>26.2</td>
</tr>
<tr>
<td>0.2</td>
<td>137.9</td>
<td>52.4</td>
<td>223.4</td>
<td>42.7</td>
</tr>
<tr>
<td>0.1</td>
<td>189.6</td>
<td>81.5</td>
<td>297.7</td>
<td>54.0</td>
</tr>
<tr>
<td>0.04</td>
<td>272.9</td>
<td>125.6</td>
<td>420.3</td>
<td>73.7</td>
</tr>
<tr>
<td>0.02</td>
<td>346.8</td>
<td>163.0</td>
<td>530.6</td>
<td>91.9</td>
</tr>
<tr>
<td>0.01</td>
<td>421.1</td>
<td>197.9</td>
<td>644.3</td>
<td>111.6</td>
</tr>
<tr>
<td>0.002</td>
<td>646.4</td>
<td>303.8</td>
<td>989.0</td>
<td>171.3</td>
</tr>
</tbody>
</table>

This study ran four simulations to determine AEP maps. Simulations with 100, 200, 500, and 1000 different flow values from the discharge-probability curve were run. This dissertation compares the input flow histograms, AEP maps, and
average water depth maps for each of these simulations. The input flow values for the AEP map were determined by canvassing the discharge-probability curve and its associated uncertainty, the area shown in Figure 6-36.

![Figure 6-36: Canvassing the space of the discharge-probability curve](image)

Also, four simulations (with 100, 200, 500, and 1000 different flow values) were run to determine the 100-year floodplain probability maps using the mean, minimum, maximum, and standard deviation values at the 0.01 (100-year recurrence interval) probability.

6.2.5 Results

This section discusses the input and output data from running the four simulations to determine the AEP map and the four simulations to determine the 100-year floodplain probability map for the Virgin River model.
6.2.5.1 AEP Model—Discharge Values

Figure 6-37 shows the discharge value histograms used to compute the AEP map for 100, 200, 500, and 1000 simulations.

Figure 6-37: Flow histograms for 100, 200, 500, and 1000 simulations to produce an AEP map

These flow histograms become “smoother” with additional simulations, and the maximum flow becomes higher with successive simulations. For example, the maximum flow with 1000 simulations is over 900 m$^3$/s, while the maximum flow for 100 simulations is about 450 m$^3$/s. Running 1000 simulations is like simulating 1000 years of peak flow values, while running 100 simulations is like simulating 100 years of peak flow values. The results make sense, since the 0.002-probability (500-year)
mean peak flow value is 646 m$^3$/s with a maximum of 989 m$^3$/s. The 1000-year peak flow value should be above the mean 500-year peak flow value, and it is. Similarly, the 100-year peak flow value is 421 m$^3$/s with a maximum of 644 m$^3$/s.

6.2.5.2 AEP Model—AEP Maps

Figure 6-38 shows the AEP maps computed for each of the simulations.
The same contour breaks are used for each of the above simulations except the 1000-year simulation, which has a contour break for the 0.001 (the 0.1% contour showed in light orange) probability. The green areas of the map represent low exceedance probabilities (1% to 20%), while the red and pink areas of the map represent higher exceedance probabilities (50%-100%).

The AEP maps are very similar, with a few differences with each successive simulation. Theoretically, you can make the map more accurate by running more
simulations. Table 6-21 shows the root mean square (RMS), average, and standard deviation of the AEP values in the floodplain for each of the simulations. These values remain about the same for each set of simulations. However, a qualitative analysis of the input discharges shown in Figure 6-37 and the AEP map shown in and Figure 6-38 reveal an important fact: The number of simulations corresponds to running measured data from the corresponding number of years. In other words, running 100 simulations with discharge values from a discharge-probability curve is similar to running 100 simulations using measured yearly peak discharges for 100 years. This also means that you must run more than 100 simulations if you desire an accurate 100-year floodplain contour. You can model higher peak flow values with higher numbers of simulations.

Table 6-21: RMS, average, and standard deviation of AEP values for each of the AEP simulations

<table>
<thead>
<tr>
<th># of runs</th>
<th>RMS Value</th>
<th>Average</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>43.0769316</td>
<td>22.34632</td>
<td>36.82862151</td>
</tr>
<tr>
<td>200</td>
<td>43.4751068</td>
<td>22.94366</td>
<td>36.92908059</td>
</tr>
<tr>
<td>500</td>
<td>43.2359709</td>
<td>22.38118</td>
<td>36.99345675</td>
</tr>
<tr>
<td>1000</td>
<td>43.2153578</td>
<td>22.55373</td>
<td>36.86434127</td>
</tr>
</tbody>
</table>

The AEP map shows the spatial probability that any point in the floodplain will be flooded in a certain year. The reddish hues in the maps in Figure 6-38 represent exceedance probabilities of 50-100% in any given year, while the greenish hues in the maps represent exceedance probabilities of 1-20%.

Additionally, the 0.2%, 1%, 2%, 4%, 10%, 50%, and 100% (500, 100, 50, 25, 10, 2, and 1-year recurrence interval) contour breaks on the AEP map show more certain floodplain boundaries than can be determined using traditional floodplain
delineation methods. These boundary lines are not the result of a single set of modeling parameters and could not be reproduced by a single simulation, but are rather the composite of all the simulations. The AEP map produced from running 1000 simulations, shown in Figure 6-39, illustrates how the floodplain boundaries (with uncertainty incorporated) at different recurrence intervals can be determined from this set of AEP simulations.
Figure 6-39: Determining floodplain boundaries at different recurrence intervals using the AEP map produced from 1000 simulations

6.2.5.3 AEP Model—Water Depth Maps

The average water depth maps computed for each of the AEP simulations are shown in [Figure 6-40]
The average water depth maps are similar for each of the AEP simulations. Table 6-22 shows the root mean square (RMS), average, and standard deviation of the water depth values in the floodplain for each of the simulations. These values remain about the same for each set of simulations.
Table 6-22: RMS, average, and standard deviation of average water depth values for each of the AEP simulations

<table>
<thead>
<tr>
<th># of runs</th>
<th>RMS Value</th>
<th>Average</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>0.65981229</td>
<td>0.263515</td>
<td>0.604925141</td>
</tr>
<tr>
<td>200</td>
<td>0.68172205</td>
<td>0.279722</td>
<td>0.621710588</td>
</tr>
<tr>
<td>500</td>
<td>0.66162554</td>
<td>0.264831</td>
<td>0.606329551</td>
</tr>
<tr>
<td>1000</td>
<td>0.66756733</td>
<td>0.269523</td>
<td>0.610758961</td>
</tr>
</tbody>
</table>

6.2.5.4 100-Year Floodplain Model—Discharge Values

Figure 6-41 shows the discharge value histograms used to compute the 100-year floodplain probability map for 100, 200, 500, and 1000 simulations.
The primary result of running additional simulations is to create a “smoother” histogram of input flow values. For example, Figure 6-41 shows that the flow input values for 1000 simulations creates an input flow histogram that more closely approximates a normal distribution than the flow input values for 100 simulations.

6.2.5.5 100-Year Floodplain Model—Flood Probability Maps

Figure 6-42 shows the flood probability maps for each of the 100-year floodplain simulations.
Figure 6-42: 100-year flood probability maps created by running 100, 200, 500, and 1000 simulations

The flood probability maps (and the location of the 50% probability contour) are qualitatively about the same for each of the simulations. This may mean that a good flood probability map can be obtained by running relatively few (about 100) simulations. You can confirm these results by examining the statistics of the probability values for each of the simulations, listed in Table 6-23.
Table 6-23: RMS, average, and standard deviation of the probability values for each of the 100-year floodplain maps

<table>
<thead>
<tr>
<th># of runs</th>
<th>RMS Value</th>
<th>Average</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>64.83</td>
<td>44.29</td>
<td>47.34</td>
</tr>
<tr>
<td>200</td>
<td>64.83</td>
<td>44.29</td>
<td>47.34</td>
</tr>
<tr>
<td>500</td>
<td>64.82</td>
<td>44.28</td>
<td>47.34</td>
</tr>
<tr>
<td>1000</td>
<td>64.83</td>
<td>44.29</td>
<td>47.34</td>
</tr>
</tbody>
</table>

The RMS, average, and standard deviation of the probability values for each of the 100-year simulations above 100 runs remain about the same. To determine the number of runs required for the RMS, mean, and standard deviation of the probability values to stabilize, several simulations were run with numbers of stochastic runs between 5 and 250. Figures 6-43, Figure 6-44, and Figure 6-45 plot and compare the RMS, mean, and standard deviation of the probability values for these simulations.
Figure 6-43: RMS of probability values for different numbers of simulations

Figure 6-44: Mean of probability values for different numbers of simulations
Figure 6-45: Standard deviation of probability values for different numbers of simulations

These plots show that the RMS, mean, and standard deviation of the probability values begin to stabilize after close to 100 simulations. Since these simulations only used one variable (discharge) as a stochastic variable, these results are only valid for simulations with a single stochastic variable. Additional simulations may be required if additional stochastic variables exist. Most importantly, you must run enough simulations to sample all the possible scenarios for each input parameter and to create a well-defined flood probability map. Latin Hypercube simulations assist in sampling all the possible scenarios from the PDF for each input variable. The higher the number of segments for each stochastic variable, the better defined your flood probability map will be.

Figure 6-46 compares the 50% probability contour on the flood probability map for 5, 10, and 250 simulations.
Figure 6-46 shows that the 50% probability contour from very few simulations and the contour from many simulations are very similar to each other. The flood probability map becomes more accurate as the number of simulations increase, but the 50% probability contour, which shows the approximate location of the 100-year floodplain boundary, remains about the same.

Figure 6-47 compares the 100-year floodplain boundary from the 1000-simulation AEP map with the 1000-simulation, 100-year flood probability map. The 100-year floodplain boundary from the AEP map should lie somewhere within the contours of the 100-year flood probability map.
Figure 6-47: A comparison between the 100-year floodplain boundary on the AEP map and the 100-year flood probability map (1000 simulations each)
Qualitatively, the location of the 50% probability contour on the 100-year floodplain probability map and the location of the 100-year floodplain boundary on the AEP map are close to each other, but not quite the same. Though the true floodplain boundary is uncertain, the 100-year floodplain boundary on the AEP map provides a good measure of its location. The 100-year boundary on the AEP map also considers much of the knowledge uncertainty and the natural variability that can occur in the hydrologic and hydraulic models. However, a flood probability map does a better job of describing the uncertainty of a floodplain boundary. If an engineer requires a probability map of the 100-year floodplain, running simulations based on the mean, minimum, maximum, and standard deviation of the 100-year floodplain values can generate this map.

Figure 6-48 compares the 100-year floodplain boundary created using three methods: using the 1% probability contour on the AEP map, using a single simulation with mean values, and using the 50% probability contour on the flood probability map. From this image, you can see that all these simulations result in a similar floodplain boundary, though some differences exist between the different methods of creating a floodplain boundary. There is no “best” method for creating a single floodplain boundary. The “best” method of representing the floodplain boundary is not as a single boundary at all, but rather as a floodplain probability map.
Figure 6-48: Comparison between the 100-year floodplain created from the AEP map, a single simulation with mean values, and a flood probability map

6.2.5.6 100-Year Floodplain Model—Water Depth Maps

Figure 6-49 shows the average water depth maps from each of the 100-year floodplain probability maps. These maps include a line showing the contour of the 50%-probability, 100-year flood.
The average water depth maps appear to be about the same for all the 100-year floodplain simulations. Table 6-24 shows the root mean square (RMS), average, and standard deviation of the AEP values in the floodplain for each of the simulations. These values remain about the same for each number of runs. This shows that running more than 100 simulations may not significantly increase the accuracy of the 100-year flood probability map.
Table 6-24: RMS, average, and standard deviation of average water depth values for each of the 100-year floodplain simulations

<table>
<thead>
<tr>
<th># of runs</th>
<th>RMS Value</th>
<th>Average</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>1.55</td>
<td>0.85</td>
<td>1.30</td>
</tr>
<tr>
<td>200</td>
<td>1.55</td>
<td>0.85</td>
<td>1.30</td>
</tr>
<tr>
<td>500</td>
<td>1.55</td>
<td>0.85</td>
<td>1.30</td>
</tr>
<tr>
<td>1000</td>
<td>1.55</td>
<td>0.85</td>
<td>1.30</td>
</tr>
</tbody>
</table>

6.3 Conclusions

The first case study considered the 100-year floodplain along the Leith creek in North Carolina. This case study filtered LIDAR data according to the specifications in Omer et al. (2003) and. This section described a set of procedures that you can use to determine a probability map for a 100-year floodplain in any area. This case study considered four scenarios, each with a different set of stochastic variables. These scenarios considered sub-basin precipitation, curve number, and Manning’s roughness individually and concurrently as stochastic variables. Each stochastic simulation determined hydrograph peak flows, river water depths, and floodplain probability and average water depth maps.

Variability in the floodplain delineations occurred most when there was a high degree of uncertainty in input parameters. This was the case with curve number values for each of the sub-basins. The final simulation was the most comprehensive simulation. This simulation assigned each sub-basin’s curve number and precipitation and the river’s Manning’s coefficient as stochastic variables. The simulation showed that variations in these input parameters could result in a decrease of the floodplain area by as much as 15.1% or an increase in the floodplain area by as much as 7.6% for
the model run. Other locations may increase or decrease by more or less than these values, depending on the range of input parameters, the geometry of the floodplain and its watershed, and other model parameters. The floodplain probability map can be a useful tool for evaluating the spatial probability of flooding for a 100-year storm.

The Leith Creek study compared the existing 100-year floodplain boundary from the North Carolina database with the 100-year flood probability map from simulation 4. This comparison showed that the flood probability map has the capability of producing results that closely match the currently established 100-year floodplain boundaries.

An AEP map was also created for this case study, and the 100-year floodplain boundary from the AEP map closely matched the currently established 100-year floodplain boundary. Theoretically, the 100-year floodplain boundary on the AEP map considers most of the uncertainty in hydrologic and hydraulic modeling. However, the 100-year flood probability map shows the range of possible floods for the 100-year storm. You can use both maps as effective tools in floodplain planning and analysis.

Procedures for creating an AEP map from both precipitation-frequency data and discharge-frequency data were discussed. Both procedures involve fitting the data either to a log Pearson Type III distribution or to a log-linear plot. Fitting data to a log Pearson Type III distribution is the standard method of determining discharges at different recurrence intervals. (USGS, 1983)

The second case study determined the AEP map and the 100-year flood probability map for a location on the Virgin River in southern Utah. One important
difference between this case study and the first case study is that this study used the NFF model to compute the discharges. This study only executed one run of the hydrologic model (NFF), and used the values from the discharge-frequency curve created from NFF to generate flow values as input into the HEC-RAS model. Additionally, since the floodplain was flatter and wider in the Virgin River model, a wider spatial distribution of probabilities existed in the 100-year flood probability map and the AEP map for this floodplain.

This study ran 100, 200, 500, and 1000 simulations to create both an AEP map and a 100-year flood probability map for the floodplain. The locations of the 1, 2, 10, 25, 50, 100, 500, and 1000-year floodplain boundaries were determined from the AEP map. Running 500 or 1000 simulations does not significantly effect the location of the 25 or 50-year floodplain boundaries on the AEP map. However, these simulations use a smoother distribution of input values and model higher flows, allowing for the delineation of the 200 and 500-year floodplain boundaries and a more accurate delineation of the 100-year floodplain boundary. The number of simulations corresponds to running measured data from the corresponding number of years. The RMS, average, and standard deviation of the AEP values for each simulation remained about the same. The RMS, average, and standard deviation of the water depth values were also about the same for the different numbers of simulations used to create the AEP map.

One hundred simulations were sufficient to create the 100-year floodplain probability map for the Virgin River model. Though the input discharges did not create a “smooth” distribution for the lower numbers of simulations, the flood
probability maps (including the 50% contour line) were about the same for all the simulations. Also, the RMS, average, and standard deviation of all output values were the same for each simulation. Comparing the 100-year floodplain boundary on the AEP map with the 100-year flood probability map showed that the boundary lied within the boundaries of the 100-year flood probability map. However, the location of the 50% contour on the flood probability map did not coincide exactly with the location of the 100-year floodplain boundary on the AEP map. These boundaries are different because they are different types of simulations—the boundaries generated from the AEP map consider much of the uncertainty inherent in the 100-year floodplain boundary (not all of the uncertainty in the models were examined in the simulations, but theoretically they could be). However, the 100-year flood probability map proves to be a useful indicator of the probability of flooding in a 100-year event.
7 Contributions and Conclusions

This research introduces methods for describing the uncertainty of flood studies. FEMA has guidelines for delineating the extent of a floodplain at a recurrence interval, but their methods do not have a procedure for describing the uncertainty of the floodplain. In addition, the US Army Corps of Engineers has guidelines for flood damage studies, but their methods aggregate the uncertainty to a single point in the floodplain. Many of the advantages and disadvantages of the Corps approach to risk analysis in floodplain studies were outlined in a review by the National Research Council (2000).

The research presented in this dissertation evaluates the uncertainty in a floodplain by providing tools for creating two spatial maps: a flood probability map at a single recurrence interval and an annual exceedance probability (AEP) map. Developing these maps requires a stochastic link between hydrologic, hydraulic, and floodplain delineation models that allows hundreds or thousands of simulations of each of these models to be run, using the output from one model as input to the next model.

This stochastic link randomly varies selected input parameters for each of the model runs using the probability distribution function assigned to each stochastic input parameter. After running the entire range of possible values, the algorithm computes
the probability of flooding at any point in the floodplain as the number of times each point is flooded divided by the total number of simulations. The algorithm creates an AEP map by sampling a plot of precipitation vs. recurrence interval or a plot of discharge vs. recurrence interval with their associated uncertainty. These spatial flood probability and AEP maps overcome many of the obstacles outlined by the National Research Council report.

7.1 **Technical Contributions**

Several important advances in describing the uncertainty of floodplain delineation were made through this research. Some of the most important advances are as follows:

1. This research developed a method for creating a flood probability map at a flood recurrence interval. You create this map by running instances of the hydrologic, hydraulic, and floodplain delineation models until the flood probability map created from these simulations is no longer changing. If you already know a distribution of discharges, you can run the hydraulic and floodplain delineation alone without input from a hydrologic model. The algorithm varies input parameters to some or all of these models stochastically by defining a probability distribution function for each desired input parameter.

2. This research developed a method for creating an annual exceedance probability (AEP) map. If you have a curve of discharge vs. recurrence interval (probability) and its limits and probability density functions
(PDF’s) at several recurrence intervals (see Figure 7-1), the algorithm runs hydraulic and floodplain delineation models repeatedly, sampling values within the parameters of this curve for each simulation. The resulting flood probability map is an AEP map. If desired, you can use a precipitation-probability curve in the same manner with hydrologic, hydraulic, and floodplain delineation models. The result from either type of simulation (hydraulic-floodplain or hydrologic-hydraulic-floodplain) is an AEP map.

![Figure 7-1: A discharge-probability curve with uncertainty at multiple probabilities](image)

3. This research developed a method of linking hydrology, hydraulics, and floodplain delineation with stochastic modeling. This was an important part of this research because linking the models and providing an avenue for stochastic modeling with these models allows flood probability and
AEP maps to be generated. The following tools were developed to create these maps:

a. The hydrologic model HEC-1, the hydraulic model HEC-RAS, and the floodplain delineation model in WMS were all combined and linked in a single interface. Using the scripting language available in HEC-RAS, this research used the hydrograph peak flows from HEC-1 as input into HEC-RAS and the water surface elevations from HEC-RAS as input to the WMS floodplain delineation model.

b. This research implemented stochastic methods to define hydrologic and hydraulic input parameters as stochastic variables. These methods define a “key” value for a model input variable such as precipitation. Wherever this key value is used, the variable is replaced with a probability distribution for that input variable. Multiple simulations can be run to determine the range of model output values with varying model input values.

c. This research created tools for creating and visualizing probabilistic floodplains. An algorithm runs multiple simulations of the hydrologic, hydraulic, and floodplain delineation models and computes the resulting probability of flooding at each point in the floodplain. You can generate a contour map of these flood probabilities, whether they represent the probability of flooding in a 100-year event or the annual exceedance probability.
Using the tools and procedures provided through this research, you could perform floodplain risk analysis for any floodplain study. You can generate flood probability or annual exceedance probability maps with little additional work above what was previously required to find a single floodplain boundary.

### 7.2 Applications

FEMA should require floodplain probability maps as the standard for future floodplain studies. Flood insurance rates should be based on flood probability maps instead of flood insurance maps with a single in-or-out floodplain boundary. Consider the benefits of this approach. This approach reduces or eliminates litigation from incorrect floodplain maps. In litigation where the boundary of the floodplain is disputed, the floodplain can be represented as a probability map instead of a single in-or-out boundary. There will be no more “adjusting” of input parameters to suit the needs of a particular party. From this map, any person can determine the probability of flooding at any point in the floodplain.

If you still desire a single floodplain boundary, you can delineate this boundary at any recurrence interval from the AEP map. Instead of considering the uncertainty at a single recurrence interval, the AEP map considers the uncertainty at all the recurrence intervals to create a map that shows the probability of flooding at any point in the floodplain during any year. The floodplain boundary with a 100-year recurrence interval lies along the contour of the 1% exceedance probability. This single boundary considers much of the uncertainty inherent in floodplain delineation. You can obtain the boundary at any recurrence interval from the AEP map. The AEP
map can also be used in future flood damage reduction studies by the US Army Corps of Engineers.

The Leith Creek and Virgin River case studies showed several results. First, the Leith Creek case study showed that the 100-year floodplain boundary from the AEP map compared closely with the boundary in the North Carolina floodplain database. Second, this 100-year boundary also fell inside the 0-100% flood probability contours on the 100-year flood probability map. In addition, in both case studies, the location of the 100-year floodplain boundary from the AEP map closely matched the location of the 50% probability contour on the flood probability map. Third, when creating a flood probability map, it was found that running additional simulations smoothed the input data curve, but the smoother input data did not significantly affect the flood probability map. Fourth, the Virgin River case study demonstrated how the number of simulations used for creating an AEP map is like running that same number of years of data. This means that running 1000 simulations is similar to running 1000 years of data. It also means that you must run at least \( N \) simulations to determine the \( N \)-year floodplain boundary from an AEP map, but it would be better if you ran more simulations to capture the \( N \)-year event at least once. In an AEP analysis, higher numbers of simulations result in higher and less frequent discharge values.

### 7.3 Future Research

The methods and concepts presented in this dissertation can be extended in many ways. First, additional case studies should be developed. Second,
improvements can be made to the hydrologic, hydraulic, and floodplain delineation interfaces and the stochastic modeling linkages between these models. Third, methods of decreasing the time required to run stochastic hydrologic-hydraulic-floodplain delineation simulations should be explored.

First, additional case studies should be developed. These case studies should confirm the accuracy of the methods described in this dissertation. One way of determining the accuracy is to conduct a “water balance” with the floodplain model. We can compute the volume of water in the floodplain at the peak flow rate from the geometry of the floodplain and the water surface elevations. This volume can be compared with the volume of water that should be in the floodplain at the time of peak flow. The volume of water that should be in the floodplain at the peak flow rate can be determined from the inflow and outflow HEC-1 hydrographs to and from the floodplain. This type of analysis really calls for the capability of running an unsteady flow simulation, which is a capability that should be added to the hydraulic modeling component of this research. Another way of determining the accuracy of the methods presented in this dissertation is to make additional comparisons of the delineated floodplain boundary and/or the floodplain probability map with the observed floodplain boundary from an actual storm or with floodplain boundaries from previous studies. Finally, criteria should be developed to determine the number of simulations that need to be run to generate an accurate flood probability map.

Second, improvements can be made to the hydrologic, hydraulic, and floodplain delineation interfaces and the stochastic modeling linkages between these models. An interface to an unsteady hydraulic model, such as the UNET model in
HEC-RAS, should be made. Additional variables, such as sub-basin lag times (or times of concentration), river reach routing parameters, or sub-basin baseflow parameters, should be added to the list of available stochastic parameters. More thought needs to be put into how to incorporate levees and the geotechnical uncertainty of the levees into the system since “the geotechnical performance of levees is mandated for Corps levee certification studies” (Davis, 2003). This could be done by incorporating possible levee breaks into the hydraulic model runs or by creating a “levee” layer (coverage) defining the properties of each levee. Future research should implement the ability to compute floodway probability maps using ineffective flow zone boundaries as the stochastic parameter. Chapter 3 described this procedure, which should vary the ineffective flow zone widths between minimum and maximum values to determine a floodway probability map.

Third, methods of decreasing the time required to run stochastic hydrologic-hydraulic-floodplain delineation simulations should be explored. One way of decreasing the time required is to increase computational capacity. This could be done by making it possible to use parallel or network processing for a stochastic floodplain simulation. The ability to run all the floodplain delineations in a single step (instead of running the floodplain delineation for each simulation) has already been added. This ability has decreased the run time for the Leith Creek stochastic model from an average of 3.75 minutes per run to 0.66 minutes per run…nearly six times as fast.
8 References


Environmental Modeling Research Laboratory. (2003c). “Watershed modeling system tutorials, WMS 7.0.”


Nebraska Department of Natural Resources. (2001). http://www.nrc.state.ne.us/floodplain/floodplain.html


APPENDIX
A  North Carolina Case Study Results

This appendix discusses the results of the floodplain probability maps created from running the first three simulations described for the North Carolina model in Chapter 6. These first three model runs showed the effects of varying single parameters on the flood extents. In the first simulation, precipitation was set as the stochastic variable. In the second simulation, the sub-basin curve numbers were set as stochastic variables. And in the third simulation, Manning’s coefficients were set as stochastic variables. The results from these three model runs are analyzed in further detail in Chapter 6. Also, the results from a comprehensive simulation, where precipitation, Manning’s coefficient, and curve numbers were set as stochastic variables, are presented and discussed in Chapter 6.
A.1 Stochastic Model 1: Latin Hypercube Simulation with Sub-Basin Precipitation as a Stochastic Variable

A.1.1 Input Values

With precipitation defined as a stochastic parameter, WMS determined a single precipitation value for each set of simulations. This precipitation value was assigned to each sub-basin in the HEC-1 model. Figure A-1 shows the sub-basin precipitation values for each model run.

![Figure A-1: Precipitation values for each set of model runs (segment numbers correspond with a set of model runs)](image)

From Figure A-1 you can see that the precipitation increases with each segment. This is the expected outcome from a linear probability distribution. Table
A-1 shows the percent change in precipitation values from the original model precipitation.

**Table A-1: Precipitation input values for each model run with percent changes**

<table>
<thead>
<tr>
<th>Segment Number</th>
<th>Precipitation (mm)</th>
<th>Change (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original</td>
<td>201.70</td>
<td>None</td>
</tr>
<tr>
<td>1</td>
<td>191.60</td>
<td>-5.01</td>
</tr>
<tr>
<td>2</td>
<td>193.99</td>
<td>-3.82</td>
</tr>
<tr>
<td>3</td>
<td>198.56</td>
<td>-1.56</td>
</tr>
<tr>
<td>4</td>
<td>202.62</td>
<td>0.46</td>
</tr>
<tr>
<td>5</td>
<td>206.90</td>
<td>2.58</td>
</tr>
</tbody>
</table>

A.1.2 Peak Flow Values

Table A-2 lists the peak flow values for basins 4B, 2B, and outlet 2C for each HEC-1 model run. The table lists the percent change for the peak flow at outlet 2C.

**Table A-2: Peak flow values and percent changes for each HEC-1 model run**

<table>
<thead>
<tr>
<th>Run Number</th>
<th>Precipitation</th>
<th>Peak flow at 4B (m³/s)</th>
<th>Peak flow at 2B (m³/s)</th>
<th>Peak flow at 2C—Primary Outlet (m³/s)</th>
<th>Change (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original</td>
<td>201.70</td>
<td>59.09</td>
<td>26.10</td>
<td>158.65</td>
<td>None</td>
</tr>
<tr>
<td>1</td>
<td>191.60</td>
<td>53.95</td>
<td>23.90</td>
<td>144.97</td>
<td>-8.62</td>
</tr>
<tr>
<td>2</td>
<td>193.99</td>
<td>55.16</td>
<td>24.42</td>
<td>148.20</td>
<td>-6.59</td>
</tr>
<tr>
<td>3</td>
<td>198.56</td>
<td>57.48</td>
<td>25.41</td>
<td>154.37</td>
<td>-2.70</td>
</tr>
<tr>
<td>4</td>
<td>202.62</td>
<td>59.56</td>
<td>26.30</td>
<td>159.91</td>
<td>0.79</td>
</tr>
<tr>
<td>5</td>
<td>206.90</td>
<td>61.76</td>
<td>27.24</td>
<td>165.77</td>
<td>4.48</td>
</tr>
</tbody>
</table>

Table A-2 shows that the peak flow values at outlet 2C are sensitive to changes in the precipitation values. For example, a change of -5.01% from the original precipitation value (see Table A-1) results in a change of -8.62% from the peak flow at outlet 2C. Moreover, a change of 2.58% from the original precipitation value results in a change of 4.48% from the peak flow at outlet 2C. We will now see how these
peak flow changes effect the water surface elevations from the hydraulic model and the floodplain areas from the floodplain model.

A.1.3 Hydraulic Model Results

Table A-3 lists the minimum, maximum, and mean water surface elevations from each run of the hydraulic model. It also lists the percent changes in the mean water surface elevation from the original water surface elevations. The change in water surface elevations was not significant, with a maximum decrease of 0.05 meters (0.16 feet) and a maximum increase of 0.02 meters (0.06 feet). These low changes in mean water surface elevation (when compared with the changes in discharges) may be due to the high conveyance capacity in the floodplain. It is also due to the fact that the change in mean water surface elevation with respect to a change in discharge is not a linear relationship, though water surface elevation will go up as discharge goes up according to Manning’s equation. One could find the change in water surface elevation with respect to changes in discharge by differentiating Manning’s equation.

Table A-3: Hydraulic model water surface elevations and percent changes for each HEC-RAS model run

<table>
<thead>
<tr>
<th>Run Number</th>
<th>Precipitation</th>
<th>Minimum Water Elevation (m)</th>
<th>Maximum Water Elevation (m)</th>
<th>Mean Water Elevation (m)</th>
<th>Mean Water Elevation Change (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original</td>
<td>201.70</td>
<td>64.04</td>
<td>71.75</td>
<td>67.31</td>
<td>None</td>
</tr>
<tr>
<td>1</td>
<td>191.60</td>
<td>63.98</td>
<td>71.71</td>
<td>67.26</td>
<td>-0.08</td>
</tr>
<tr>
<td>2</td>
<td>193.99</td>
<td>63.99</td>
<td>71.72</td>
<td>67.27</td>
<td>-0.06</td>
</tr>
<tr>
<td>3</td>
<td>198.56</td>
<td>64.02</td>
<td>71.74</td>
<td>67.29</td>
<td>-0.04</td>
</tr>
<tr>
<td>4</td>
<td>202.62</td>
<td>64.04</td>
<td>71.76</td>
<td>67.31</td>
<td>-0.01</td>
</tr>
<tr>
<td>5</td>
<td>206.90</td>
<td>64.06</td>
<td>71.77</td>
<td>67.33</td>
<td>0.02</td>
</tr>
</tbody>
</table>
A.1.4 Floodplain Delineation Results

Table A-4 shows the effects of the precipitation input values on the maximum and mean floodwater depths and on the floodplain areas.

Table A-4: Floodplain water depths, areas, and percent area changes

<table>
<thead>
<tr>
<th>Run Number</th>
<th>Precipitation</th>
<th>Maximum Flood Water Depth (m)</th>
<th>Mean Flood Water Depth (m)</th>
<th>Floodplain Area (m²)</th>
<th>Area Change (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original</td>
<td>201.70</td>
<td>2.947</td>
<td>0.849</td>
<td>631521.8</td>
<td>None</td>
</tr>
<tr>
<td>1</td>
<td>191.60</td>
<td>2.889</td>
<td>0.819</td>
<td>618919.2</td>
<td>-2.00</td>
</tr>
<tr>
<td>2</td>
<td>193.99</td>
<td>2.902</td>
<td>0.826</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>198.56</td>
<td>2.928</td>
<td>0.836</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>202.62</td>
<td>2.951</td>
<td>0.845</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>206.90</td>
<td>2.974</td>
<td>0.858</td>
<td>635020.6</td>
<td>0.55</td>
</tr>
</tbody>
</table>

From Table A-4 you can see that there is very little change in the maximum and mean floodwater depths. For example, in the first run, a decrease of 5.01% in the precipitation value results in a change of only 0.058 meters (2.28 inches) in the maximum flood water depth and a change of 0.030 meters (1.18 inches) in the mean flood water depth. However, the area of the floodplain decreases by 2.0% at its minimum extents and increases by 0.55% at its maximum extents from the stochastic model runs. Figure A-2 shows the contours of floodplain water depths at the floodplain’s minimum extent in the stochastic simulation.
Figure A-2: Minimum water depth contours (all values in meters)

Figure A-3 shows contours of water depths at the floodplain’s maximum extents in this stochastic simulation. When compared with each other, Figure A-2 and Figure A-3 do not seem very different. However, there are some slight differences. These differences can be determined by producing a flood impact map from two different simulations as described by Noman (2001). However, a more sophisticated approach is to run a range of stochastic simulations (as was done with this study) and determine the probability of flooding at various points in the floodplain.
One result from running a stochastic simulation is a map of average water depths in the floodplain. WMS obtains this map by averaging the water depths from all the simulations at each TIN vertex. The average water depth map for the precipitation LH simulation is shown in Figure A-4. Since the range of precipitation values did not have a significant effect on the floodplain, the average water depth contours appear similar to the minimum and maximum water depth contours in this simulation. However, these three sets of contour maps vary significantly in other stochastic simulations.
Another result from running a stochastic simulation is a contour map showing the flood probability at each vertex in the floodplain. The algorithm determines the probability by dividing the number of times each vertex flooded by the number of runs. This gave a value between 0.0 and 1.0, which is converted to a percentage by multiplying by 100. Figure A-5 shows the probability map for the precipitation LH simulation.
Figure A-5: Probability of flooding (values in percent)

Figure A-6 shows a close-up view of the lower portion of the probability map. Because a well-defined channel exists for this floodplain, changes in the precipitation, as defined by the computed stochastic parameters and resulting stream flow values, do not have a significant effect on the boundary of the floodplain. Nevertheless, Figure A-6 shows that there is some variation in flood probabilities in the floodplain.
Figure A-6: Probability of flooding—close-up area (values in percent)

Figure A-7 and Figure A-8 show histograms showing numerical values from the images in Figure A-4 to Figure A-6.

Vertices outside the floodplain have a 0% probability of flooding, and most of the vertices were inside or outside of the floodplain. However, a few points were flooded for some simulations and not flooded for others. These are the points between 0 and 100 percent in Figure A-8.
Figure A-7: Average flood depth histogram showing the number of vertices on the TIN with different water depth values for simulation 1
Figure A-8: Probability histogram showing the number of vertices on the TIN with different probability values for simulation 1

A.2 Stochastic Model 2: Latin Hypercube Simulation with Sub-Basin Curve Number as a Stochastic Variable

A.2.1 Input Values

For each simulation, the algorithm assigns a segment to each stochastic parameter until all the combinations of segments are exhausted. There were three stochastic parameters with three segments each, making 27 possible segment combinations. Thus, this stochastic run executed 27 HEC-1, HEC-RAS, and
floodplain delineation simulations. Figure A-9 shows a plot of the curve number input values for each segment.

Figure A-9: Curve number values used for each segment

A.2.2 Peak Flow Values

Table A-5 lists the peak flow values for basins 4B, 2B, and outlet 2C for each HEC-1 model run. The table lists the percent change for the peak flow at outlet 2C.
Table A-5: Peak flow values and percent changes for each HEC-1 model run

<table>
<thead>
<tr>
<th>Run Number</th>
<th>3B, 4B, 6B CN</th>
<th>2B, 5B CN</th>
<th>1B, 7B CN</th>
<th>Peak flow at 4B (m³/s)</th>
<th>Peak flow at 2B (m³/s)</th>
<th>Peak flow at 2C—Primary Outlet (m³/s)</th>
<th>Change (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original</td>
<td>65.4, 65.1, 68.5</td>
<td>65.8, 66.6, 69.4</td>
<td>59.088, 26.101, 158.654</td>
<td>None</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>57.24, 50.96, 62.26</td>
<td>43.717, 13.677, 107.549</td>
<td>-32.21</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>51.51, 57.68, 68.79</td>
<td>33.037, 19.156, 119</td>
<td>-24.99</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>47.61, 52.18, 81.54</td>
<td>26.185, 14.66, 125.143</td>
<td>-21.12</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>58.04, 61.17, 60.50</td>
<td>45.263, 22.022, 122.049</td>
<td>-23.07</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>51.13, 70.11, 71.20</td>
<td>32.356, 29.261, 141.792</td>
<td>-10.63</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>58.30, 67.39, 83.02</td>
<td>45.767, 27.086, 168.837</td>
<td>6.42</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>48.37, 72.41, 52.85</td>
<td>27.494, 31.073, 113.823</td>
<td>-28.26</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>58.76, 72.42, 68.34</td>
<td>46.659, 31.08, 157.729</td>
<td>-0.58</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>52.79, 71.64, 77.78</td>
<td>35.348, 30.47, 113.936</td>
<td>-21.12</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>68.40, 47.24, 57.99</td>
<td>65.421, 10.746, 116.518</td>
<td>-26.56</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>63.64, 48.22, 71.09</td>
<td>56.164, 11.505, 131.279</td>
<td>-17.25</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>63.66, 59.33, 83.28</td>
<td>56.203, 20.512, 166.966</td>
<td>5.24</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>62.93, 63.45, 62.33</td>
<td>54.779, 23.889, 137.668</td>
<td>-13.23</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>60.30, 63.28, 66.86</td>
<td>49.652, 23.75, 140.084</td>
<td>-11.70</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>59.47, 68.74, 80.64</td>
<td>48.037, 28.17, 169.661</td>
<td>6.94</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>65.91, 81.06, 62.20</td>
<td>60.588, 37.513, 171.912</td>
<td>8.36</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>17</td>
<td>59.96, 81.76, 69.30</td>
<td>48.99, 37.998, 171.767</td>
<td>8.27</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>18</td>
<td>60.85, 71.72, 83.88</td>
<td>50.723, 30.532, 181.592</td>
<td>14.46</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>19</td>
<td>74.26, 51.37, 57.81</td>
<td>76.616, 14.006, 133.728</td>
<td>-15.71</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>78.10, 58.34, 65.11</td>
<td>83.713, 19.698, 164.824</td>
<td>3.89</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>21</td>
<td>76.09, 59.72, 82.60</td>
<td>80.029, 20.832, 191.512</td>
<td>20.71</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>22</td>
<td>76.88, 62.87, 56.34</td>
<td>81.486, 23.415, 155.588</td>
<td>-1.93</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>23</td>
<td>69.86, 70.14, 65.44</td>
<td>68.239, 29.285, 167.168</td>
<td>5.37</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>24</td>
<td>80.13, 64.82, 80.07</td>
<td>87.348, 25.005, 203.747</td>
<td>28.42</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>25</td>
<td>78.30, 72.86, 60.41</td>
<td>84.075, 31.423, 180.769</td>
<td>13.94</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>26</td>
<td>72.93, 82.28, 63.33</td>
<td>74.106, 38.354, 189.005</td>
<td>19.13</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>27</td>
<td>75.92, 80.77, 73.89</td>
<td>79.715, 37.31, 209.838</td>
<td>32.26</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table A-2 shows that the peak flow values at outlet 2C are sensitive to changes in the sub-basin curve numbers. This is expected since, besides precipitation, rainfall losses are one of the key factors in determining how much runoff a watershed has. The large changes in curve numbers created an even larger range of flow values compared to using precipitation as a stochastic parameter (-32.21 % to 32.26 %)
instead of -8.62 % to 4.48 % in Table A-1). We will now see how these peak flow changes effect the water surface elevations from the hydraulic model and the floodplain areas from the floodplain model.

A.2.3 Hydraulic Model Results

Table A-6 lists the minimum, maximum, and mean water surface elevations from each run of the hydraulic model. It also lists the percent changes in the mean water surface elevation from the original water surface elevations. The change in mean water surface elevations was significant, with a maximum decrease of 0.24 meters (0.80 feet) and a maximum increase of 0.16 meters (0.53 feet).
Table A-6: Hydraulic model water surface elevations and percent changes for each HEC-RAS model run

<table>
<thead>
<tr>
<th>Run Number</th>
<th>3B, 4B, 6B CN</th>
<th>2B, 5B CN</th>
<th>1B, 7B CN</th>
<th>Minimum Water Elevation (m)</th>
<th>Maximum Water Elevation (m)</th>
<th>Mean Water Elevation (m)</th>
<th>Mean Water Elevation Change (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original</td>
<td>65.8</td>
<td>66.2, 66.6</td>
<td>68.5, 69.4</td>
<td>64.035</td>
<td>71.754</td>
<td>67.31427</td>
<td>None</td>
</tr>
<tr>
<td>1</td>
<td>57.24</td>
<td>50.96</td>
<td>62.26</td>
<td>63.814</td>
<td>71.618</td>
<td>67.12092</td>
<td>-0.29</td>
</tr>
<tr>
<td>2</td>
<td>51.51</td>
<td>57.68</td>
<td>68.79</td>
<td>63.871</td>
<td>71.624</td>
<td>67.12229</td>
<td>-0.29</td>
</tr>
<tr>
<td>3</td>
<td>47.61</td>
<td>52.18</td>
<td>81.54</td>
<td>63.898</td>
<td>71.521</td>
<td>67.0706</td>
<td>-0.36</td>
</tr>
<tr>
<td>4</td>
<td>58.04</td>
<td>61.17</td>
<td>60.50</td>
<td>63.885</td>
<td>71.681</td>
<td>67.19548</td>
<td>-0.18</td>
</tr>
<tr>
<td>5</td>
<td>51.13</td>
<td>70.11</td>
<td>71.20</td>
<td>63.968</td>
<td>71.803</td>
<td>67.20927</td>
<td>-0.16</td>
</tr>
<tr>
<td>6</td>
<td>58.30</td>
<td>67.39</td>
<td>83.02</td>
<td>64.074</td>
<td>71.77</td>
<td>67.277</td>
<td>-0.06</td>
</tr>
<tr>
<td>7</td>
<td>48.37</td>
<td>72.41</td>
<td>52.85</td>
<td>63.848</td>
<td>71.83</td>
<td>67.16653</td>
<td>-0.22</td>
</tr>
<tr>
<td>8</td>
<td>58.76</td>
<td>72.42</td>
<td>68.34</td>
<td>64.017</td>
<td>71.83</td>
<td>67.28507</td>
<td>-0.04</td>
</tr>
<tr>
<td>9</td>
<td>52.79</td>
<td>71.64</td>
<td>77.78</td>
<td>64.031</td>
<td>71.821</td>
<td>67.24506</td>
<td>-0.10</td>
</tr>
<tr>
<td>10</td>
<td>68.40</td>
<td>47.24</td>
<td>57.99</td>
<td>63.86</td>
<td>71.727</td>
<td>67.20019</td>
<td>-0.17</td>
</tr>
<tr>
<td>11</td>
<td>63.64</td>
<td>48.22</td>
<td>71.09</td>
<td>63.925</td>
<td>71.68</td>
<td>67.1884</td>
<td>-0.19</td>
</tr>
<tr>
<td>12</td>
<td>63.66</td>
<td>59.33</td>
<td>83.28</td>
<td>64.067</td>
<td>71.68</td>
<td>67.28037</td>
<td>-0.05</td>
</tr>
<tr>
<td>13</td>
<td>62.93</td>
<td>63.45</td>
<td>62.33</td>
<td>63.951</td>
<td>71.714</td>
<td>67.25952</td>
<td>-0.08</td>
</tr>
<tr>
<td>14</td>
<td>60.30</td>
<td>63.28</td>
<td>66.86</td>
<td>63.961</td>
<td>71.712</td>
<td>67.24275</td>
<td>-0.11</td>
</tr>
<tr>
<td>15</td>
<td>59.47</td>
<td>68.74</td>
<td>80.64</td>
<td>64.077</td>
<td>71.786</td>
<td>67.29133</td>
<td>-0.03</td>
</tr>
<tr>
<td>16</td>
<td>65.91</td>
<td>81.06</td>
<td>62.20</td>
<td>64.085</td>
<td>71.911</td>
<td>67.38146</td>
<td>0.10</td>
</tr>
<tr>
<td>17</td>
<td>59.96</td>
<td>81.76</td>
<td>69.30</td>
<td>64.085</td>
<td>71.917</td>
<td>67.34721</td>
<td>0.05</td>
</tr>
<tr>
<td>18</td>
<td>60.85</td>
<td>71.72</td>
<td>83.88</td>
<td>64.121</td>
<td>71.822</td>
<td>67.32496</td>
<td>0.02</td>
</tr>
<tr>
<td>19</td>
<td>74.26</td>
<td>51.37</td>
<td>57.81</td>
<td>63.935</td>
<td>71.774</td>
<td>67.2799</td>
<td>-0.05</td>
</tr>
<tr>
<td>20</td>
<td>78.10</td>
<td>58.34</td>
<td>65.11</td>
<td>64.059</td>
<td>71.802</td>
<td>67.36642</td>
<td>0.08</td>
</tr>
<tr>
<td>21</td>
<td>76.09</td>
<td>59.72</td>
<td>82.60</td>
<td>64.156</td>
<td>71.788</td>
<td>67.38784</td>
<td>0.11</td>
</tr>
<tr>
<td>22</td>
<td>76.88</td>
<td>62.87</td>
<td>56.34</td>
<td>64.023</td>
<td>71.794</td>
<td>67.36729</td>
<td>0.08</td>
</tr>
<tr>
<td>23</td>
<td>69.86</td>
<td>70.14</td>
<td>65.44</td>
<td>64.067</td>
<td>71.803</td>
<td>67.36466</td>
<td>0.07</td>
</tr>
<tr>
<td>24</td>
<td>80.13</td>
<td>64.82</td>
<td>80.07</td>
<td>64.198</td>
<td>71.819</td>
<td>67.44052</td>
<td>0.19</td>
</tr>
<tr>
<td>25</td>
<td>78.30</td>
<td>72.86</td>
<td>60.41</td>
<td>64.118</td>
<td>71.835</td>
<td>67.43677</td>
<td>0.18</td>
</tr>
<tr>
<td>26</td>
<td>72.93</td>
<td>82.28</td>
<td>63.33</td>
<td>64.147</td>
<td>71.921</td>
<td>67.44464</td>
<td>0.19</td>
</tr>
<tr>
<td>27</td>
<td>75.92</td>
<td>80.77</td>
<td>73.89</td>
<td>64.219</td>
<td>71.909</td>
<td>67.47624</td>
<td>0.24</td>
</tr>
</tbody>
</table>

A.2.4 Floodplain Delineation Results

Table A-7 shows the effects of the precipitation input values on the maximum and mean floodwater depths and on the floodplain areas.
Table A-7: Floodplain water depths, areas, and percent area changes

<table>
<thead>
<tr>
<th>Run Number</th>
<th>Maximum Flood Water Depth (m)</th>
<th>Mean Flood Water Depth (m)</th>
<th>Floodplain Area (m²)</th>
<th>Area Change (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original</td>
<td>65.4, 66.2, 68.5, 65.8</td>
<td>2.947096, 2.710965, 2.770695, 2.797744</td>
<td>631521.8</td>
<td>None</td>
</tr>
<tr>
<td>1</td>
<td>57.24, 50.96, 62.26</td>
<td>2.710965, 2.770695, 2.797744</td>
<td>581889.60</td>
<td>-7.86</td>
</tr>
<tr>
<td>2</td>
<td>51.51, 68.79, 69.4</td>
<td>2.770695, 2.797744, 2.78633</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>50.71, 68.79, 69.4</td>
<td>2.770695, 2.797744, 2.78633</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>51.13, 71.20, 71.20</td>
<td>2.78633, 2.770695, 2.770695</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>58.30, 67.93, 63.28</td>
<td>2.985498, 2.985498, 2.968203</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>58.40, 57.99, 57.99</td>
<td>2.759748, 2.759748, 2.759748</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>48.37, 72.41, 68.34</td>
<td>2.747699, 2.747699, 2.747699</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>50.71, 68.79, 69.4</td>
<td>2.770695, 2.797744, 2.78633</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>52.79, 71.64, 77.78</td>
<td>2.940868, 2.940868, 2.940868</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>68.40, 47.24, 57.99</td>
<td>2.759748, 2.759748, 2.759748</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>63.64, 48.22, 71.09</td>
<td>2.827624, 2.827624, 2.827624</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>63.66, 59.33, 83.28</td>
<td>2.977783, 2.977783, 2.977783</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>62.93, 63.45, 62.33</td>
<td>2.857273, 2.857273, 2.857273</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>60.30, 63.28, 66.86</td>
<td>2.86689, 2.86689, 2.86689</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>59.47, 68.74, 80.64</td>
<td>2.988984, 2.988984, 2.988984</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>65.91, 81.06, 62.20</td>
<td>2.999386, 2.999386, 2.999386</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td>17</td>
<td>59.96, 61.76, 69.30</td>
<td>2.99862, 2.99862, 2.99862</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td>18</td>
<td>60.85, 71.72, 83.88</td>
<td>3.034997, 3.034997, 3.034997</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td>19</td>
<td>74.26, 51.37, 57.81</td>
<td>2.839643, 2.839643, 2.839643</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>78.10, 58.34, 65.11</td>
<td>2.970605, 2.970605, 2.970605</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td>21</td>
<td>76.09, 59.72, 82.60</td>
<td>3.072111, 3.072111, 3.072111</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td>22</td>
<td>76.88, 62.87, 56.34</td>
<td>2.934172, 2.934172, 2.934172</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td>23</td>
<td>69.86, 70.14, 65.44</td>
<td>2.980616, 2.980616, 2.980616</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td>24</td>
<td>80.13, 64.82, 80.07</td>
<td>3.115795, 3.115795, 3.115795</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td>25</td>
<td>78.30, 72.86, 60.41</td>
<td>3.033683, 3.033683, 3.033683</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td>26</td>
<td>72.93, 82.28, 63.33</td>
<td>3.063884, 3.063884, 3.063884</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td>27</td>
<td>75.92, 80.77, 73.89</td>
<td>3.137513, 3.137513, 3.137513</td>
<td>673131.1</td>
<td>6.59</td>
</tr>
</tbody>
</table>

From the Table A-7, you can see that there is a noticeable change in the maximum and mean floodwater depths. The mean flood depth decreases by 0.11 meters (0.35 feet) in the first model run, and increases by 0.09 meters (0.30 feet) in the last model run. The floodplain area decreases by 7.86 % at its minimum extents and increases by 6.59 % at its maximum extents from the stochastic model runs. Figure A-10 shows
the contours of floodplain water depths at the floodplain’s minimum extent in the stochastic simulation.

Figure A-10: Minimum water depth contours (all values in meters)

Figure A-11 shows contours of water depths at the floodplain’s maximum extents in this stochastic simulation.
Figure A-11: Maximum water depth contours (all values in meters)

Figure A-12 shows the average water depth map for the curve number LH simulation. The average water depth contours appear similar to the minimum and maximum water depth contours. Some differences are noticeable between the minimum, maximum, and average water depth contour maps. The flood probability map is an effective way of showing these differences.
Figure A-12: Averaged water depth contours from all floodplain delineations (all values in meters)

Figure A-13 shows the probability map for the curve number LH simulation.
Figure A-13: Probability of flooding (values in percent)

Figure A-14 shows a close-up view of the lower portion of the probability map. Figure A-14 shows that there is some variation in flood probabilities in this lower portion of the floodplain.
Figure A-14: Probability of flooding—close-up area (values in percent)

Figure A-15 and Figure A-16 show histograms with numerical values from the images in Figure A-12 to Figure A-14. Figure A-15 shows the frequency distribution of flood depths in the floodplain. This graph shows that most of the flood depths are in the 0-1.5 meter range, and that a few flood depths reach up to 2.75 meters.
Figure A-15: Average flood depth histogram showing the number of vertices on the TIN with different water depth values for simulation 2

Figure A-16 shows that most of the floodplain vertices have either a 0% or a 100% probability of flooding, but there are several vertices with probabilities between these values. These areas flood a certain percentage of the time, defined by the percentage assigned to the vertex.
Figure A-16: Probability histogram showing the number of vertices on the TIN with different probability values for simulation 2

A.3 Stochastic Model 3: Latin Hypercube Simulation with Material Manning’s Coefficient as a Stochastic Variable

A.3.1 Input Values

This simulation assigned a segment ID from one to three to each of the three Manning’s coefficient materials for each of the possible simulations. To exhaustively search through all the possible combinations of segment numbers with each of the
three materials required 27 simulations. Figure A-17 shows a plot of the Manning’s coefficient input values for each segment.

Figure A-17: Manning’s coefficient values used for each segment

A.3.2 Peak Flow Values

For this simulation, the peak flows remained constant for all the simulations. The peak flows used are the same values used for the original simulation. Table A-8 shows these values for Basins 2B, 4B, and outlet 2C.

Table A-8: Peak flow values for selected locations in the hydrologic model

<table>
<thead>
<tr>
<th>Peak flow at 4B (m³/s)</th>
<th>Peak flow at 2B (m³/s)</th>
<th>Peak flow at 2C--Primary Outlet (m³/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>59.088</td>
<td>26.101</td>
<td>158.654</td>
</tr>
</tbody>
</table>
A.3.3 Hydraulic Model Results

Table A-9 lists the minimum, maximum, and mean water surface elevations from each run of the hydraulic model. It also lists the percent changes in the mean water surface elevation from the original water surface elevations. The change in mean water surface elevations was not significant, with a maximum decrease of 0.05 meters (2.05 inches) and a maximum increase of 0.04 meters (1.61 inches).
### Table A-9: Minimum, maximum, and mean water surface elevations for each simulation

<table>
<thead>
<tr>
<th>Run Number</th>
<th>Manning's Coefficient—Deciduous Forest Land</th>
<th>Manning's Coefficient—Cropland and Pasture</th>
<th>Manning's Coefficient—River</th>
<th>Minimum Water Elevation (m)</th>
<th>Maximum Water Elevation (m)</th>
<th>Mean Water Elevation (m)</th>
<th>Mean Water Elevation Change (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original</td>
<td>0.120</td>
<td>0.040</td>
<td>0.035</td>
<td>64.035</td>
<td>71.754</td>
<td>67.31427</td>
<td>None</td>
</tr>
<tr>
<td>1</td>
<td>0.106</td>
<td>0.034</td>
<td>0.031</td>
<td>63.954</td>
<td>71.757</td>
<td>67.26931</td>
<td>-0.076</td>
</tr>
<tr>
<td>2</td>
<td>0.100</td>
<td>0.041</td>
<td>0.033</td>
<td>63.997</td>
<td>71.75</td>
<td>67.28984</td>
<td>-0.036</td>
</tr>
<tr>
<td>3</td>
<td>0.112</td>
<td>0.044</td>
<td>0.032</td>
<td>63.99</td>
<td>71.748</td>
<td>67.2872</td>
<td>-0.040</td>
</tr>
<tr>
<td>4</td>
<td>0.122</td>
<td>0.032</td>
<td>0.032</td>
<td>63.985</td>
<td>71.758</td>
<td>67.28088</td>
<td>-0.050</td>
</tr>
<tr>
<td>5</td>
<td>0.119</td>
<td>0.039</td>
<td>0.030</td>
<td>63.949</td>
<td>71.752</td>
<td>67.26224</td>
<td>-0.077</td>
</tr>
<tr>
<td>6</td>
<td>0.118</td>
<td>0.045</td>
<td>0.031</td>
<td>63.971</td>
<td>71.747</td>
<td>67.27535</td>
<td>-0.058</td>
</tr>
<tr>
<td>7</td>
<td>0.141</td>
<td>0.034</td>
<td>0.031</td>
<td>63.959</td>
<td>71.757</td>
<td>67.26592</td>
<td>-0.072</td>
</tr>
<tr>
<td>8</td>
<td>0.155</td>
<td>0.042</td>
<td>0.033</td>
<td>64.007</td>
<td>71.75</td>
<td>67.29545</td>
<td>-0.028</td>
</tr>
<tr>
<td>9</td>
<td>0.145</td>
<td>0.047</td>
<td>0.031</td>
<td>63.955</td>
<td>71.746</td>
<td>67.26797</td>
<td>-0.069</td>
</tr>
<tr>
<td>10</td>
<td>0.113</td>
<td>0.035</td>
<td>0.034</td>
<td>64.017</td>
<td>71.755</td>
<td>67.29843</td>
<td>-0.024</td>
</tr>
<tr>
<td>11</td>
<td>0.107</td>
<td>0.038</td>
<td>0.034</td>
<td>64.02</td>
<td>71.753</td>
<td>67.3014</td>
<td>-0.019</td>
</tr>
<tr>
<td>12</td>
<td>0.116</td>
<td>0.048</td>
<td>0.036</td>
<td>64.045</td>
<td>71.752</td>
<td>67.31756</td>
<td>0.005</td>
</tr>
<tr>
<td>13</td>
<td>0.123</td>
<td>0.034</td>
<td>0.036</td>
<td>64.057</td>
<td>71.758</td>
<td>67.31991</td>
<td>0.008</td>
</tr>
<tr>
<td>14</td>
<td>0.125</td>
<td>0.040</td>
<td>0.036</td>
<td>64.056</td>
<td>71.756</td>
<td>67.32101</td>
<td>0.010</td>
</tr>
<tr>
<td>15</td>
<td>0.127</td>
<td>0.048</td>
<td>0.034</td>
<td>64.025</td>
<td>71.75</td>
<td>67.30675</td>
<td>-0.011</td>
</tr>
<tr>
<td>16</td>
<td>0.140</td>
<td>0.037</td>
<td>0.034</td>
<td>64.013</td>
<td>71.753</td>
<td>67.29733</td>
<td>-0.025</td>
</tr>
<tr>
<td>17</td>
<td>0.149</td>
<td>0.041</td>
<td>0.035</td>
<td>64.033</td>
<td>71.753</td>
<td>67.30922</td>
<td>-0.008</td>
</tr>
<tr>
<td>18</td>
<td>0.139</td>
<td>0.048</td>
<td>0.034</td>
<td>64.011</td>
<td>71.749</td>
<td>67.29958</td>
<td>-0.022</td>
</tr>
<tr>
<td>19</td>
<td>0.103</td>
<td>0.036</td>
<td>0.039</td>
<td>64.096</td>
<td>71.763</td>
<td>67.34162</td>
<td>0.041</td>
</tr>
<tr>
<td>20</td>
<td>0.111</td>
<td>0.040</td>
<td>0.038</td>
<td>64.084</td>
<td>71.759</td>
<td>67.33584</td>
<td>0.032</td>
</tr>
<tr>
<td>21</td>
<td>0.116</td>
<td>0.046</td>
<td>0.040</td>
<td>64.115</td>
<td>71.766</td>
<td>67.35524</td>
<td>0.061</td>
</tr>
<tr>
<td>22</td>
<td>0.130</td>
<td>0.035</td>
<td>0.040</td>
<td>64.118</td>
<td>71.766</td>
<td>67.35295</td>
<td>0.057</td>
</tr>
<tr>
<td>23</td>
<td>0.127</td>
<td>0.042</td>
<td>0.040</td>
<td>64.113</td>
<td>71.765</td>
<td>67.35263</td>
<td>0.057</td>
</tr>
<tr>
<td>24</td>
<td>0.118</td>
<td>0.043</td>
<td>0.038</td>
<td>64.084</td>
<td>71.759</td>
<td>67.33736</td>
<td>0.034</td>
</tr>
<tr>
<td>25</td>
<td>0.150</td>
<td>0.032</td>
<td>0.039</td>
<td>64.106</td>
<td>71.765</td>
<td>67.34501</td>
<td>0.046</td>
</tr>
<tr>
<td>26</td>
<td>0.147</td>
<td>0.043</td>
<td>0.037</td>
<td>64.077</td>
<td>71.758</td>
<td>67.33337</td>
<td>0.028</td>
</tr>
<tr>
<td>27</td>
<td>0.142</td>
<td>0.048</td>
<td>0.039</td>
<td>64.11</td>
<td>71.765</td>
<td>67.35343</td>
<td>0.058</td>
</tr>
</tbody>
</table>
A.3.4 Floodplain Delineation Results

Table A-10 shows the effects of the Manning’s coefficient input values on the maximum and mean floodwater depths and on the maximum and minimum floodplain areas.

Table A-10: Floodplain water depths, areas, and percent area changes

<table>
<thead>
<tr>
<th>Run Number</th>
<th>Manning’s Coefficient—Deciduous Forest Land</th>
<th>Manning’s Coefficient—Cropland and Pasture</th>
<th>Manning’s Coefficient—River</th>
<th>Maximum Flood Water Depth (m)</th>
<th>Mean Flood Water Depth (m)</th>
<th>Floodplain Area (m²)</th>
<th>Area Change (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original</td>
<td>0.120</td>
<td>0.040</td>
<td>0.035</td>
<td>2.947096</td>
<td>0.848804</td>
<td>631521.8</td>
<td>None</td>
</tr>
<tr>
<td>1</td>
<td>0.106</td>
<td>0.034</td>
<td>0.031</td>
<td>2.872742</td>
<td>0.822234</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0.100</td>
<td>0.041</td>
<td>0.033</td>
<td>2.911278</td>
<td>0.838109</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>0.112</td>
<td>0.044</td>
<td>0.032</td>
<td>2.905096</td>
<td>0.836659</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>0.122</td>
<td>0.032</td>
<td>0.032</td>
<td>2.900481</td>
<td>0.83245</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>0.119</td>
<td>0.039</td>
<td>0.030</td>
<td>2.885555</td>
<td>0.821777</td>
<td>619396.3</td>
<td>-1.920</td>
</tr>
<tr>
<td>6</td>
<td>0.118</td>
<td>0.045</td>
<td>0.031</td>
<td>2.888111</td>
<td>0.829582</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>0.141</td>
<td>0.034</td>
<td>0.031</td>
<td>2.876925</td>
<td>0.823948</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>0.155</td>
<td>0.042</td>
<td>0.033</td>
<td>2.91975</td>
<td>0.84124</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>0.145</td>
<td>0.047</td>
<td>0.031</td>
<td>2.873743</td>
<td>0.825588</td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>0.113</td>
<td>0.035</td>
<td>0.034</td>
<td>2.929368</td>
<td>0.842553</td>
<td></td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>0.107</td>
<td>0.038</td>
<td>0.034</td>
<td>2.931934</td>
<td>0.844351</td>
<td></td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>0.116</td>
<td>0.048</td>
<td>0.036</td>
<td>2.954918</td>
<td>0.852145</td>
<td></td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>0.123</td>
<td>0.034</td>
<td>0.036</td>
<td>2.966204</td>
<td>0.854</td>
<td></td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>0.125</td>
<td>0.040</td>
<td>0.036</td>
<td>2.965104</td>
<td>0.854353</td>
<td></td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>0.127</td>
<td>0.048</td>
<td>0.034</td>
<td>2.93655</td>
<td>0.846794</td>
<td></td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>0.140</td>
<td>0.037</td>
<td>0.034</td>
<td>2.925748</td>
<td>0.842254</td>
<td></td>
<td></td>
</tr>
<tr>
<td>17</td>
<td>0.149</td>
<td>0.041</td>
<td>0.035</td>
<td>2.943838</td>
<td>0.847844</td>
<td></td>
<td></td>
</tr>
<tr>
<td>18</td>
<td>0.139</td>
<td>0.048</td>
<td>0.034</td>
<td>2.923749</td>
<td>0.843906</td>
<td></td>
<td></td>
</tr>
<tr>
<td>19</td>
<td>0.103</td>
<td>0.036</td>
<td>0.039</td>
<td>3.001945</td>
<td>0.866354</td>
<td></td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>0.111</td>
<td>0.040</td>
<td>0.038</td>
<td>2.990476</td>
<td>0.863431</td>
<td></td>
<td></td>
</tr>
<tr>
<td>21</td>
<td>0.116</td>
<td>0.046</td>
<td>0.040</td>
<td>3.019844</td>
<td>0.874992</td>
<td>641395.0</td>
<td>1.563</td>
</tr>
<tr>
<td>22</td>
<td>0.130</td>
<td>0.035</td>
<td>0.040</td>
<td>3.022028</td>
<td>0.872983</td>
<td></td>
<td></td>
</tr>
<tr>
<td>23</td>
<td>0.127</td>
<td>0.042</td>
<td>0.040</td>
<td>3.017845</td>
<td>0.873198</td>
<td></td>
<td></td>
</tr>
<tr>
<td>24</td>
<td>0.118</td>
<td>0.043</td>
<td>0.038</td>
<td>2.990759</td>
<td>0.86471</td>
<td></td>
<td></td>
</tr>
<tr>
<td>25</td>
<td>0.150</td>
<td>0.032</td>
<td>0.039</td>
<td>3.011127</td>
<td>0.868502</td>
<td></td>
<td></td>
</tr>
<tr>
<td>26</td>
<td>0.147</td>
<td>0.043</td>
<td>0.037</td>
<td>2.984575</td>
<td>0.86205</td>
<td></td>
<td></td>
</tr>
<tr>
<td>27</td>
<td>0.142</td>
<td>0.048</td>
<td>0.039</td>
<td>3.015662</td>
<td>0.87396</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
In Table A-10 there is a slight change in the maximum and mean floodwater depths from the original simulation. The mean flood depth decreased by 0.027 meters (1.06 inches) between the original simulation and the simulation with the minimum mean floodwater depth. The mean flood depth increased by 0.026 meters (1.03 inches) between the original simulation and the simulation with the maximum mean floodwater depth. The floodplain area decreases by 1.920 % at its minimum extents and increases by 1.563 % at its maximum extents from the stochastic model runs. Figure A-18 shows the contours of floodplain water depths at the floodplain’s minimum extent in the stochastic simulation.
Figure A-18: Minimum water depth contours (all values in meters)

Figure A-19 shows contours of water depths at the floodplain’s maximum extents in this stochastic simulation.
Figure A-19: Maximum water depth contours (all values in meters)

Figure A-20 shows the average water depth map for this simulation. The average water depths, minimum water depths, and maximum water depths appear very similar, with only small differences.
Figure A-20: Averaged water depth contours from all floodplain delineations (all values in meters)

Figure A-20 shows the flood probability map for this simulation.
Figure A-21: Probability of flooding (values in percent)

Figure A-22 shows a close-up view of the lower portion of the probability map. This close-up is from the same area as Figure A-6 and Figure A-14 and you can compare it with these figures.
Figure A-22: Probability of flooding—close-up area (values in percent)

Figure A-23 and Figure A-24 show histograms showing numerical values from the images in Figure A-20 to Figure A-22. Figure A-23 shows the frequency distribution of flood depths in the floodplain. Once again, most of the flood depths are in the 0-1.5 meter range, with a few flood depths reaching up to 2.75 meters.
Figure A-23: Average flood depth histogram showing the number of vertices on the TIN with different water depth values for simulation 3

Figure A-24 shows that most of the floodplain vertices have either a 0% or a 100% probability of flooding, but some of the vertices have probabilities between these values.
Figure A-24: Probability histogram showing the number of vertices on the TIN with different probability values for simulation 3