FLOOD HAZARD HYDROLOGY:

INTERDISCIPLINARY GEOSPATIAL PREPAREDNESS AND POLICY

By

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Abstract

Floods rank as the deadliest and most frequently occurring natural hazard worldwide, and in 2013 floods in the United States ranked second only to wind storms in accounting for loss of life and damage to property. While flood disasters remain difficult to accurately predict, more precise forecasts and better understanding of the frequency, magnitude and timing of floods can help reduce the loss of life and costs associated with the impact of flood events.

There is a common perception that 1) local-to-national-level decision makers do not have accurate, reliable and actionable data and knowledge they need in order to make informed flood-related decisions, and 2) because of science–policy disconnects, critical flood and scientific analyses and insights are failing to influence policymakers in national water resource and flood-related decisions that have significant local impact. This dissertation explores these perceived information gaps and disconnects, and seeks to answer the question of whether flood data can be accurately generated, transformed into useful actionable knowledge for local flood event decision makers, and then effectively communicated to influence policy.

Utilizing an interdisciplinary mixed-methods research design approach, this thesis develops a methodological framework and interpretative lens for each of three distinct stages of flood-related information interaction: 1) data generation—using machine learning to estimate streamflow flood data for forecasting and response; 2) knowledge development and sharing—creating a geoanalytic visualization decision support system for flood events; and 3) knowledge actualization—using heuristic toolsets for translating scientific knowledge into policy action. Each stage is elaborated on in three distinct research papers, incorporated as chapters in this dissertation, that focus on developing practical data and methodologies that are useful to scientists, local flood event decision makers, and policymakers. Data and analytical results of this research indicate that, if certain conditions are met, it is possible to provide local decision makers and policy makers with the useful actionable knowledge they need to make timely and informed decisions.

Dedication Page

My PhD endeavors and this dissertation research venture was made manageable by my wife Elaine's faithful commitment to me, and particularly, by her belief that I had an academic mind that could see this PhD project through to the very end. I am eternally grateful!

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Chapter 1 Introduction

1.1 Background

Floods are the most frequent naturally occurring and deadly hazards worldwide. In 2013, floods in the United States ranked second only to wind storms in accounting for loss of life and damage to property (IFRC, 2014). While many factors remain unknown about the causes and full nature of flood disasters, and they remain difficult to accurately predict, more precise forecasts and better understanding of the frequency, magnitude and timing of floods can help reduce the loss of life and costs associated with the impact of such events. For almost a century, the United States Government has been collecting flood hazard damage estimates and impact cost reports. The primary purpose of these efforts has been to save human life and livelihood by better prediction, preparation and mitigation of flood events. In 1983, Congress ordered the U.S. Army Corps of Engineers to begin providing annual reports of flood damages and estimated yearly costs of damage, starting as far back as possible. Multiple reports demonstrate that over the decades, flood damage estimates have increased from $10 million in 1926, to $86 million in 1962 (Pielke, 2002), expanding to $672 million estimated in 1992, jumping to $4.7 billion in paid flood insurance claims by 2006 (Michel-Kerjan, 2010), and again increasing at a rate of $7.9 billion per year through 2015 (NOAA, 2016). According to FEMA, since 1978, the National Flood Insurance Program alone has paid more than $55 billion on flood insurance claims (FEMA, 2016). This flood insurance program is voluntary, however, and the majority of property owners in flood impact areas do not carry insurance, so it is not representative of the full cost of flooding.

Flood hazard data and research analysis can provide emergency management personnel, local, state, and federal policymakers and residents with better information to aid in such flood management activities as flood policy, better evacuation planning, and road closures to save lives and property. Timely flood-inundation information provides local emergency responders, government agencies and the general public with assessments of flood extent during certain peak-flow flood events.

Despite the recognized need for information, there is a common perception that 1) local-to national-level decision makers do not have accurate, reliable and actionable data and knowledge they need in order to make informed flood-related decisions, and 2) because of science–policy disconnects, critical flood and scientific analyses and insights are failing to influence policymakers in national water resource and flood-related decisions that have significant local impact.

Lack of reliable streamflow flood data

During flooding events, decision makers and first responders depend on streamflow and flood inundation information for situational awareness, giving them the ability to effectively allocate resources, enable evacuations, and reduce property losses. Risk awareness is largely dependent on the collection, analysis, and communication of accurate hydrologic data from various sources, one of the most important being real-time and historical streamflow data provided by U.S. Geological Survey (USGS) streamgages. These gages can be damaged by high water and debris, however, and stop transmitting data. Because uninterrupted transmittal of accurate streamflow data is critical for hydrological prediction systems and effective decision-making based on flood forecasts and unfolding real-time events, any missing data due to disruption has significant and wide-ranging implications (NHWC, 2006; Holmes *et al.*, 2012). To address this issue, the weather forecasting community has long sought to develop functioning and effective streamflow prediction models, the importance of which is reflected in a growing body of literature that focuses on streamflow dynamics.

Inadequate flood event decision support framework and actionable information at the local level

In order to make effective decisions, first responders and other key local level decision makers involved in flood emergency management require both timely ground-level and contextualized flood information and the means of making sense of, and drawing insight from, that information. Local decision makers formulate and implement plans and anticipate and respond to flood events based on many hydrologic factors, but the most critical decisions are dependent upon an awareness of the three variables of knowing when (historical, real-time and forecasted times), where (temporal location of streamflow and inundation), and how much (depth, volume and inundation extent, velocity) the flooding is occurring or will occur. For true situational awareness, decision makers need to know when and where the rising rivers will occur or are occurring, what depth the inundation is at locations of concern, what points, places and people of interest are being affected, and where potential access and evacuation routes and directions exist for first responders.

Despite technological advances and new research in areas related to flood analysis and decision-making, challenges remain, particularly in the area of providing accurate streamflow and flood inundation data for remote and/or ungaged streams (Ganora *et al.*, 2009), developing high resolution digital elevation models for producing highly granular and locally scalable geovisual flood maps (real-time and predictive), and delivering reliable, useful flood data to local decision makers during flood events (Brakenridge *et al.*, 2012). Even when these complex issues are addressed, the challenge remains of making sense of large amounts of data in such a way as to be easily understood and effectively utilized by individual practitioners, while at the same time providing a common operating picture and knowledge framework across the various groups involved in flood emergency management.

Science-policy disconnect: the influence of science on policy

Science research is providing new insights and methodological tools regarding flood prediction and information that can be used to advance national and regional flood hazard preparedness. To be applicable, however, this knowledge needs to be integrated and shared collaboratively with analysts and decision makers, and then communicated in such a way that it adequately informs those who create the policies that address this need. Currently, the process of flood data dissemination is complex, often leaving gaps in emergency management and policy collaboration between federal, state, and local levels. Too often, by the time flood-related decisions are implemented by decision makers in local communities, the communities are already in harm’s way when flooding occurs.

Traditionally policymakers have called upon science and other fields of knowledge to produce and disseminate more relevant information for better decision making. Such information, it is argued, would improve the process by clarifying issues and choices and help decision-makers successfully make the rational judgments that lead to desired outcomes (McNie, 2007). Increasing the supply of accurate scientific information does not alone address this issue if decision makers do not perceive the information to be relevant or useful. Yet, funding often continues for research that does not correlate with the knowledge needs of the users (Cash *et al*., 2003).

Both researchers and decision makers share the perception—for different reasons—that research has limited influence on policy. While scientists believe they are not being heard nor their research received, policymakers often perceive that the research is not relevant or useful. There has been considerable discussion over the last decade or so devoted to how to best bridge the perceived divide between science and policy and make information more useful to decision makers.

From the call for more and "better" science to the perception and receptivity of decision makers to that science, an interpretive lens has been designed for refocusing on these issues of research structuring, funding, and results framing. Over the past decade and a half, this focus on policy utility has spawned numerous studies, calls for action, research methods, and models for science–policy interfaces (SPIs) and decision making. Many, if not most, of these studies are written by or for scientists and specialists and are aimed at improving the shape of research, packaging research results, and crafting more effective communication in order to achieve greater influence of science on policy-making. However, despite the growing body of analytic literature and improvements, the perception persists that science continues to have relatively little impact on policy, regardless of this new focus on receptivity.

Research overview

This dissertation explores the perceived information gaps and disconnects listed above, and seeks to answer the question of whether flood data can be accurately generated, transformed into useful actionable knowledge for local flood event decision makers, and then effectively communicated to influence policy. This question specifically frames the three interrelated issues and questions in this dissertation, namely:

1. Is there a way to produce accurate forecast and real-time flood data even when streamgages are missing or not transmitting?
2. Can this forecasted data and relevant ancillary data be communicated as visualized geoanalytic knowledge that is easily understood by local decision makers and useful in supporting flood event related decisions?
3. What factors impact the transfer of flood hazards and other scientific knowledge so as to influence policy-makers' decisions and actions?

1.2 Methodology approach

1.2.1 Interdisciplinary approach

To address these issues and answer the primary question, this dissertation utilized an interdisciplinary, three-phase, mixed-methods research design approach and developed a methodological framework and interpretative lens for each of three distinct stages of flood-related information interaction: 1) *Data generation*—using machine learning to estimate streamflow flood data for forecasting and response (result elements: hard data; prediction); 2) *Knowledge development and sharing*—creating a geoanalytic visualization decision support system for flood events (result elements: unbiased collaborative data); and 3) *Knowledge actualization*—using heuristic toolsets for translating scientific knowledge into policy action (result elements: informed decision making).

Since these questions spanned several academic disciplines, an interdisciplinary approach provided the best context to explore the multifaceted aspects of this research. The core areas researched across the disciplines are: 1) flood hazards and watershed level prediction analysis, 2) integrating remote sensing and in-situ data using geospatial enabled interface tools to create flood forecasting and visualization resources, and 3) understanding of how science-policy interface impacts policy makers' decisions through the lens of social science research.

1.2.2 Research design and mixed methodology

The choices of the research design and methodology were made early in the research process according to the determination as to which provided the best approach in answering the research questions.

Considering the interdisciplinary areas of inquiry and types of research involved in addressing the underlying dissertation queries, a *mixed method* research approach was chosen as the most appropriate option. *Mixed Methods* research involves the collection, analysis and mixing of both quantitative and qualitative data (Creswell and Clark, 2011), with *quantitative* research analysis using numbers, equations, and modeling, and built on answering "closed-ended" questions, and *qualitative* research built on communication, interviews, and human investigation using "open-ended" questions (Rea and Parker, 2005). This mixed methodology is also related to the dissertation's pragmatic philosophical worldview and research methods (see Figure 1.1). The combination of methods allows the researcher to answer both basic science and applied real-world questions, and provides a more complete picture of the research problem (Gliner *et al.,* 2009).

Figure 1.1 Integration of three-phase framework for research

Table 1.1 Advantages and disadvantages of the three research approaches

Quantitative Research		**Qualitative Research**		**Mixed Methods Approach**	
In situ & remote sensed data (close-end questions)		Process & inquiry (open-ended questions)		New pattern & new theme	
Ability to apply multiple research analysis tools together into one research project		Best approach to focus on any one unique research area vs. combined research platform		Analysis using broad methodology analysis approach on human inquiry application research	
Advantage	**Disadvantage**	**Advantage**	**Disadvantage**	**Advantage**	**Disadvantage**
Cover larger research civil engineering field studies	Not able to focus on one area or inquiry	**Integration of science and policy**	Balance between both areas of research	**Comparing relationship between instrumentation & policy**	Connections lost comparisons /perspectives
Cooperative research	Limited time in the field for research	**Cooperative research**	Research on both flood & drought	**Merging datasets Quan & Qual**	Unable to combine research
Integration of Machine Learning (ML) Statistics	No useful outcomes from ML	**Integration of grounded theory analysis**	No useful outcome from research	**Develop better instrumentation**	Unable to connect research
Add to civil engineering literature review	Complexity to develop new ideas	**Add to literature review**	Interviews not available for publication	**Add to literature review**	Unable to combine complex results
Building on instrumentation variables	Unable to understand variables	**Building on intervening variables**	Unable to understand variables	**Positive or null results**	Loss of connecting complexity

My research philosophy integrates four key concepts: *pragmatic*: building on important concepts for situational awareness for water flow dynamics and consequences of action if flooding impacts a whole community; *explanatory*: in which the researcher first conducts "basic" science (quantitative analysis) basing the research on real water flow impact in order to explain patterns found within; *sequential:* underpinning the idea that research builds on a progression of data, and the previous data integrates with other datasets or results into the next research step in the methodology; and finally *experimental*: here the "cause-effect interface" come together in science and policy. Inland river systems were chosen in Chapters 2 and 3 to utilize a case study approach for research. The Boise River, Idaho, and Tanana River, Alaska, were the two central analysis focal points, but several other riverine systems were added for purpose of quality control, quality assurance, baseline comparative analysis, and diversity of physical regions to test this study's hypothesis and models during the sequential and experimental research phases. This phase of research strategy centered around hard science and civil engineering applications by collecting current and historic data quantitatively and utilizing *in situ* and remote sensed instruments, and which could be analyzed later to evaluate flood impact on flood prone communities.

The three core design elements and studies of this overall research are outlined in a schematic (Figure 1.2) that visually portrays the research approach and how Chapters 2, 3, and 4 interact and build on basic and applied research (Joyner *et al.*, 2013).

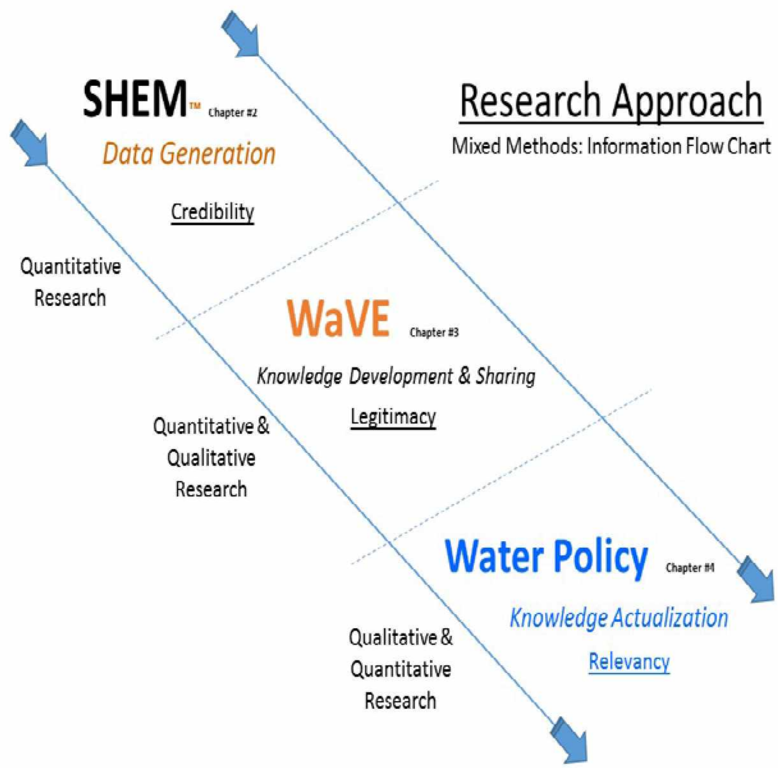

Figure 1.2 Author's basic research schematic for an interdisciplinary, mixed methods approach

1.2.3 Research Study 1 - Flood data generation

Overview

This study (see Chapter 2 Streamflow Hydrology Estimate using Machine Learning (SHEM) Research) addresses whether a predictive estimate can accurately replicate actual streamflow data during a streamgage failure scenario, and do so in a sufficiently timely manner to be useful to decision makers and first responders. SHEM is a new methodology that incorporates machine learning and big-data testing to quickly and accurately impute missing data from a variety of both historical and real-time data sources when a streamgage station stops transmitting streamflow information. The methodology is based on the hypothesis that the multiple sources of water entering a river system impact the streamflow in a proportionate manner, and that this proportionality can be calculated to create interpolated data that can be used to fill the gaps when one or more of the gages becomes inoperative.

Based on the preceding quantitative analysis, this methodology was tested on the Boise River and validated on three other rivers, resulting in an integrated qualitative evaluation analysis (Creswell, 2015). The sequential research development then is used to demonstrate research progress for decision-making concerning future flood hazards resources for any given watershed and flood inundation mapping along river systems.

Results reveal a high correlation between SHEM-estimated missing data and actual recorded data for tested periods. Training using available long-term hydrology datasets from other watersheds is bound to refine the machine learning, making SHEM more scalable for global applicability and improving the accuracy of predictions. Using SHEM, missing streamflow information can be accurately estimated to maintain data continuity and empower first responders to make timely decisions during flooding events.

Research Approach - Study 1

The approach of this study built on quantitative research literature concerning existing ground-based water resources, flood hazard platforms and looked at how remote sensing and machine learning can add resource capacity for ground-based instrumentation (streamgages).

During flooding events, streamgages damaged by high water and debris can stop transmitting data, thus significantly limiting the situational awareness. Because uninterrupted transmittal of accurate streamflow data is critical for decisions based on unfolding real-time flood events, any missing data due to disruption has significant and wide-ranging implications. To explore this question regarding lost streamflow data, a case study analysis was conducted that compares and contrasts hydrologic waterflow with outcomes resulting from historic streamflow data. The river system selected to apply the case study style of research was the Boise River in Idaho. This research approach utilized quantitative science, statistics, computer aided analysis, and civil engineering hydrology applications by collecting current and historic data using in-situ instruments.

Advancements in research technology are producing multiple new sources of hydrological data from in-situ platforms resulting in civil and environmental applications for both engineering fields. The in-situ and possible remote sensing data available from these new sources can be used complementarily to provide answers to critical water resource management and flood inundation questions. The quantitative analyses that identify which combination of data resources will offer the most effective methodology for quantifying hydrological variables will establish new best practices for water resources and flood hazard management.

1.2.4 Research Study 2 - Knowledge development and sharing

Overview

This second study (Chapter 3 - "Flood Forecasting GIS Water-flow Visualization Enhancement (WaVE): A Case Study") explores how flood data can be transformed into useful actionable knowledge that can be developed, shared and used by flood event decision makers.

This third chapter introduces and describes the testing and results of Water-flow Visualization Enhancement (WaVE), a new geospatial visualization framework and decision support toolset designed for first responders, water resource managers, scientists and other decision makers. WaVE's extensible and flexible framework and toolset transforms historic, real-time and forecasted streamflow and flood inundation data into accurate actionable intelligence, enables down-scaled geospatial analysis and visibility, and provides users with easy-to-use and customizable decision support tools.

Using WaVE, stream flows are predicted using computer modeling methodologies with highly technical water flow information, geological baseline data, forecasted weather prediction models, and earth science applications. WaVE's toolsets integrate this complex data and then automatically generate a dynamic multi-scaled visual hydrography and topography map. Testing WaVE's geoanalytic visualization tools, river discharge flow scenarios are portrayed in such a way that the water community can view the visual map as a web service and allow timely decisions.

Research Approach - Study 2

The research of Study 1 (Chapter 2) is extended in the research of Study 2 (Chapter 3) with qualitative "open-ended" inquiry, thus building the mixed methodology. The qualitative research approach provided the best process for communicating to the policy decision making community the developing resources for flood hazards needed by floodplain managers, scientists and first responders. An in-depth literature review process furthered the scope of the present understanding of where flood hazard forecasting methodology is heading, and the need to build localization of critical flood hazard data resources.

1.2.5 Research Study 3 - Knowledge actualization

Overview

Research Study 3 (Chapter 4 - " Bridging Science-Water Policy Action Boundaries: Information influences on U.S. congressional legislative staff decision making") provides an interpretative lens for exploring how policy-makers practically interact with information, make decisions, and act upon policy-related information. To explore the influence of information in crossing water policy knowledge boundaries and linking policy decision-making and action, a grounded theory research study was conducted with key congressional legislative staff in the U.S. House and Senate involved in federal water policy development and oversight. Federal legislative water policies are largely shaped and developed by senior congressional legislative staff, whose policy priorities, decisions and actions are influenced by policy-related information. This research implemented a framework called RCL that focuses on three quality criteria agreed upon by many as essential for transferring information across knowledge boundaries and influencing policy—*relevance* (salience), *credibility*, and *legitimacy* (RCL) (Cash *et al*., 2002). In response to the perception that research has limited influence on policy because it is neither relevant nor useful, considerable discussion has taken place to identify how best to bridge the so-called divide between science and policy and make information more useful to decision makers.

Research approach - Study 3

This mixed methods study used at its core a "qualitative" grounded theory (GT) methodology (Corbin and Strauss, 2008), with an embedded "quantitative" component for comparison and contextual analysis. This policy decision making approach relies upon the knowledge and experience of congressional legislative water resources staff for the purpose of better understanding the gaps between science and policy for future flood hazard science.

1.3 Organization of the dissertation

Chapters 2, 3, and 4 have been written and designed for three different peer reviewed journal publications. Therefore, this dissertation followed the publication manuscript guidelines outlined by the University of Alaska for journal publication. Using this framework and multiple research methodological processes within each chapter, this research examined not only a science landscape process question, but also a human interface question critical to health, safety, and the possible reduction of life-threatening situations to local communities living in potential flood hazard watersheds. The mixed methods research approach builds from a 21st century concept of shaping effective research science and communicating the science to decision makers in order to support good science and create good policy.

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Chapter 2 Streamflow Hydrology Estimate using Machine Learning (SHEM) Research[1]

2.1 Abstract

Continuity and accuracy of near real-time streamflow gauge (streamgage) data are critical for flood forecasting, assessing imminent risk, and implementing flood mitigation activities. Without these data, decision makers and first responders are limited in their ability to effectively allocate resources, implement evacuations to save lives, and reduce property losses. The Streamflow Hydrology Estimate using Machine Learning (SHEM) is a new predictive model for providing accurate and timely proxy streamflow data for inoperative streamgages. SHEM relies on machine learning ("training") to process and interpret large volumes ("big data") of historic complex hydrologic information. Continually updated with real-time streamflow data, the model constructs a virtual dataset index of correlations and groups (clusters) of relationship correlations between selected streamgages in a watershed and under differing flow conditions. Using these datasets, SHEM interpolates estimated discharge and time data for any indexed streamgage that stops transmitting data. These estimates are continuously tested, scored and revised using multiple regression analysis processes and methodologies. The SHEM model was tested in Idaho and Washington in four diverse watersheds, and the model's estimates were then compared to the actual recorded data for the same time period. Results from all watersheds revealed a high correlation, validating both the degree of accuracy and reliability of the model.

2.2 Introduction

Continuity and accuracy of streamflow gauge (streamgage) data are critical for hydrological prediction systems and effective decision-making in flood forecasting and flood impact reduction activities during flood events (Holmes *et al.*, 2012). There are two main categories of impact reduction activities, mitigation and risk awareness (knowledge of the actual and potential elevation and spatial extent of flooding). Risk awareness is largely dependent on the collection, analysis, and communication of accurate hydrologic data from various sources, one of the most important of which is real-time and

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1 Petty, T. R. and P. Dhingra (in press). Streamflow Hydrology Estimate using Machine Learning (SHEM) Research. *Journal of the American Water Resources Association*.

historical streamflow data provided by U.S. Geological Survey (USGS) streamgages. In the U.S., flood forecasting is the responsibility of the National Weather Service (NWS).

The elevation and volume of water flow within any watershed basin typically fluctuate in accordance with such weather events and variables as melting snow, rain, surface runoff, subsurface flow and, in regulated streams, by such variables as dams, storage reservoirs, and levees. Streamgages are devices that monitor and test surface bodies of water within watershed basins, with their primary function generally being the hydrologic measurements of water level surface elevation (also referred to as 'gage height' or stream 'stage'). The volumetric amount of water flowing in a stream (discharge) is calculated with a formula that uses a mathematical rating curve to correlate stage measurements (in feet) to corresponding discharge measurements (in cubic feet per second). Physical discharge measurements are collected over both time and range of stages (from low flow to flood stage) to develop the rating curve, and the stage-discharge relation varies for every streamgage according to stream topography. But because of the strong mathematical relation between elevation and discharge, a continuous record of streamflow can be calculated by continuously measuring water elevation (Kiang *et al.*, 2013).

Although multiple private and public entities use and operate streamgages throughout the U.S., the primary source of streamgage data is the USGS, a federal agency tasked with overseeing the deployment, operation, and maintenance of streamgages. In partnership with more than 800 cooperating national, state and local agencies, the Water Resources Division of the USGS is responsible for roughly 8,000 streamgages that continually collect and communicate current stage and discharge data (USGS, 2016). The USGS makes the recorded streamflow data available through the National Streamflow Information Program (NSIP) (Hirsch and Norris, 2001).

Streamgages commonly measure and record these data at fixed intervals of between 15 and 60 minutes. More than 90% of this information is automatically uploaded from streamgages in the national network and transmitted through the Geostationary Operational Environmental Satellite system in near real-time to the USGS's National Water Information System (NWIS), a network that collects, processes and stores national water data. The NWIS has more than 850,000 station years of time-series surface water data (e.g., stream elevation levels and discharge, rainfall, and reservoir and lake levels), much of which is publicly available via the NWIS web portal (U.S. Geological Survey, National Water Information System. Accessed June 10, 2016 http://waterdata.usgs.gov/nwis/sw).

Streamflow data are also transmitted in near real-time directly to the NWS and the U.S. Army Corps of Engineers (USACE), where the data are used to prepare daily forecasts and to make other decisions. USACE uses USGS streamflow data and NWS precipitation predictions for such flood mitigation activities as managing hundreds of flood control reservoirs, floodway outlets, diversions, levees, and navigation locks. Water managers need timely and accurate forecasts and streamflow data to predict inflows to reservoirs and pool elevations to determine downstream discharge, as well as for daily decisions regarding adjustment of water elevation levels in reservoirs to minimize downstream flooding and maximize storage (NHWC, 2006). During flooding events, decision makers often rely on real-time water elevation and time data, along with ancillary information such as river velocity and depth, for situational awareness and such emergency operations as fighting floods, evacuations, closing bridges, rivers, and roads, etc. (Holmes *et al.*, 2012; Kirchner, 2006).

During flooding events, streamgages damaged by high water and debris can stop transmitting data, thus limiting the situational awareness of decision makers and first responders and their ability to effectively allocate resources, enable evacuations, and reduce property losses. Because uninterrupted transmittal of accurate streamflow data is critical for decisions based on flood forecasts and unfolding real-time events, any missing data due to disruption has significant and wide-ranging implications (NHWC, 2006; Holmes *et al.*, 2012).

To address this issue, the weather forecasting community has long sought to develop functioning and effective streamflow prediction models, the importance of which is reflected in a growing body of literature that focuses on streamflow dynamics. Existing research models provide useful techniques for examining streamflow advancements, with promising implications for interpolation and extrapolation of discharge rate, including: hydrology streamflow modeling (Gupta *et al.*, 1999, 2005), hydrological time series modeling (Salas *et al.,* 1988), hydrological daily streamflow series (Smakhtin, 1999), hydrological spatial patterns (Grayson and Bloschl, 2000), hydrological statistical methods (Helsel *et al.*, 2002), watershed calibration models (Duan *et al*., 2003), watershed discharge rate modeling (Yang *et al*., 2004), hydrological space-time runoff (Skøien and Blöschl, 2006 and 2007), altered streamflow modeling (Armstrong *et al.*, 2008), streamflow prediction (Mohoamoud, 2008), river discharge modeling (Sauqueth, 2006; Sauqueth *et al.*, 2008), streamgage streamflow modeling (Archfield and Vogel, 2010), prediction in ungaged basins (Hrachowitz *et al*., 2013), and complex networks for streamflow dynamics (Sivakumar, 2014; Sivakumar and Woldemeskel, 2014; Sivakumar *et al.*, 2015). Booker and Woods (2014) have also analyzed the physical and empirical research to compare and contrast the effectiveness of hydrological estimates.

Challenges still exist when streamgage loss or damage results in missing information and an inability to accurately predict streamflow. Some studies have focused on estimating missing streamflow data in gaged catchments using regression tools and other methodologies (Sivakumar and Woldemeskel, 2014; Tencaliec *et al.*, 2015; Ng *et al.*, 2009). These approaches have generally employed models of varying complexity that analyze wide-ranging multivariate parameters (e.g., distance relationships, variability, location attributes, degree of regulation) and processes (Booker and Snelder, 2012), which require significant time and resources to construct predictive estimates from large amounts of historical data (Pechlivanidis *et al.*, 2011; Ye *et al.*, 2012). Despite advancements in methodologies and tools, significant limitations remain if existing predictive models are to be used in actual flood events when decision makers need real-time data or quickly-generated proxy data that are accurate and reliable.

A promising tool for meeting this need is machine learning. Machine learning is a developing field of study into how computers can learn without explicit programming, i.e., a type of artificial intelligence whereby computers assimilate data and then use algorithms to make increasingly accurate predictions as they are exposed to new data (Cheamanunkul and Freund, 2014). A growing number of researchers are studying how machine learning can be applied to hydrology (Booker and Snelder, 2012; Booker and Woods, 2014; Pechlivanidis *et al.*, 2011).

This article introduces SHEM, a new methodology that incorporates machine learning and big-data testing to quickly and accurately impute missing data from a variety of both historical and real-time data sources when a streamgage station stops transmitting streamflow information. SHEM is based on the hypothesis that the multiple sources of water entering a river system impact the streamflow in a proportionate manner, and that this proportionality can be calculated to create interpolated data that can be used to fill the gaps when one or more of the gages becomes inoperative.

In this article, the authors address whether a predictive estimate can accurately replicate actual streamflow during a streamgage failure scenario, and do so in a sufficiently timely manner to be useful to decision makers and first responders.

The remaining sections of this article (1) examine the design and methodologies used in the SHEM model to develop, test, validate and score proxy streamflow data, and describe a case study of how the model was applied and tested using streamgages in the Boise River Watershed in Idaho, (2) discuss issues and implications of results from the model and the case study, and (3) summarize the authors' conclusions.

2.3 Methods

SHEM uses an integrated three-phase approach (Figure 2.1) to build a model and set of methodologies that can be used to estimate timely, accurate streamflow proxy data for any given USGS streamgage.

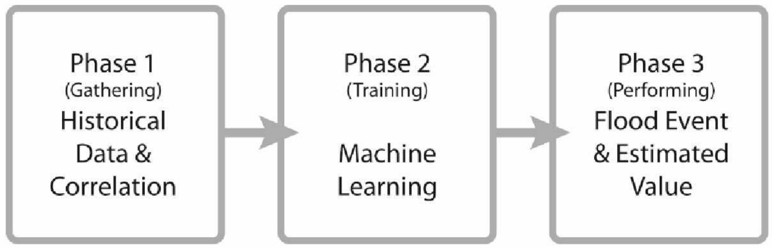


Figure 2.1 Diagram of basic SHEM research approach: Gathering, Training and Performing.

The design process flow and methodologies used in the three phases are described below (Figure 2.2).

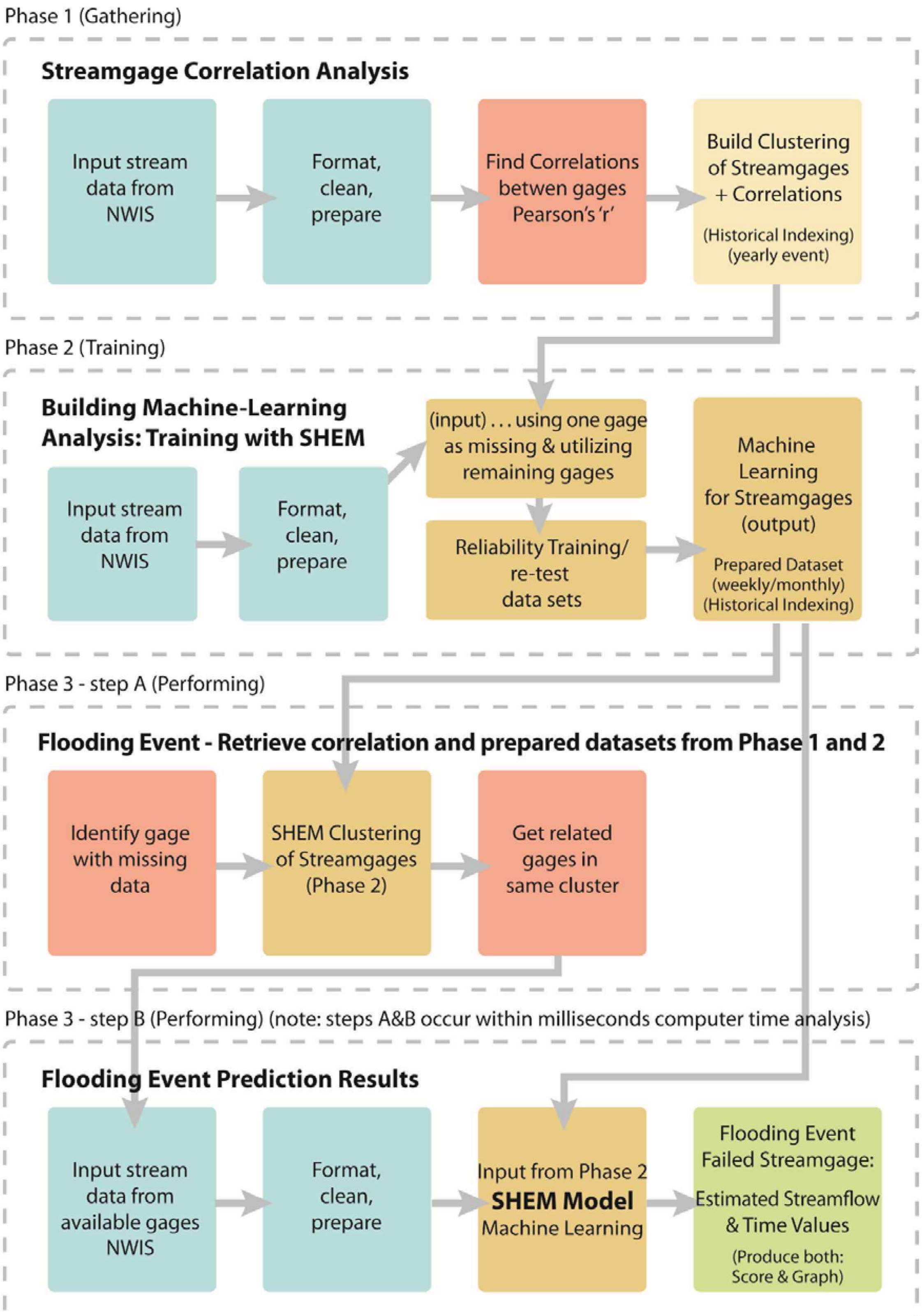


Figure 2.2 Design of the SHEM research methodology phases.

2.3.1 Phase 1: Gathering (streamgage correlation analysis)

Phase 1 involves selecting a regional watershed of interest and building a historical baseline of streamgage data obtained from the NWIS-Web datasets by entering time and discharge data for each streamgage. Streamgage data from NWIS are imported, formatted, cleaned, and prepared. Depending on the age of the streamgage, the gathered data can cover multiple decades.

To quantify the discharge rate network pattern within the watershed and to create a historical profile (a yearly event), SHEM then uses two regression analysis methodologies to find correlations between streamgages and clusters of streamgage correlations. The Pearson product-moment correlation coefficient (commonly referred to as Pearson's r), which measures the degree of linear correlation between two variables (Ganora *et al.*, 2009), is used to identify the correlation among the streamgages. The reliability and validity of these correlation results are analyzed using sweep parameter, tests and scoring. Once validated, the results are again formatted and cleaned. Next, clustering coefficient analysis is used to examine the connections within the streamflow network and group the streamgages into sets (clusters) according to degrees of specific correlation (Sivakumar and Woldemeskel, 2014; Koo *et al.*, 2005).

To validate the correlation clusters, SHEM uses established peer-reviewed methodologies (the same as used in research studies listed in the Introduction). Reference analysis is used to determine relationships among streamgages in closest geographical proximity (Helsel and Hirsch, 2002). Distance relationship correlation selects reference streamgages that are spatially correlated with an ungaged catchment (Archfield and Vogel, 2010). These two analyses and their output are then used by two other methodologies for validating the clusters: network dynamics, which clusters complexity and variables within watershed basin and streamflow theory processes (Sivakumar, 2007; Sivakumar and Singh, 2012), and virtual streamgage estimates for ungaged streams, which determine streamflow accuracy via index streamgages that are relationship-dependent (Smakhtin and Batchelor, 2005; Mohamoud, 2008; Patil and Stieglitz, 2012; Booker and Woods, 2014).

2.3.2 Phase 2: Training (building machine-learning analysis)

In the second phase, SHEM takes output (regression analysis of relationships between streamgages) from Phase 1 and uses machine learning to build a platform that constructs predictive algorithms, while simultaneously continuing to import, format, clean and prepare new data from NWIS. The machine first uses this information to identify patterns of high correlation relationships and clustering factors (Rokach and Maimon, 2005) of the streamgages in any given watershed, and to learn the variability between each of the streamgages. It is during this second phase that the greatest number of datasets are accessed, as SHEM incorporates the variables of the historic discharge rate and time relationship. Using Reliability Training, SHEM retests the datasets and uses machine learning to output weekly and monthly streamgage datasets.

The next step is to build and predict the relationship between the complex datasets from Phase 1 and the newly constructed datasets. To predict the discharge rate outcome required for building a near-real time hydrology estimate model that can be used during a flood event, four regression techniques (i.e., Monte Carlo Model, Multi-Classification Model, Boosted Decision Tree Model, and the Random Forests Model) were tested. From these, Random Forests (Breiman, 2001) was chosen, as it was found to be most effective in building and predicting these relationships.

Random Forests (RF) works by combining many regression ensembles, referred to as "regression trees," to produce more accurate sets of data patterns. Using this technique, SHEM shapes a basic principal method process using machine-learning by combining many "regression trees" into a mutual selection of streamflow analysis to produce a more accurate regression computation (Cutler *et al.*, 2007; Booker and Woods, 2014).

The process builds its big data structure using long-term historical data from each gaging station, plotting the correlations of relevant streamgages, analyzing complex watershed relationships, and placing the RF of streamgages into a discharge rating percentage correlation to demonstrate proportionality and relevance for estimated discharge rate and time parameters (Lin and Jeon, 2006). These two parameters were chosen for estimating streamflow because the RF analysis depends on the value of random vectors.

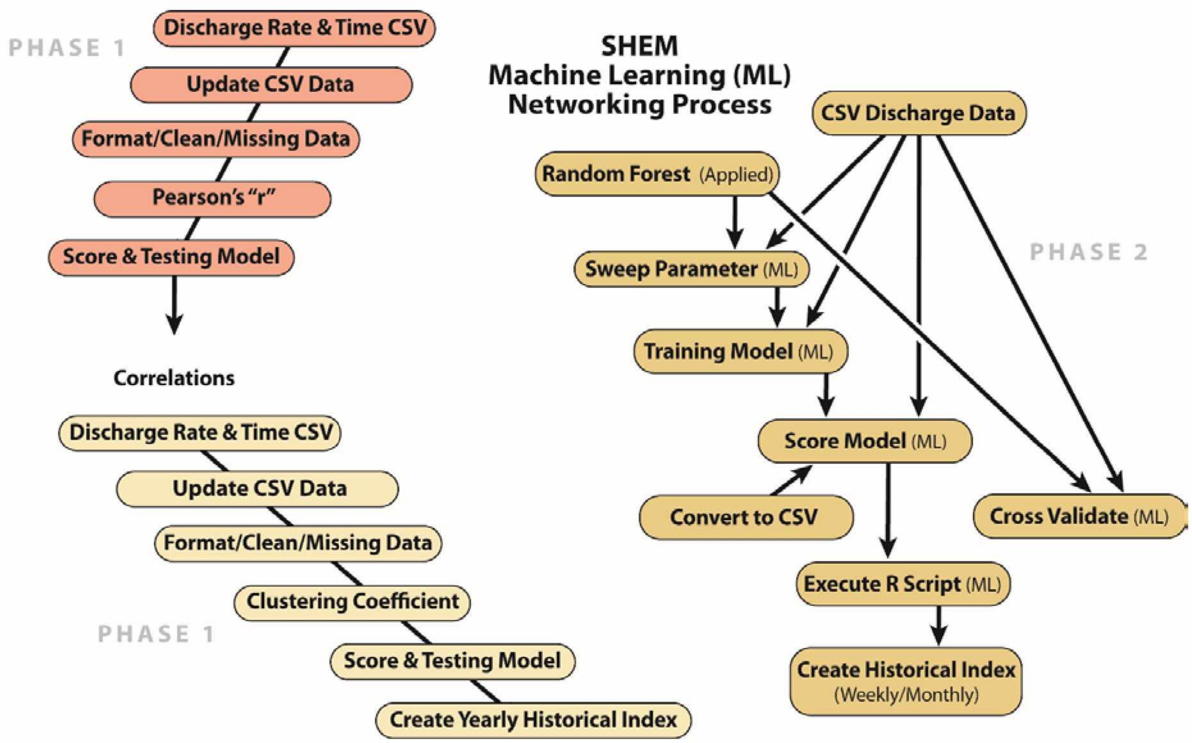


Figure 2.3 SHEM machine learning process.
The schematic depicts the calculation analysis of Phases 1 and 2 used by SHEM in machine learning and its complex interaction with Random Forest and other regression analysis methodologies.

The correlated hydrology data patterns produced by the RF technique are further analyzed and refined by the SHEM machine learning process by employing the iterative mathematical models of Sweep Parameter, Training Model, Cross Validation, Score Model and R Script (Figure 2.3).

When a streamgage fails, loses discharge data, and/or stops sending a data signal, SHEM uses the machine-learning process to analyze the correlated relationship of data from that failed streamgage with the data from other functional streamgages included in the common correlations and relationship clusters index. The streamflow data from each of the streamgages serve as predictive discharge rate and time reference points in establishing correlation relationships with the other streamgages. The resulting prediction model produces accurate regression computations that identify historical streamflow relationships. A discharge rate pattern, also known as an RF dataset, starts to develop through the combined data generated by each streamgage. The SHEM training model then applies its predictive regression algorithm to these datasets to estimate the discharge rate within a watershed at the location where the streamgage failed.

This model can be applied to any streamgage that has been correlated with a set of related streamgages. As discussed later, the time it takes to initialize the model (i.e., complete Phases 1 and 2) for a set of indexed streamgages depends on the number of streamgages in the set, the amount of historical data to be analyzed, and the computing resources available. When the first two phases of the SHEM model are applied to that set—the platform is built, tested and validated, and an index of historical relationships and clustered correlations is created—estimated proxy data (generated in Phase 3) are immediately available to be substituted for missing data for any indexed streamgage in the set during a flood event. The initial setup of Phases 1 and 2 is a one-time event for each set of indexed streamgages, and subsequently requiring only annual updates of datasets (for constructing historical profiles) for Phase 1, and weekly and monthly updates of streamflow datasets in Phase 2.

2.3.3 Phase 3: Performing

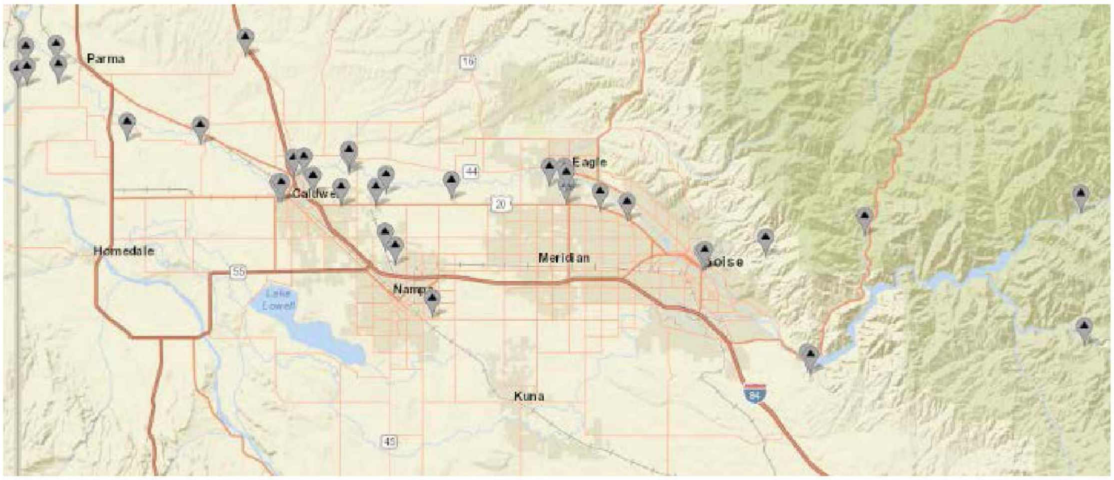
The third phase of SHEM takes place during an actual flood event, and involves two steps that occur milliseconds after the completion of Phase 2 and that build on the datasets and predictive model constructed and trained during the first two phases. In a flood event, SHEM first identifies the missing streamgage data, retrieves correlated datasets from the first two phases, i.e., from the machine learning and the clustering of streamgages, and then finds related streamgages in the same cluster. In the second step, which occurs within milliseconds of the first step, SHEM then makes, tests, validates and scores flood event data estimates. It takes the clustered data, prepares and inputs these data (while continually adding new and formatted data from the indexed NWIS gages), imports the output from Phase 2 into SHEM's machine learning, and, depending on the execution parameters established, automatically estimates streamflow and time values for the missing data from the failed streamgage as soon as the streamgage stops transmitting. These proxy data are then tested, and the results of the tests are scored and graphed.

2.3.4 Case Study: SHEM methodology applied to the Boise River Watershed

To demonstrate and test the methodology of SHEM, the Boise River Watershed was selected as a case study because of the availability of many years of informationally-rich, well-documented streamgage data for the watershed. Together with near real-time data, this historical data can be measured using outcome analysis, and then tested and retested for reliability. During a flood event, large amounts of information from functioning streamgages can be used to estimate highly reliable and accurate discharge water rates of failed or “offline” streamgages.

The first phase of SHEM began by selecting a target streamgage with missing data and a set of related functioning streamgages (without missing data) from which correlations and clusters were identified. Nineteen USGS gages in regulated and unregulated streams in the Boise River Watershed

(Figure 2.4) were originally evaluated. Eight were selected according to the following criteria: demonstrated data consistency, provision of proper data fields, full functionality for a sufficient length of time, and the fulfillment of basic data-collection inventory practices. Eleven streamgages did not meet these criteria and were therefore eliminated.

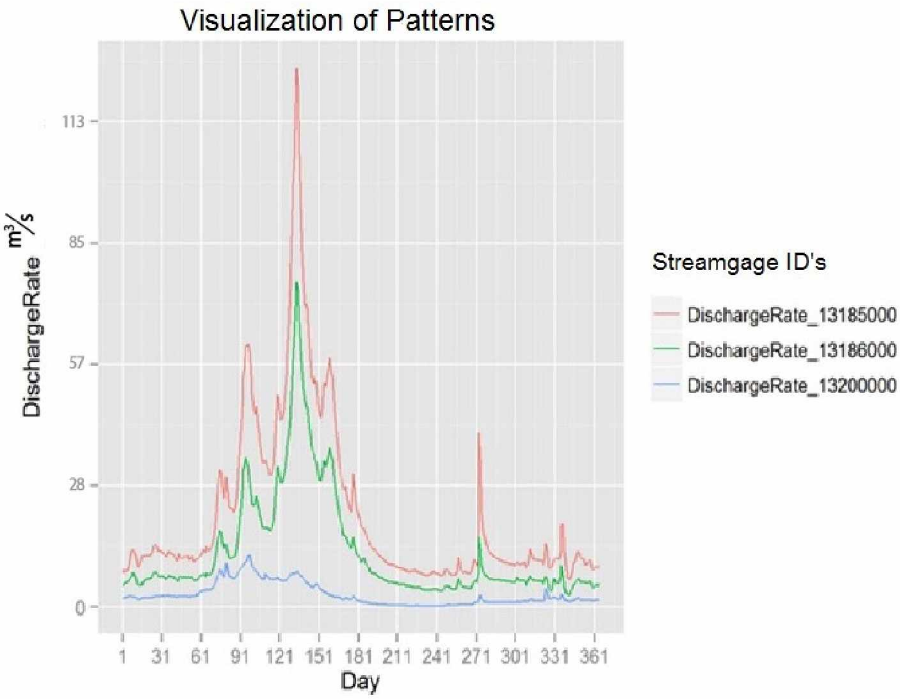


USGS National Water Information System–streamgages and spatial map at http://waterdata.usgs.gov/id/nwis/nwis

Figure 2.4 USGS streamgage locations in the Boise River Watershed, Idaho.

The process of formatting the data began when the eight streamgages were screened and selected. In this case study, five years of data (2011 to 2015) were analyzed from the eight selected Boise River streamgages in both unregulated and regulated streams. The raw big data from each gauging station were organized into three categories: (1) streamgage station ID, (2) date and time stamp, and (3) discharge rate. To later find the missing values in the data, a calendar was created with start and end dates that correlated to each of the eight streamgages. Then, to analyze discharge rates from multiple streamgages, the data from all the streamgages were merged and brought into a single dataset defined by the restructuring and formatting process (Figure 2.2).

SHEM then inserted the streamgage dataset into two regression-analysis applications. Pearson's r identified the correlation among the streamgages, and clustering coefficient analysis was then used to examine the connections within the Boise River network of streamflow relationships. As a final step in Phase 1, SHEM utilized a custom R Script python program (R Development Core Team, 2015) to strengthen the correlation relationship of the Boise River streamgage datasets with Pearson's r and clustering coefficient method and analysis. Using applied statistical metrics for strong correlation analysis (Cowan, 1998), a cutoff specific for this case study was set, i.e., any streamgage with greater than 0.75 accuracy was considered to be correlated. As discussed in the subsequent section on case study results, the correlation analysis measured how the two variables (flow rate and time) directly strengthened their relationship as a positive correlation (Figure 2.5).



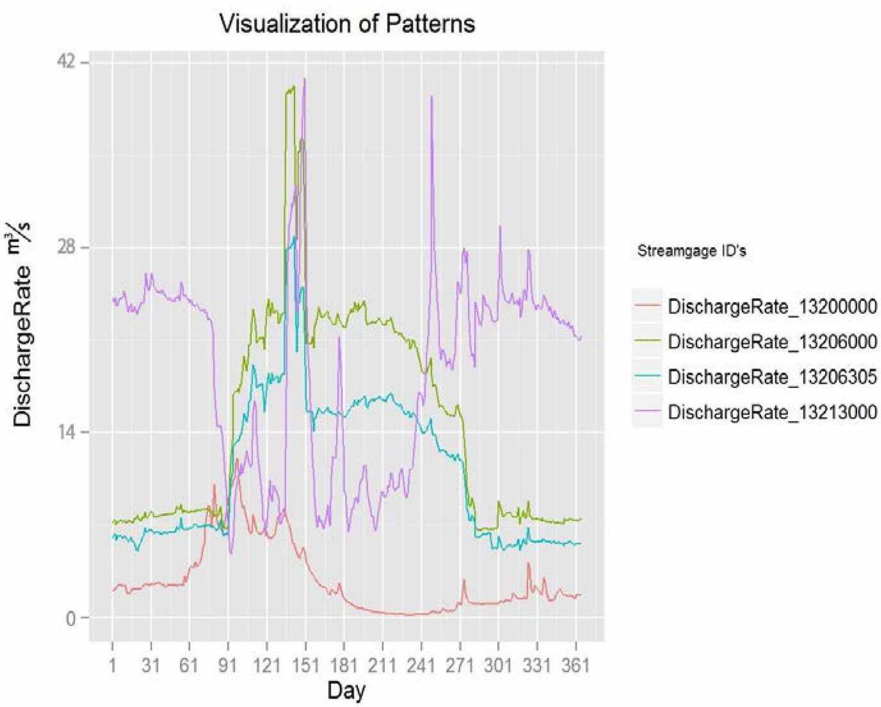


Figure 2.5 Graphical visualization of fluctuating discharge rate.
Select unregulated and regulated streams in the Boise River Watershed Basin over 2013 Calendar Year. These datasets plot the discharge rate (cubic feet per second) on the Y-axis and the calendar (number of days) parameters on the X-axis for the specific streamgages indicated by ID numbers and color-coded on the graphs. The first graph depicts patterns of discharge for three unregulated streams. The relationship of the patterns in the three unregulated streams is designated by SHEM to be statistically significant. The second and third graphs depict the complexity of streamflow fluctuation and discharge rate patterns in four and five regulated streams.

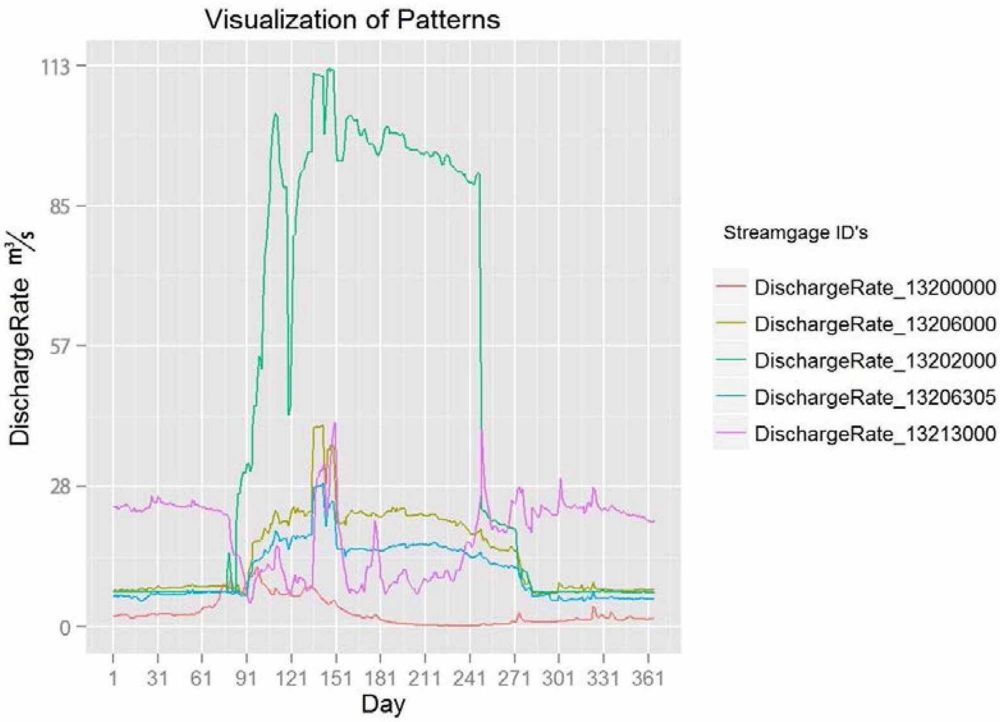


Figure 2.5 (continued)

For Phase 1 of the Boise River case study, the processes of selecting streamgages, cleaning and preparing the five years of data, and building correlation datasets, together took a couple of days of processing time.

As applied to the case study, the second phase of SHEM highlights the significant use of machine learning and training, whereby the five years' worth of Boise River streamflow data gathered in Phase 1 were used to build a modeling process in Phase 2 for future prediction of a flooding event (Phase 3). SHEM tested the streamgage data built in Phase 1 by using a splitting data process to show accuracy and error in prediction (Refaeilzadeh *et al.*, 2009). For the purposes of testing and training the machine learning process, the data from the five years were split in an 80:20 ratio of four years to one year (Martin, 1997). The testing and training resulted in SHEM learning the relationship and time parameters among all correlated streamgages in the Boise River and creating a historical index of those correlations and relationship clusters.

Validation of methodology

To confirm the validity and reliability of the Phase 1 and 2 data results, the following three standard methods were used to calculate error analysis: Root Mean Squared Error (RMSE), Mean

Absolute Error (MAE) and R square (RSQR) (Moriasi *et al*., 2007). Standardized prediction values were indexed for each method. Employing a machine-learning calculation, this error analysis builds on previous data modeling research on efficiency for bias (Nash and Sutcliffe, 1970) and research on scaling analysis and problems in hydrology (Gupta, *et al.*, 1986).

Building thousands of discharge rate datasets from each streamgage using the RF process revealed the proportional correlation among the other streamgages. Identifying these discharge rate patterns strengthened SHEM's predictive capability (Breiman, 2001; Lin and Jeon, 2006).

To measure the value of the error analysis as applied to the Boise River, the training and correlation of the output data were again computed using the RF process for each correlated streamgage dataset (Figure 2.3). This test/retest process is used to validate and determine "goodness-of-fit" and reliability, of the scoring model of this streamgage dataset (Legates and McCabe, 1999).

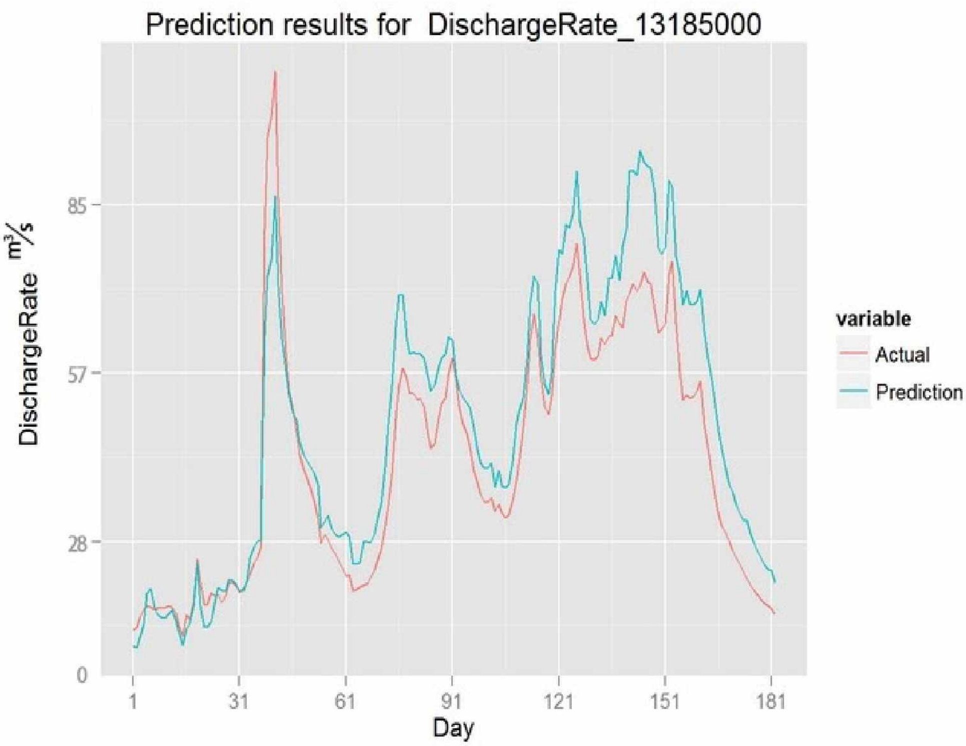
Together, the processes involved in Phase 2 for the case study required between six to twelve hours of computer processing time. By the end of Phase 2, an index of correlations and relationship clusters for all eight streamgages was generated.

In the third phase of the case study, SHEM was ready to use the index and apply the trained model from Phases 1 and 2 to support a flood event when any of the eight might fail. Watershed data that were prepared, documented, analyzed and indexed by SHEM in Phases 1 & 2 were available to instantly predict missing data during a flood event when a streamgage went "offline."

To imitate a flood scenario for this case study, the authors individually applied a protocol to each streamgage whereby SHEM had no predetermined data available from the streamgages, while still collecting data from the other streamgages. SHEM then estimated the discharge rate and the time parameters for each non-functioning streamgage based entirely on the other streamgages' actual data and the already-documented correlation among the functioning streamgages. SHEM's estimated flow and time prediction were recorded. At that point, actual information for that time was retrieved, and predictive values and actual values for that streamgage were graphed for comparison (Figure 2.6).

2.4 Results and discussion

Initial results from testing the SHEM model in the Boise River Watershed Basin case study indicated a "good" to "high" correlation of accuracy between estimates and actual historical data.



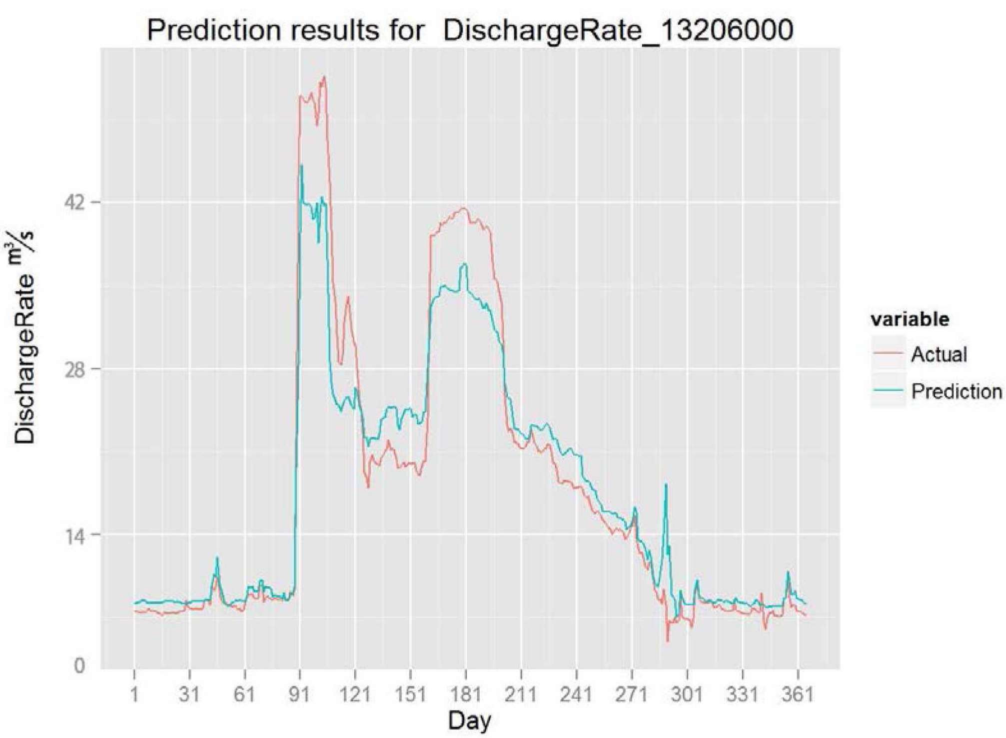


Figure 2.6 Results of estimated and actual discharge rates & times.
For calendar year 2013 the three graphs portray the case study of viable correlations of estimated and actual discharge rates and time parameters (six months and one year) of two regulated (1320600 & 13213000) and one un-regulated (13185000) stretch of the Boise River from streamgage locations.

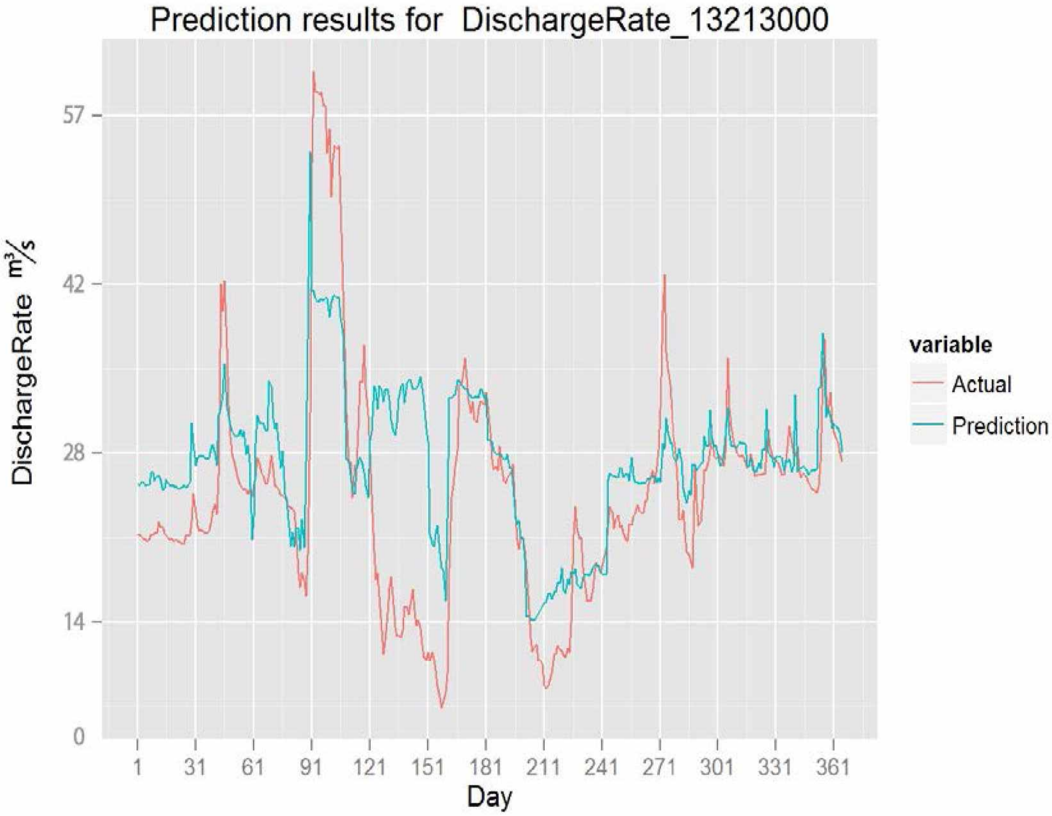


Figure 2.6 (continued)

These results were replicated and validated through multiple tests of missing datasets chosen randomly from the eight streamgages in the case study (Table 2.1).

Table 2.1 Correlation accuracy among eight Boise River streamgages. Depicts the accuracy of the correlation between streamgage streamflow data using the two parameters of elevation and time. Most of the streamgages were tested two to three times by correlating their data with different gages. The first accuracy association for the eight sample streamgages showed an average correlation of 0.92, the second (for seven gages) averaged 0.84, and the third (for five gages) averaged 0.85, thus all showing high correlation using the two basic parameters of stream discharge and time.

USGS Gage ID #	Streamgage name	First Correlated Streamgage & Accuracy Association		Second Correlated Streamgage & Accuracy Association		Third Correlated Streamgage & Accuracy Association	
13185000	Twin Springs Boise River NF	13086000	0.99	13200000	0.79		
13186000	Featherville Boise River SF	13185000	0.99				
13200000	Mores Creek near Arrowrock	13185000	0.79	13206000	0.78	13213000	0.79
13202000	Lucky Peak Boise River	13190500	0.83	13206000	0.84	13206305	0.87
13190500	Anderson Ranch Boise R SF	13202000	0.84	13206305	0.78	--	--
13206000	Glenwood Bridge Boise R	13213000	0.97	13202000	0.84	13206305	0.95
13206305	Eagle Boise River	13206000	0.99	13213000	0.93	13202000	0.87
13213000	Parma Boise River	13206000	0.97	13206305	0.93	13200000	0.79
		Average	*0.92*		*0.84*		*0.85*
		Median	*0.97*		*0.84*		*0.87*

To further validate the reliability of these results, the model was subsequently applied to three other watershed basins in Washington State—Naselle, Willapa, and Satsop. These basins included both regulated and unregulated streams. The results from applying the model in these locations were rigorously tested and validated. These results, which showed similarly high correlation and predictive factors, were then compared to those of the initial case study. Comparison of all the locations affirmed the validity and reliability of the SHEM methodology, and demonstrated that the model could be applied in other locations with the same high degree of replicability, clarity, stability, definition of parameters, and correlation accuracy.

Constraints on model effectiveness and utility

While the case studies validated the functionality and accuracy of the methodology, the effectiveness and utility of the model are largely dependent upon both the time and computing resources required for building machine learning correlation indices and the availability of adequately-sized and accurate historical streamflow datasets. The time it takes to build the SHEM platform in Phases 1 and 2 depends on the number of streamgages and amount of historical data used, as well as the computational processing resources available. While the model can be applied to any correlated set of streamgages (regardless of the number of streamgages in the set), in order to generate near real-time proxy estimates for missing data for one or more streamgages in the set, the model must be initialized for each set by completing Phases 1 and 2. In the Boise River case study, the process of cleaning, confirming and preparing the five years of data in Phase 1 took one to two days, while the data processing in Phase 2 took between six to twelve hours. However, depending on the computational resources available, these processing times can be significantly shortened once the procedures and processes are standardized and optimized. Lowering the processing times in Phases 1 and 2 is necessary if SHEM is to be deployed and applied to large regions or nationwide.

Because the scope of the initial application and testing of SHEM focused on the production of timely and accurate estimates, the model used only two key data parameters—stream stage (elevation) and time. These parameters were chosen because of their high statistical correlation, their central importance in flood forecasting and mitigation, and the wide availability of USGS streamflow data. Limiting the analysis to two parameters also reduced processing time and computational resource requirements, as well as the complexity and potential for error.

For both ungaged regulated and unregulated environments, SHEM requires adequate historical stream stage and time data from correlated streams in order to calculate accurate estimates. The accuracy of the model's results depends on the availability and processing of sufficient historical data to both train the machine learning model and enable SHEM to develop its index of clustered correlations. As shown in the research of Sivakumar and Singh (2012) and Sivakumar *et al.* (2015), accuracy is also affected by the degree of complexity and variability involved in streamflow fluctuation. The smaller the amount of historical streamflow data and the greater the complexity of streamflow fluctuation, the higher the error potential in predictability. However, the greater the amount of historical streamflow data, the lesser the degree to which complexity of streamflow fluctuation affects the accuracy (Gupta *et al.*, 1999, 2005).

Opportunities for further research

As highlighted by Archfield and Vogel (2010), technologies and research related to gaged and ungaged streamflow have made steady progress, though the need remains for methodologies and tools that quickly and more effectively access, analyze, and predict streamflow information in ungaged river systems. This need appears to be made even more acute given the limited resources available for replacing and expanding needed streamgage stations, as well as the implications of these limitations for flood forecasting and mitigation, water resources, water security, natural disasters, environmental challenges, ecosystem management, and agricultural resources.

During the development and testing of the initial model, the authors determined that SHEM's underlying machine learning and analytical processes could be used to extend the current research on streamflow estimates—such as that of Archfield and Vogel (2010), Sivakumar (2014), Mohamoud (2008), Booker and Woods (2014)—and be used to extrapolate estimated data from ungaged streams as well as interpolate data estimates from gaged streams with missing data.

Furthermore, the SHEM model could potentially be applied in remote ungaged catchment areas by building on recent models and research (Srinivasan *et al.*, 2015; Li and Wong, 2010; Brakenridge *et al.*, 2012; Gleason and Smith, 2014; Gleason *et al.*, 2014) on generating streamgage data using new technologies related to remote satellite sensing and measurement (e.g., synthetic aperture radar), digital aerial surveillance (e.g., video, photo, thermal imaging) from unmanned aerial vehicles and manned aircraft, and other telemetry methodologies. Using these tools, SHEM could potentially construct and build historical index datasets and correlated clusters of stream stage and time relationships and train itself to produce streamflow data estimates for any watershed basin in the United States or the world.

Another potential area of study, elaborated below, is the use of SHEM to identify the optimal locations to position physical streamgages for measuring discharge, or identify locations for conducting remote monitoring and telemetric measurement in areas that are too inaccessible for physical streamgage positioning. Extending the research of Hrachowitz *et al.* (2013) on long-term prediction analysis and Ganora *et al.* (2009) on duration curve prediction for ungaged basins, SHEM could apply the three-phase approach (Figure 2.1) to estimate streamflow for ungaged regions. While SHEM can train itself and construct estimates for these ungaged water catchments using historical discharge datasets derived from remote telemetry, the model is faced with a challenge when such measurements are available for shorter time periods than those normally used for constructing relationship datasets and training the machine learning model. To address this challenge of generating adequate historical data correlations, SHEM could integrate or utilize the results of Gleason and Brakenridge's previously mentioned river watersheds models based on remote sensing and telemetry capabilities that calculate streamflow discharge, together with incorporating or utilizing the results of Cheamanunkel and Freund's computer assimilation data predictions (2014) and Booker and Woods' hydrology machine learning. More research and study is required to determine the efficacy of using these new remote telemetry tools for creating streamflow data histories.

As referenced in an earlier section, another area of future study is the addition of other correlated streamflow parameters (e.g., such as the topographical attributes and precipitation parameters used by Skøien and Blöschl, or extending the research of Archfield and Vogel and Gupta related to the parameters of stream discharge and time) to retest the model in order to determine the effects of additional correlated variables on processing time, resource requirements, and the accuracy of estimates, particularly when limited streamflow data histories are available.

2.5 Conclusions

Streamflow data from USGS streamgages are critical for flood forecasting, assessing imminent risk, and planning and implementing flood mitigation activities. The research topic of interest was whether a predictive estimate can accurately replicate actual streamflow during a streamgage failure scenario, as well as to do so in a sufficiently timely manner to be useful to decision makers and first responders. The SHEM model was specifically designed to construct accurate and timely proxy streamflow data estimates that can be substituted for missing data when streamgages stop transmitting accurate data.

To test the model, the Boise River Watershed Basin was chosen as the site for the initial case study, and five years of streamflow data from eight streamgages in the watershed were correlated, clustered and analyzed. Employing machine learning and a variety of regression methodologies and statistical validation tools, SHEM created a virtual streamflow relationship index of the Boise River Watershed. Using those relational datasets and clusters—which are continually updated with new real-time data—SHEM was able to quickly produce accurate proxy discharge and time data for any indexed streamgage that stopped transmitting data. The model was tested by randomly removing actual data, generating and substituting estimated proxy data in place of the missing data, and then comparing the proxy estimates with the corresponding actual data that had been removed. SHEM tested and validated the reliability of the predicted value estimates through rigorous integrated testing methodologies, and then scored and graphed the output.

The accuracy and reliability of the Boise River case study results were further validated when the model was subsequently applied to three other watershed basins in Washington, all of which indicated similarly high correlation and predictive factors.

The results of these error analysis methods affirms the scientific integrity of the SHEM methodology. When these statistical processes and equations are applied to streamflow hydrology datasets, they effectively produce a result that can be used by first responders and decision makers responding to flooding events.

The SHEM construct affirmatively supports the authors' question of whether a predictive estimate can accurately replicate actual streamflow during a streamgage failure scenario, and in a timely manner so as to be useful to decision makers and first responders.

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Chapter 3 Flood Forecasting GIS Water-flow Visualization Enhancement (WaVE): A Case Study[2]

3.1 Abstract

Riverine flood event situation awareness and emergency management decision support systems require accurate and scalable geoanalytic data at the local level. This paper introduces the Water-flow Visualization Enhancement (WaVE), a new framework and toolset that integrates enhanced geospatial analytics visualization (common operating picture) and decision support modular tools. WaVE enables users to: (1) dynamically generate on-the-fly, highly granular and interactive geovisual real-time and predictive flood maps that can be scaled down to show discharge, inundation, water velocity, and ancillary geomorphology and hydrology data from the national level to regional and local level; (2) integrate data and model analysis results from multiple sources; (3) utilize machine learning correlation indexing to interpolate streamflow proxy estimates for non-functioning streamgages and extrapolate discharge estimates for ungaged streams; and (4) have time-scaled drill-down visualization of real-time and forecasted flood events. Four case studies were conducted to test and validate WaVE under diverse conditions at national, regional and local levels. Results from these case studies highlight some of WaVE's inherent strengths, limitations, and the need for further development. WaVE has the potential for being utilized on a wider basis at the local level as data becomes available and models are validated for converting satellite images and data records from remote sensing technologies into accurate streamflow estimates and higher resolution digital elevation models.

3.2 Introduction

In order to make effective decisions, first responders and other key local level decision makers involved in riverine (channel) flood emergency management require both timely ground-level and contextualized flood information and the means to make sense of and draw insight from that information.

[2] Petty, T. R., N. Noman, D. Ding, and J. B. Gongwer (2016). Flood Forecasting GIS Water-Flow Visualization Enhancement (WaVE): A Case Study. *Journal of Geographic Information System, 2016, 8, 692-728.*

Local decision makers formulate and implement plans and anticipate and respond to flood events based on many hydrologic factors, but the most critical decisions are dependent upon an awareness of the three variables of knowing when (historical, real-time and forecasted times), where (temporal location of streamflow and inundation), and how much (depth, volume and inundation extent, velocity) the flooding is occurring or will occur. For true situational awareness, decision makers need to know when and where the rising rivers will occur or are occurring, what depth the inundation is at locations of concern, what points, places and people of interest are being affected, and where potential access and evacuation routes and directions exist for first responders.

Despite technological advances and new research in areas related to flood analysis and decision-making, challenges remain, particularly in the area of providing accurate streamflow and flood inundation data for remote and/or ungaged streams, developing high resolution digital elevation models for producing highly granular and locally scalable geovisual flood maps (real-time and predictive), and delivering reliable, useful flood data to local decision makers during flood events (Chapman *et al.*, 2015). Even when these complex issues are addressed, the challenge remains of making sense of large amounts of data in such a way as to be easily understood and effectively utilized by individual practitioners. At the same, it is vital to provide a common operating picture and knowledge framework across the various groups involved in flood emergency management.

In this article, we introduce and test Water-flow Visualization Enhancement (WaVE), a new geospatial visualization framework and decision support (DS) toolset designed for first responders, water resource managers, scientists and other decision makers. WaVE's extensible and flexible framework and toolset transforms historic, real-time and forecasted streamflow and flood inundation data into accurate actionable intelligence, enables down-scaled geospatial analysis and visibility, and provides users with easy-to-use and customizable DS tools.

The following sections of this article (1) provide background information on flood geospatial analytics and decision support; (2) describe the three development phases of the WaVE design framework, including future development of the framework for enhancing the platform and review of case studies that test and demonstrate WaVE's capabilities; (3) discuss issues and implications of results from the model and the case study; and (4) summarize the authors' conclusions.

3.3 Background

3.3.1 Flood data—where, when and how much

Two groups in particular require and utilize local-to-regional scaled historical, real-time, and forecasted riverine water flow and flood inundation data—floodplain water managers and first response emergency management teams.

The first group, floodplain and water resource managers, require these data for effective planning and operations. They gather and assimilate data from research scientists, issue warnings and alerts, create emergency plans for flood scenarios, communicate flood stages to the community, and create predictive models. Water resource managers, such as those from the U.S. Army Corps of Engineers (USACE), use flow data and precipitation predictions for such flood mitigation activities as managing flood control reservoirs, floodway outlets, diversions, levees, and navigation locks. They need timely and accurate forecasts and flow data to predict inflows to reservoirs and pool elevations in order to determine downstream discharge, as well as to make daily decisions regarding adjustment of water elevation levels in reservoirs to minimize downstream flooding and maximize storage (Hester *et al.,* 2006).

Similarly, first responders and emergency management operations—both before and during actual flooding events—rely on historical and real-time water elevation, time, and water velocity data for situational awareness and executing such emergency operations as fighting floods, evacuations, closing bridges and roads, etc. When and how these tasks are implemented can determine the degree to which lives and property are saved (Holmes *et al.*, 2012; Kirchner, 2006).

For these groups, time sensitive decisions are often based on information and attributes related to fluctuations in channel and flood water. The elevation and volume of water flow within any watershed basin typically fluctuate in accordance with such weather events and variables as melting snow, rain, surface runoff (the flow over the earth's surface of excess water from storm water, snowmelt or other sources), subsurface flow, and in regulated streams by such variables as dams, storage reservoirs, and levees. Heavy precipitation and snowmelt runoff in upstream areas of a catchment can cause high water volumes in river streams, full capacity in river reservoirs, and riverine flood inundation (i.e., extending beyond its channel boundaries) of normally dry areas. The extent of flood inundation is influenced by such factors as channel depth, volumetric discharge, stream velocity and geomorphological features outside of the channel.

Two hydrologic data parameters—water elevation and time—are essential for addressing these issues. Using these two fundamental pieces of geospatial information, hydrologists can calculate: (1) the volume rate (Q) of water flow (also referred to as streamflow, discharge or flow rate) in a channel—calculated as the product of a cross-sectional area (A) and the mean velocity ($\bar{u}$) of a stream, and typically expressed as cubic feet/second (f^3/s) or cubic meters per second (m^3/s); and (2) the inundation of water that extends outside of normal channel banks.

Traditionally, these streamflow data have been recorded using physical streamgages, devices that monitor and test surface bodies of water within watershed basins and that primarily function to measure water level surface elevation. For hydraulic models and flood maps in the United States, the most important source of real-time and historical streamflow data records is provided by the U.S. Geological Survey (USGS), a federal agency tasked with overseeing the deployment, operation, and maintenance of roughly 8,000 streamgages throughout the U.S.

3.3.2 Flood mapping

Different models and measurement tools historically have been used to identify or predict flood situations that occur in a variety of geographical and topographical landscapes. These have ranged from traditional static flood maps, historical flood tables, datasets and statistics developed by analysts and cartographers, to newer tools that leverage developments in digital elevation and terrain that feature modeling, geospatial analysis and geovisualization, and that integrate hydraulic models with visualized geospatial data and interactive flood maps. Analysts and planners can use digital inundation maps overlaid on city maps and combined with other overlaid geographic information systems (GIS) layers to assess potential flood risks and damages. These tools are used to help predict flood occurrences and inundation extent, achieve situational awareness during events, and communicate risks and consequences of current and predicted flooding.

Digital maps are created by superimposing "layers" of pixel or raster-based images that represent geocoded geomorphological features on "top" of digital elevation models (DEMs)—digital models or three-dimensional representations of terrain surfaces (Farr *et al.*, 2007). These models are developed using terrain elevation data acquired and recorded by such means as direct land surveys, remote sensing, and photogrammetry. Some earlier coarse resolution DEMs were interpolated from digital contour maps based on direct land surveys, although increasingly these models are higher resolution and generated from remote sensing.

Modern hydrological flood mapping models combine data from historic flood inundation maps with real-time data to predict inundation of current and future flood events. To visualize flood data, a hydraulic model is combined with a digital ground surface elevation model according to a grid cell layout, whereby the digital representation of the elevation of surface water is overlaid onto a time-sequenced digital representation of ground surface elevation in a geospatially corresponding grid area to determine how far flooding will extend beyond normal channel banks. Inundation extent is then calculated for each grid cell.

The vertical accuracy and spatial resolution (ground surface area within a grid cell) of the base DEM (primary topography) influences the degree of accuracy of hydraulic models and flood maps (David *et al.,* 2013; Vaze *et al*., 2010). The higher the number of cells in a unit area, the greater the resolution and scalability (i.e., the finer the resolution of rasterized data at smaller distances from ground surface elevation, the more accurate the representation of ground surface topography).

Developments in the field of remote sensing (RS)—the passive recording or active detection and measurement of objects and areas by aerial sensor technologies—have enabled greater efficiencies in creating more accurate digital elevation maps, measuring streamflow, and analyzing and predicting floods. RS was traditionally largely passive, conducted using manned or unmanned aircraft and, to a lesser extent, land-based applications. This method uses such sensing instruments as infrared and film photography to gather and record information about the radiation (from the sun or other sources) reflected or emitted by the target area or object. The reach and options of passive RS increased significantly with the launching of Landsat in 1972 and the advent of satellite platform-based RS. By contrast, active sensors emit energy to detect remote targets and then measure the radiation reflected back or backscattered from those targets. Advances in active RS using satellite, airborne and terrestrial altimetry technologies have led to increased insights into river flow dynamics and provide alternatives to traditional methods.

Hydrological model-based analysis used in flood forecasting and building static hazard maps for situational awareness historically have been dependent on discharge data from *in situ* streamgage networks. While foundational to much of hydrologists' understanding of surface water, gage networks are limited in the information they can provide about local floodplain flow and watershed dynamics. During a flood event, these *in situ* sources provide only a one-dimensional, point-based set of surface water data (Juracek and Fitzpatrick, 2009), without addressing the additional challenge of extrapolating downstream volume after the water passes the monitor and predicting what the water will do if it rises and extends beyond its normal channel. The limited availability of *in situ* streamflow measurement resources hampers flood detection in river areas and restricts the ability to validate real-time flood forecasting models (Madsen and Skotner, 2005). Furthermore, these streamgages are physically vulnerable and can stop transmitting critical flood water data during storm events or at other critical times.

This risk was illustrated in the August 2016 flood event in Baton Rouge, Louisiana. During the floods, 15 USGS streamgages were damaged or destroyed (Burton and Demas, 2016). For three key days during the storm, stations in critical locations stopped sending vital near real-time data to first responders (see Figure 3.1) who relied on the data for situational awareness about the rising of the river, warning and evacuating at-risk people, and taking steps to protect property (U.S. Geological Survey, 2016).

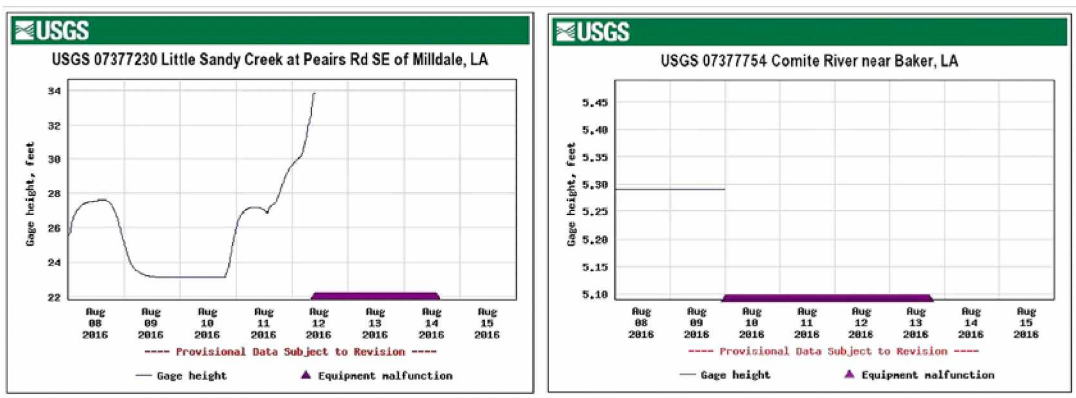

Figure 3.1 USGS hydrographs from the National Streamflow Information Program. Illustrations of the streamflow condition and equipment malfunction during the August 10-15, 2016, Baton Rouge, LA, flood event. http://waterdata.usgs.gov/la/nwis/rt.

These risks are among the reasons that RS is increasingly being advocated as a complement to *in situ* streamflow measurement and for providing vital data where no streamgages exist (Schumann, Bates *et al.*, 2009; Gleason *et al.*, 2014; Revilla-Romero *et al.*, 2014). This interest is reflected in the growing body of research related to validating inundation maps used during actual flood events, RS models and applications, techniques for working alongside *in situ* methods, and building proxy streamflow measurement models (Baldassarre *et al.*, 2009) (Giustarini *et al.*, 2011) (Chen *et al.*, 2014) (Wanders *et al.,* 2014) (Revilla-Romero *et al.*, 2015).

RS is also increasingly being used for developing DEMs of higher resolution and greater accuracy. Today, flood inundation maps are commonly derived from passive microwave sensors or moderate resolution spectroradiometer imagery (i.e., MODIS and Landsat TM) (Tarpanelli *et al.*, 2013; Domeneghetti *et al.*, 2014; Gleason *et al.*, 2014). Testing and experimental remote sensing systems are being set up to detect and map spatial resolution in near real-time, as well as monitor ongoing floods by comparing imagery with on-the-ground data information obtained from flood disasters (Jongman *et al.*, 2015). Results from studies indicate that daily spatial resolution results and measurement data from passive microwave satellite observations and satellite altimeters (Roux *et al.*, 2010; Callow and Boggs, 2013; Allen and Pavelsky, 2015) correlate well with *in situ* streamflow and are suitable for analyzing and predicting streamflow and flood events at national and regional scales.

The demand for higher spatial resolution, accurate DEMs, and hydraulic and channel flow routing model output that can be scaled from the regional to local level, has spurred the growth of related research and applied resources. In the U.S., an important step toward this goal is the continual development and enhancement of The National Map (TNM), the collaborative effort of USGS and its partners to provide publicly-available digitized topographic data—elevation, boundaries, transportation, structures, land cover, geographic names, hydrography, aerial photographs, etc. In 2011, the U.S. Government completed the National Enhanced Elevation Assessment, a result of which is the 3D Elevation Program (3DEP), an initiative launched by the USGS. Its initial services and products begun in 2015, 3DEP collects and adds to the seamless layers of TNM's high-quality topographic and enhanced elevation light detection and ranging (lidar) data for the coterminous United States, Hawaii and the U.S. territories, and interferometric synthetic aperture radar (InSAR, or commonly abbreviated as IfSAR) data for Alaska (Arundel *et al.*, 2015).

This first active RS source, lidar, is a surveying and elevation measuring technology that works by actively illuminating (pulsing) a target with laser light—different parts of the visible and near-infrared sections of the electromagnetic spectrum—and measuring the distance of the return signal of the pulse reflected back (Kinzel *et al.,* 2012), thus providing the precise location of the target (e.g., surface area, vegetation, hard surface buildings, etc.). Conventional lidar measures only the elevation of water surfaces, but specific spectrum laser light (blue-green wavelength) can penetrate water and be used for river bathymetry (Pan *et al.*, 2015). While lidar can be carried out with terrestrial, airborne, satellite, or mobile platforms, most enhanced elevation scanning and measurement for elevation models is carried out using airborne platforms such as fixed-wing manned aircraft or unmanned aerial vehicles (UAVs), the latter being explored and developed as an economical alternative to manned aircraft, particularly in more remote areas.

IfSAR, on the other hand, is an active RS technology generally used in places like Alaska, where cloud cover and the remote locations of target areas make the use of lidar less effective and relatively impractical. Radar from satellites can penetrate overcast weather and provides valuable continued round-the-clock imagery during storm events (Stoker *et al*., 2016). This active sensing technique combines two or more synthetic aperture radar (SAR) images that are derived from recording the stereoscopic effect caused by the differences in the phases of radiation waves that return from the target area after it is struck by a narrow radar beam transmitted from an antenna on a satellite platform-based sensor.

In addition to lidar and IfSAR, other laser scanning (LS) technologies for airborne (ALS), mobile (MLS) and set-terrestrial (TLS) laser scanning platforms are also being developed for flood mapping support (Gordon *et al.*, 2015).

A growing body of research studies has focused on flood impact at the regional watershed level, some of which have analyzed the results from RS flood extent and *in situ* streamflow measurements (Brakenridge and Anderson, 2006; Tarpanelli *et al.*, 2013). Other research has explored the use of data from multispectral and microwave sensors to supplement *in situ* stream data (Tarpanelli *et al.*, 2015). Some studies have explored the use of inundation maps derived from higher resolution images to ground truth, while others have focused on testing and validating the accuracy and effectiveness of using RS image datasets for flooding events and inundation maps (Huang *et al.*, 2014; Memon *et al.*, 2015). Once RS images and derived data are recorded, it greatly impacts the efficacy of the tool for measuring real-time, local impact during flood events, given that satellites used for those events may not be at the optimal location for the right times and durations required for best coverage. Despite these limitations, streamflow time series from simulated satellite RS models have been developed, tested, and are starting to improve flood inundation maps (Schumann, Baldassarre *et al.*, 2009; Khan *et al*., 2011; Chapman *et al.*, 2015).

3.3.3 Flood data visualization for decision support

Streamflow and flood inundation data from traditional and RS sources can be analyzed and visualized using either stand-alone flood mapping tools or those integrated into sets of other emergency management decision support systems (EMDSS)—computerized or hybrid human and computer-based information systems used by organizational management to facilitate the solving of unstructured and partially-structured problems and making decisions related to planning, management, and operations processes (Rolland *et al.*, 2010). The appropriate use of EMDSS can help emergency management teams address workload and labor requirements, schedules and deadlines, resource availability and other constraints, and assist them in making more effective time-sensitive labor assignments and resource allocations (Rolland *et al.*, 2010). High-profile emergency response decision failures during disaster events like Hurricane Katrina and other large-scale national and international flood scenarios have highlighted the need for better decision-making processes and systems (Comfort, 2007; Thompson *et al*., 2006). The growing public perception of this need has been reflected in the field of theoretical and applied research on EMDSS for floods and other crises (Walle and Turoff, 2008), as well as in the development of systems, hardware and communication technologies to assist practitioners in these areas.

The development of EMDSS has been further enabled by advances in data storage, retrieval and processing technologies that greatly increase the potential accuracy and efficiency of these systems. Technologies now exist for creating platforms that can combine many different data sources (including discharge data derived from such active and passive remote sensors as lidar and active sensor SAR), compute billions of data elements to identify multivariate correlations across diverse environments, analyze and multi-scale that data, and transform that data into customizable and visualized knowledge needed by decision makers.

One area of significant growth in the past few years is the processing of “big data”—data sets that are too large for computation by traditional computing. It is estimated that since the 1980s the world's per-capita capacity to store data has doubled every 40 months (Hilbert and Lopez, 2011). Large data sets related to streamflow and flood inundation, plus myriad ancillary emergency management data that in the past required the computing power of supercomputers, can now be processed by running massively parallel software on tens-to-thousands of powerful and smaller servers in multiple locations, all linked together in a "grid". These grids form virtual supercomputers that can also utilize "cloud computing"—remotely-located shared processing and storage resources for computers and applications that are available on-demand from anywhere for customers with high-speed Internet connections.

This rapid growth in available and interrelated data and the need to process and make sense of it all has overwhelmed traditional data analysis methods. A promising area being explored as a potential solution is machine learning, a developing field of study of how computers can learn without explicit programming—a type of artificial intelligence whereby computers assimilate data and then use algorithms to make increasingly accurate predictions as they are exposed to new data (Cheamanunkul and Freund, 2014). A growing number of researchers are studying how machine learning can be applied to hydrology (Booker and Snelder, 2012; Booker and Woods, 2014). Even with the use of machine learning and other means to analyze large amounts of statistical and other structured data, there still remains the challenge of presenting analytic results in such a way as to be easily accessible and understood, both by analysts and by decision maker practitioners.

One approach to this issue has been to provide users with visual and graphical representations of data analysis. Such information visualization attempts to help users comprehend, analyze and make sense out of large-scale data sets by representing that data in graphical and other visual display means. Visual analytics, on the other hand, have been described as interactively combining information visualization and data mining by integrating human factors and data analysis with visualization in order to assist analytical reasoning (Keim, 2010). Bertini and Lalanne (Bertini and Lalanne, 2009) argue that the goal of visual analytics should be to combine natural and artificial intelligences through the collaboration of human abilities and the power of data mining. Visual analytics help provide a means of exploring and analyzing large amounts of data to support complex problem solving and decision making by combining the data storage and processing of computers with the exploration (finding, action) and verification (insight, hypothesis) loops of knowledge generation (Sacha *et al.*, 2014).

The integration of flood maps with other tools are examples of a subset of information visualization and visual analytics called geovisual analytics (or geospatial visual analytics)—a multidisciplinary field that seeks to develop new approaches to solving complex problems related to geographical space and objects, events, processes and phenomena within that geo-temporal context (Maceachren *et al.*, 2004). It is multidisciplinary in that it combines information, scientific and geographical visualization with the computational processing capabilities of statistical analysis and modeling, machine learning, data mining, and geographical analysis and modeling (Andrienko *et al.*, 2011).

3.4 Methods

3.4.1 WaVE design framework

In response to the need for visualizing and characterizing flood water and related impact factors, WaVE is being designed and developed in collaboration with and for first responders, water managers and other decision makers to provide flood decision makes with a common operating picture and decision support. It consists of a geospatial analytics visualization framework and DS toolset (currently under development) that transforms historic, real-time and forecasted streamflow and flood inundation data into accurate analytic results, down-scaled visibility, and customizable DS tools. The geospatial design, research and testing for the study areas are performed and developed using an Esri ArcGIS (Version 10.3) platform.

WaVE's extensible and flexible framework and toolset is designed to provide users with easy-to-use and customizable tools to:

- Generate moderate to highly granular and interactive geovisual real-time and predictive flood maps that can be scaled down to show discharge, inundation and water velocity (and ancillary geomorphology, hydrology and elevation data) at any point along a mapped stream at the national and regional levels, with some locations providing enough high resolution data to enable maps to also be available on a local level.

- Integrate data from multiple sources and analysis results from commercial, open source or user's own tools and models.
- Utilize machine learning correlation indexing to interpolate streamflow proxy estimates for non-functioning streamgages and extrapolate discharge estimates for ungaged streams, while also providing a streamflow baseline to use computational analysis to test and rate the degree of reliability of the various geospatial data sources and forecast estimates being analyzed.
- Supply ancillary GIS data visualization of environmental features, alternate evacuation routes, city and community analysis of socio-economic demographics, webcams, points of interest, e.g., residences, schools, roads, hospitals (see Figure 3.2).

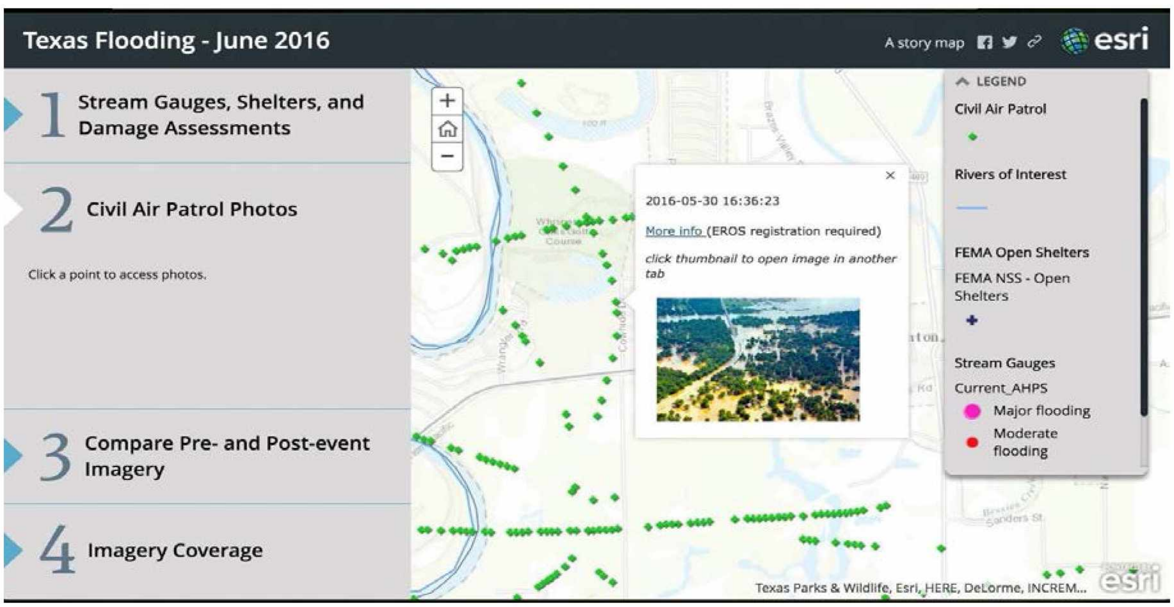

Figure 3.2 Screenshot of an interactive Texas flooding ArcGIS Story Map.
An example of ancillary flood data that can be integrated into WaVE—Screenshot of an interactive June 2016 Texas flooding ArcGIS Story Map, showing Civil Air Patrol flight path with clickable markers of aerial reconnaissance photos of flood area.

WaVE's common operating geospatial intelligence applications and toolsets for decision makers are developed through a three-phase process: (1) Gathering, (2) Processing, and (3) Performing. These three phases are described in Table 3.1.

Table 3.1 Key variables and three phases of the WaVE design process.

Key Variables of Flood Water Flow and Inundation	**When** **Where** **How much**	Time (historical, real-time, forecasted) Location and extent Volumetric discharge and velocity	
	Phase 1 (Gathering)	**Phase 2 (Processing)**	**Phase 3 (Performing)**
What (Content / Tools)	**Streamflow and inundation data** Historical Real-time Forecasted	**Geospatial** Platform Framework Applications/toolsets	**Flood event decision support** Common operating geovisual intelligence system and applications Server, desktop & mobile-based
How (Functions)	Selection Inputs & aggregation Preparation (clean, code and scale)	Integration Mapping Analysis & estimation Testing & evaluation Validation & scoring	Geovisualization Scalable localization Interactive customization Contextualization

3.4.1.1 Phase 1—Gathering

The first phase consists of selecting, aggregating, and preparing historical, real-time and forecasted streamflow and inundation data.

Selection

The first phase begins by selecting the primary historical and forecasted streamflow and flood inundation datasets WaVE will use for preparing its baseline analyses, model results, estimate comparisons, and geovisual tools. WaVE develops its baseline datasets from historical and forecasted data derived from weather forecasts provided by the following American and European forecasting modeling systems: the U.S. Weather Research and Forecasting Hydrological (WRF-Hydro) model and the European Centre for Medium-Range Weather Forecasts (ECMWF) model. In Phase 1, WaVE begins building its baseline by gathering datasets from either WRF-Hydro or ECMWF to complete the baseline of its framework.

For coverage of the U.S., WaVE uses historical and forecasted gridded discharge and inundation data from WRF-Hydro. This modeling extension package was developed by the federally funded U.S. National Center for Atmospheric Research (NCAR) and its research partners, and through affiliated research projects.

WRF-Hydro is both a community-based and supported stand-alone hydrological modeling system and coupling architecture designed to link multi-scale process models of the atmosphere and terrestrial hydrology on different spatial grids, as well as to provide accurate and reliable streamflow prediction across scales. WRF-Hydro integrates the following hydrological models: column land surface models, terrain routing models (overland, subsurface flow modules), and channel and reservoir routing models (hydrologic and hydraulic modules). WRF-Hydro receives data (one-way coupling) from gridded meteorological analysis models, nowcasts and forecasts, as well as data (two-way coupling) from weather and climate predictions—using Multi-Radar/Multi-Sensor System radar-gauge observed precipitation data, High Resolution Rapid Refresh, Rapid Refresh, and Climate Forecast System forecast data. It also receives critical numerical prediction results from the global computer models and variation analyses of the Numerical Weather Prediction and U.S. National Weather Service's Global Forecast System (GFS).

Within WRF-Hydro, the GFS model is essential for the forecasting component for WaVE as it generates medium-range forecasts every six hours for up to 16 days out, with decreasing resolution after 10 days. WRF-Hydro inputs this data using its driver and data assimilation tools, and then processes this data, conservatively regridding and downscaling as needed for use in its various models. The WRF-Hydro system features possible component configurations for streamflow prediction, including 5 channel flow schemes (Gochis *et al.*, 2015). As described later, one of these, RAPID-Muskingum for NHDPlus, is used by WaVE.

WaVE can also use ECMWF as an option to utilize flood forecasting. ECMWF is an independent intergovernmental organization based in the United Kingdom that operates one of the largest supercomputer complexes in Europe and has the world's largest archive of numerical weather prediction data (ECMWF, 2016). ECMWF's operational global meteorological forecasting model, the Integrated Forecast System (IFS) inputs and assimilates meteorological data collected and transmitted by satellites and earth observation systems, and uses these data in computerized atmospheric models to generate medium-range (up to 15 days ahead), monthly, and seasonal weather forecasts. Every twelve hours, IFS generates deterministic and ensemble operational forecasts of up to ten days out. IFS' deterministic forecasts are double the resolution of the ensemble forecasts, but require more computational resources, whereas the ensemble forecasts use a variation of Monte Carlo analysis and generate a representative sample of possible forecast predictions by running the model 51 times in parallel under slightly different initial conditions (Ye *et al.*, 2013). ECMWF makes publicly available some of the IFS model's most important forecast data and calculations, which can be incorporated into WaVE.

Both the ECMWF (Pappenberger *et al.*, 2009) and WRF-Hydro systems provide precipitation forecasts and precipitation runoff predictions that are plotted according to a geospatial grid, transforming rainfall runoff forecasts from weather-hydro forecast models into gridded streamflow (discharge) runoff predictions and inundation forecasts (Alfieri *et al*., 2014; Yucel *et al.*, 2015).

Input and aggregation

To input gridded discharge runoff and inundation prediction data, WaVE creates connectivity files and inflow files from ECMWF and WRF-Hydro runoff database tables, and then creates RAPID-Muskingum parameter files and subset files.

Data downscaling and preparation

Because gridded forecast data from ECMWF and WRF-Hydro are provided at the global or regional level, there is a spatial resolution gap between the forecast values and local impact assessments. Even if one can zoom in to see higher resolution of surface areas or objects within a grid cell, there is still only one forecast for the entire area, thus potentially providing a completely inaccurate runoff prediction at the local level. As the highest resolution global model is neither detailed enough nor scalable, its usefulness at the local level is significantly limited (Snow *et al.,* 2016). Since the global model result cannot be used directly, this spatial resolution gap needs to be bridged so that the scaled forecast values can correspond to the local level resolution (Seyyedi *et al.*, 2014).

WaVE framework tools bridge the spatial resolution gap by downscaling the forecasted streamflow runoff and inundation data from the global and regional models for later input into flow routing models. Downscaling is a two-step process (see Figure 3.3) using Python Geoprocessing Workflows: (1) Create weight table by overlaying catchments on a computational grid, and (2) Create inflow file by computing the weighted average runoff for each catchment. Dividing the downscaling process into two steps increases efficiency because once the weights are computed and the table created (the most time consuming part of the conversion and downscaling process), these weights can be reused with a new forecast.

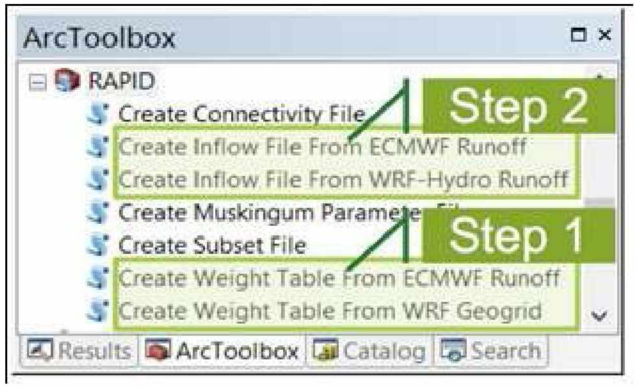

Figure 3.3 The two-step downscaling process.

In the first step, weight tables are created (and continually updated) from the previously created files derived from WRF-Hydro or ECMWF runoff and geogrid data (a program in the Weather Research and Forecasting Model Preprocessing System that defines model domains and interpolates static geographical data to the grids). These tables are developed by overlaying watershed catchments on a computational grid of the earth's surface and using a geospatial digital elevation map (DEM) as a base. This grid can be either low or high resolution. Watershed catchments (also referred to as drainage basins) are areas of land where surface water comes together at a single point to drain into another body of water. Smaller catchments drain hierarchically into larger catchments. The catchment data layer is represented by polygons generated from elevation data using a web service. As shown in Figure 3.4, forecast data are then run through a series of geoprocessing operations to spatially overlay the gridded runoff forecast (at the top) with the watershed polygons (at the bottom), and the total runoff per watershed is summarized for each time step.

The grid cells associated with each catchment are identified and calculated using NHDPlus hydrological flow characteristics and terrain surface and digital elevation data. Each grid cell is given a relative weight (W) assigned at each geospatial gridded cell point (i) where the total area (Ai) of each cell is divided by the catchment area ($A_{catchment}$) (see Equation 1).

$$W_i = A_i/A_{catchment} \tag{1}$$

A collection of open source Python script tools (which can be extended or modified to support other types of runoff or forecast data) are then used to store the identification of the catchment, cells they fall into, and the associated weights in a file. This file serves as the weight table used in the second step of the downscaling process.

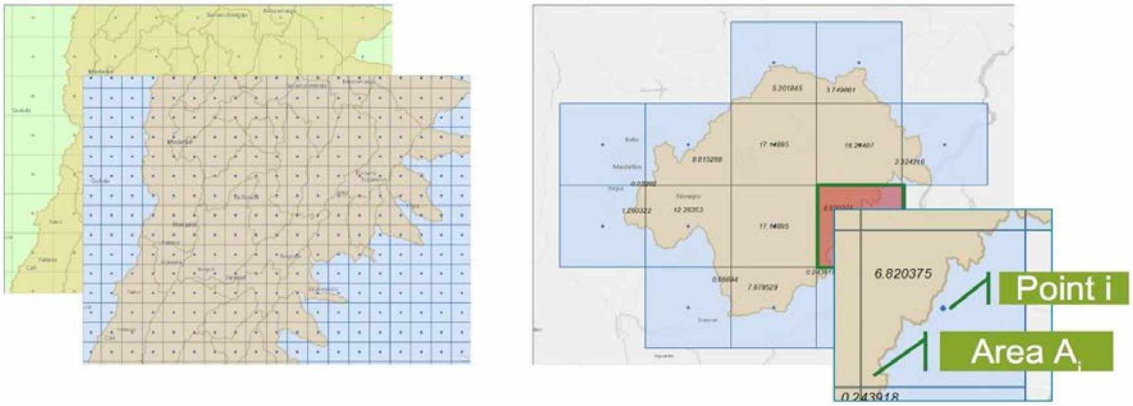

Figure 3.4 Gridded runoff forecast spatially overlaid on top of watershed polygons.

Total runoff is then calculated using the appropriate weights divided by the areas of the contributing points.

The second step consists of creating an inflow file for the model forecast by computing weighted average runoff for each catchment. To do this, the WaVE tool extracts forecasted runoff time series (for all time steps) from each grid cell associated with a respective catchment, multiplies them by the appropriate weight (or area) to generate Q, or river discharge, and then adds all the grid cells. As shown in Equation 2, the total run-off ($Runoff_{total}$) for the combined catchment areas of all cells is equal to the sum total of all the cells ($\sum$) of cell grid run-off ($Runoff_i$) multiplied by the weight (W_i) for each cell grid point (i), and multiplied by the catchment area ($A_{catchment}$) for each cell (Equation 2).

$$Runoff_{total} = \sum (Runoff_i \times W_i \times A_{catchment}) \quad (2)$$

The process is repeated for all catchments. This step results in the weighted inflows that can be used to map streamflow and inundation.

3.4.1.2 Phase 2—Processing

Once prepared, in Phase 2, WaVE processes and integrates the data with results and output from other hydraulic and analytic models, estimates forecasts, analyzes, tests and evaluates results, and validates and scores results for accuracy and uncertainty.

Integration

In order to analyze and geovisualize the prepared data, WaVE integrates and utilizes a variety of existing open source, public and commercial hydraulic, geospatial analytic, machine learning algorithms, and geovisualization models and tools. As discussed later, WaVE's flexible framework allows it to easily add and integrate new and existing technologies from its geospatial application toolbox.

Weighted inflow data from processed historical, real-time and forecasted streamflow runoff in Phase 1 can then be visualized by computing discharge and choosing selections from flow routing models. Once it is known how much water runoff comes from each watershed at each time step, WaVE models the flow routing in catchments using the Routing Application for Parallel Computation of Discharge (RAPID).

RAPID is a river routing model that can compute the flow and volume of surface and groundwater inflows and water flows anywhere within river networks, and, assuming basic connectivity, can be adapted for any river network. To route the waterflow, RAPID uses a matrix version of the commonly used Muskingum hydrologic routing method (David *et al.*, 2016). Muskingum model uses uniform calculation procedures that build on river characteristics that include: (channel geometry, upper and lower watershed reach and length of a river, surrounding topography, slope of the river) to estimate the river water flow parameters including both the inflow and outflow hydrology without intricate and time-consuming algebraic solutions (Karahan *et al.*, 2013). The model parameters can be easily optimized to reflect the multivariate differences for individual sub-catchments (e.g., presence of major manmade infrastructure) or water withdrawals on a river network. RAPID is written in FORTRAN and can be run on a wide range of computing devices, from personal computers and networked servers to grid and cloud-based servers for evaluating big data (David *et al.*, 2016). While other more sophisticated flow routing models could be used and would be appropriate at finer scales, RAPID works well for this WaVE process because it handles a large number of watersheds.

For flow routing of water networks within the United States, RAPID utilizes the NHDPlus dataset, an integrated geospatial hydrologic framework, and datasets built by the U.S. Environmental Protection Agency and U.S. Geological Survey. NHDPlus combines the vector National Hydrology Dataset (NHD) stream network and Watershed Boundary Dataset (WBD) hydrologic unit boundaries, together with the National Elevation Dataset (NED) gridded land surface, to show each NHD stream segment's local catchment area. A catchment area layer contains water flowline, sink-points, area features and bodies of water. NHDPlus produces the stream network datasets' flowline attributes using five flow estimation models.

The first version of NHDPlus (NHDPlus V1) launched in 2006, and NHDPlus version 2 (V2), debuted in 2012. Both feature the NHD 1:100,000-scale stream network and the 30-meter ground spacing (1 arc-second) NED. NHDPlus V2 features over a thousand isolated networks in the NHD, NED coverage for over 40% of the country, and WBD expanded to cover all the U.S. (Wieferich *et al.*, 2015). Currently under development is the USGS High Resolution NHDPlus (HR-NHDPlus), with the stream network resolution increased to a 1:24,000-scale and the 10-meter ground spacing (⅓ arc-second) NED (Moore and Dewald, 2016).

The model estimates streamflow by associating stream segments in each catchment with temperature, rainfall and runoff data. NHDPlus uses elevation to compute stream slope, streamflow and velocity, and other associated attributes (David *et al.*, 2011).

Analysis and Estimates

In order to test the methodology for visualization analysis, a comparison and contrast system was developed to better understand the dataset relationships and dataset requirements for any given watershed tested. For this analysis, a watershed basin case study was developed in order to analyze for both a quantitative and qualitative measurement perspective regarding the interaction between watershed basin datasets available for each given watershed tested and the basic methodology correlation comparison between the given watersheds tested. (See summary analysis in the Study Regions section and the Discussion section.)

Mapping streamflow and inundation forecasts

For this large model array to be visualized, the data needs to be mapped. WaVE uses an integrated automated process to geoenable (i.e., associate with geospatial properties) and publish these runoff forecast data using a multi-scale temporal map service. The maps are published at multiple scales in order to be viewed and show varying degrees of detail at different levels.

NHDPlus provides an identification number for each stream segment within a watershed. The time series for each identification number gets loaded into a geodatabase, where each stream reach is a mapped feature with an attached time series flow forecast. Knowing the associated time is particularly important in visualizing forecasted streamflow on a timescale. For flood awareness and mitigation, WaVE combines streamflow forecasts from NHDPlus with visualization of flood extents (i.e., inundation mapping) and the impact by inputting data from a flood inundation database and using the multi-scale temporal map service to generate visualizations of flood extents and impacts. This flood inundation database is rendered on a geo-enabled rating curve that correlates flood depth with flood extent for each watershed reach. To visualize water flow and understand depth for purposes of developing an inundation map, terrain is analyzed and pre-calculated for each modeling reach. Flood extent, depth of flooding, and water surface elevation are all calculated for a series of incremental depths. A pre-existing observed rating curve can be used, or a synthetic one can be derived based on proven and tested hydraulic assumptions.

Once the streamflow and inundation forecast data are prepared, the WaVE toolset can generate down-scalable flood maps using a Raster Function Template (RFT) model. Using the RFT model, several analytical functions available right out of the box are chained together to create a complex model that can be used to perform on-the-fly analysis. This analytical capability can be extended using the Python Raster Function and Height Above Nearest Drainage (HAND) (Nobre *et al.*, 2011). Flood maps are then created using a combination of HAND Raster Mosaic, Catchment Raster and the resulting visual model. HAND is a terrain model that normalizes topography according to the local relative water heights found along the drainage network by combining flood inundation mapping catchments and flow lines with elevation (DEM). The model defines river channel geometry and flood inundation extent for 5 million kilometers of stream reaches over the continental U.S.

3.4.1.3 Phase 3—Performing

In the third and final phase of WaVE, the performing step is publishing the forecast data and mapping the results as web services. Forecasted visualization maps can be consumed in a wide variety of web and mobile application services for a broad spectrum of end users. The capabilities of the applications are determined by the kinds of services that are published, as well as by the capabilities of the user applications. These variable map applications include: flow at a location, flow along a reach, depth at a location, and depth raster needs. By publishing the modeling results as web services, the results become widely accessible, not just to specialists in the science, water resources managers and emergency management communities, but to the concerned public, including residents living in a floodplain or business owners affected by potential floods.

The multi-scale temporal map services are then used by various web applications related to predicting and responding to hydrologic events. Configurable application template builders are available on a larger platform based toolset to easily create and publish interactive analytic applications (see Figure 3.5).

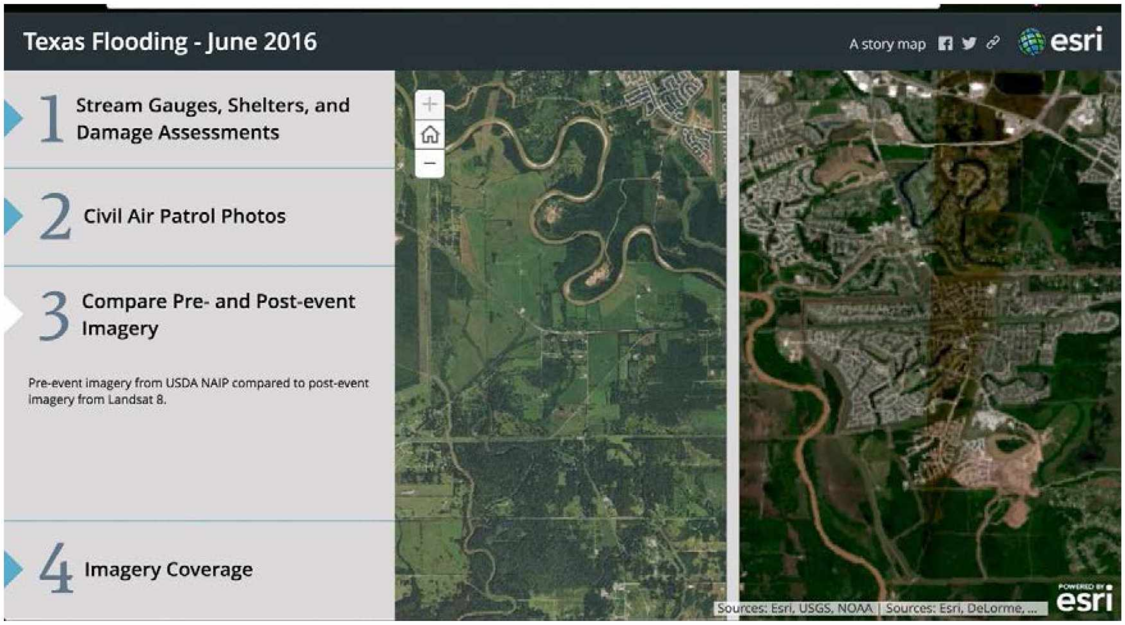

Figure 3.5 Screenshot of an interactive June 2016 Texas flooding ArcGIS Story Map. An example of ancillary flood data that can be integrated into WaVE, showing moveable split screen comparing pre- and post-event satellite imagery of flood area.

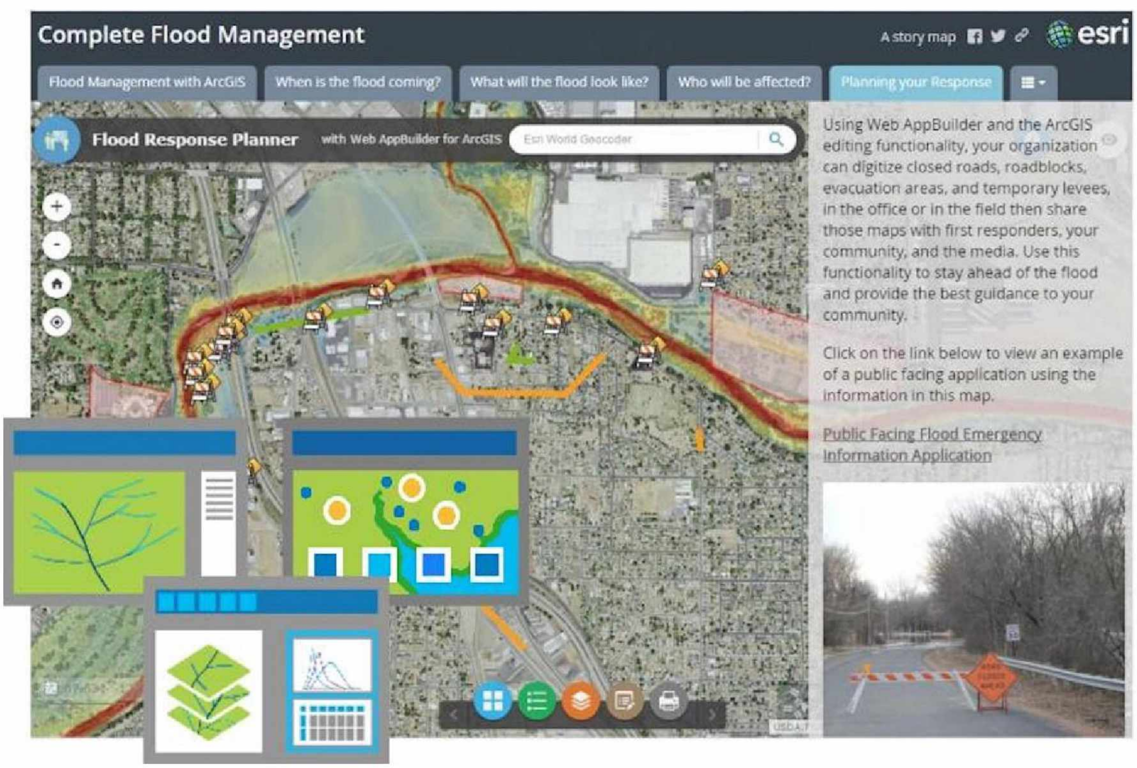

Figure 3.6 Screenshot of a dynamic interactive flood inundation map and ArcGIS Story Map. An example of ancillary flood data that can be integrated into WaVE.

Web applications like these are now much easier to create by using prebuilt configurable application templates or creating the user's own design using drag and drop widgets, including the user's published web maps, and mashing them up with other data. These apps can be 2D, 3D, time-enabled and combined with analysis tools, and can all be built responsively for browser, tablet, or phone. Based on the availability of national, regional and local data, WaVE's GIS based pre- and post-processing tools are available to support a modular framework for runoff forecast impact analysis anywhere in the world by selecting either the WRF-Hydro or ECMWF forecasting model systems (see Figures 3.5 and 3.6).

3.4.2 Building the future model—enhancing the framework for accuracy and localization

Transforming knowledge into action

In order to be confident that first responders are making decisions that accurately reflect the reality of a crisis event, decision makers need to be confident that they have previously considered and made sense of all the relevant observations and information before they can strategize, plan, create and implement response scenarios (Walle and Turoff, 2008).

Muhren and Walle (2010) define this sense-making as contextualizing and making understandable a situation or scenario when there is an absence or loss of meaning, a period often precipitated by "unforeseen changes in the environment which break the imaginary link between expectation and reality and force actors to reevaluate what they are doing and where they should go." To make sense of all the various bits of structured and unstructured data and often conflicting human interpretations, responders need and search for the right frame of reference they can use in order to interpret, contextualize and draw insight for making decisions and acting.

In crisis situations, where events often unfold very quickly and there is a high degree of uncertainty regarding what is known or needed to be known, responders usually either lack an adequate frame of reference (ambiguity) or are confronted with multiple, conflicting interpretations and frames (equivocality). Decision makers can develop an adequate frame of reference or reduce the equivocality of multiple frames by making use of a variety of sources to notice what is going on around them, interact with others, and communicate with others to enable action. A well-designed EMDSS can provide the means for dealing with ambiguous or equivocal frames of reference (Muhren and Walle, 2010).

Having a common operating picture (knowledge base), the conditions for which must be developed before a crisis event, is essential for sharing information, coordination, focused action and support among different geographically diverse organizations and jurisdictions. While in reality, sense-making, decisions and actions are carried out at individual group levels according to roles and competencies, emergency management without a common operating picture tends to revert to hierarchy as a means of control (Comfort, 2007).

WaVE is an integrated support system that aggregates relevant hydrologic and ancillary data, analyzes that data, and publishes the geoanalytic results using commonly-shared (yet providing user-defined customization) geovisualization platform and toolsets for flood event situational awareness and EMDSS (see Figure 3.7).

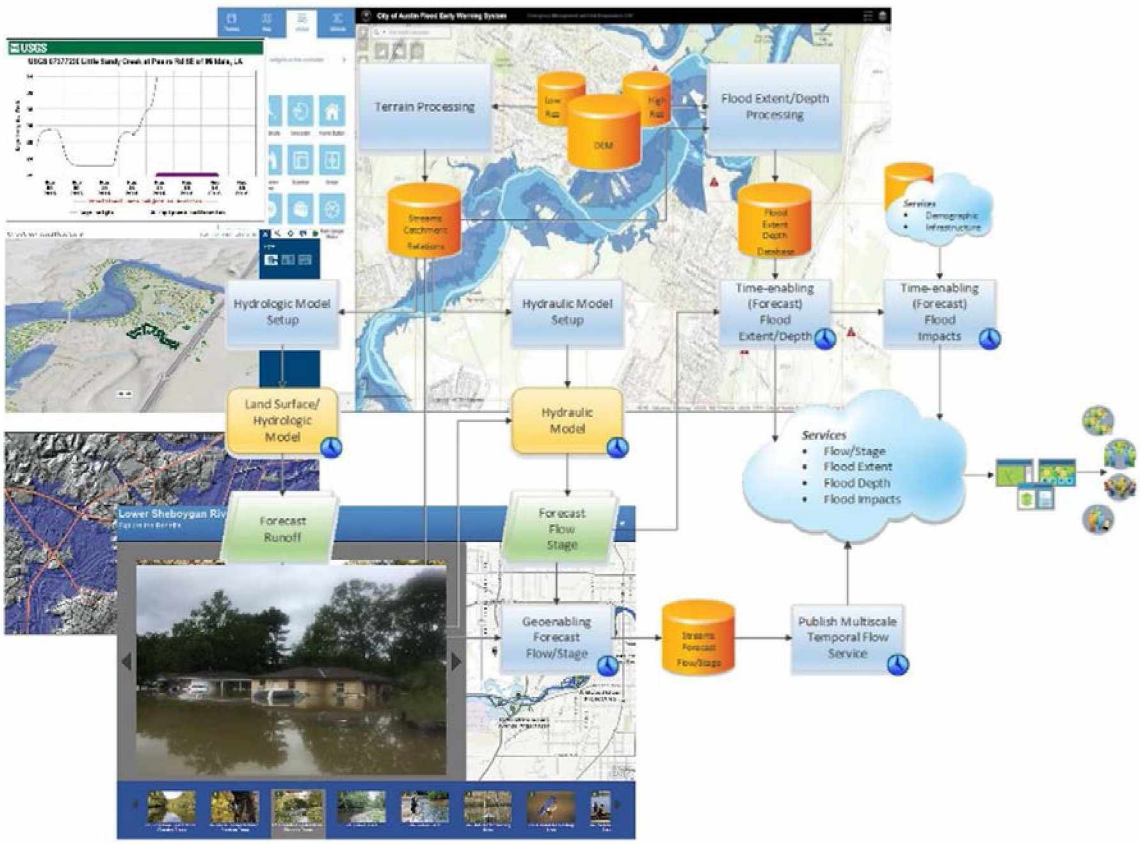

Figure 3.7 Integrating geospatial analytics, visualization and machine learning.
WaVE's common operating picture framework and decision support toolset. Images courtesy of Esri.

Integrating Machine Learning for enhancing river flow accuracy

Accuracy and reliability of data are critical for decision makers, not only as a basis for making time-sensitive and effective choices, but also as factors that influence the level to which decision makers trust, adopt and use these tools. The next phase of development of WaVE will likely integrate a hydrologic machine learning predictive model developed and tested by the authors (and currently under peer review for publication). This new model will interpolate and extrapolate streamflow and inundation data for gaged and ungaged catchment channels, and test, analyze and score the degree of both accuracy and uncertainty for results from other hydraulic models.

Developed in collaboration with researchers from Microsoft and leveraging the latest Esri GIS hydrology and Microsoft Azure cloud computing technologies, this new predictive model of SHEM (either standalone or integrated with WaVE) can:

- Provide accurate and timely proxy streamflow data for inoperative streamgages (i.e., offline or damaged during flood events).
- Interpolate data from ungaged streams deemed to be similar to proximally indexed gaged streams.
- Be used to identify the optimal locations for positioning physical streamgages.
- Estimate streamflow in ungaged water catchments using datasets derived from satellites and other remote sensors.
- Create a virtual streamgage historical index for interpolation of missing discharge data and extrapolation of forecasted discharge.
- Compare and test runoff forecasts developed from WRF-Hydro and ECMWF models.

Using cloud computing to compute billions of data elements, the model relies on machine learning to process (i.e., teach itself) and interpret large volumes ("big data") of historic complex hydrologic information. The model uses this information to construct a virtual dataset index of correlations and groups (clusters) of relationship correlations between selected streamgages in a watershed and under differing flow conditions. These estimates are continuously tested, scored and revised using multiple regression analysis processes and methodologies. WaVE can then integrate this continually updated, forecasted and real-time streamflow data into its framework.

Integrating this machine learning correlation indexing model enables WaVE to utilize large volumes of forecasted data to make more accurate predictions and better test local-downscaled inundation map models in the future.

Developing satellite remote sensing to derive streamflow data

The United States has upwards of 8,000 streamgages, yet there is a continued demand from water resource managers and flood emergency managers for more streamflow information, especially during a flooding event. Many streams and large portions of streams throughout the country lack *in situ* gauge measurement resources. In response to this lack of streamgage availability, Gleason (Gleason and

Smith, 2014) designed the At Many-stations Hydraulic Geometry (AMHG) model to derive streamflow discharge data estimates solely from multiple satellite imagery. This innovative computational riverine research is an example of RS application being developed to meet the demands of the quantity and quality of data required for WaVE framework integration. In the AMHG model, Gleason describes its functional research relationship to river streamflow by using RS and computational analytic river flow width (w), mean streamflow depth (d), and mean velocity (v) in order to build a critical discharge (Q), where Q = wdv. Significant practical applications using this discharge data can be developed for the building of inundation maps with WaVE's framework, by using RS discharge river datasets, building a historical indexing river (Q) dataset system, and then integrating new methodology applications outlined in the machine learning analysis. Three of the four watersheds highlighted in the case study section below used AMHG methodology for measuring river discharge which can then be used for building historical and actual inundation maps using the streamflow estimation methodology and WaVE framework.

3.4.3 Study regions: Testing integration analysis

WaVE was studied and tested at watershed sites in four U.S. geographical regions, chosen for their diversity in topography, river geomorphology, climatic conditions, population in the environs and the amount of available data from various hydrologic computation models: (1) Southwest United States (Texas), (2) Central United States (Louisiana), (3) Northwest United States (Idaho), and (4) the far north Arctic region (Alaska). The broad variety of local conditions in these settings belong to five of the ten main land cover classes by GlobCover (GlobCover, 2016) and represent four of the five types of climate classification (see Table 3.2) (Peel *et al.*, 2007).

Table 3.2 Land cover & climate characteristics of watersheds

	Land cover (Peel)	Climate (GlobCover)
Texas: Colorado River Watershed	Sparse vegetation and crops, Urban	Arid
Louisiana: Mississippi River at Baton Rouge Region Watershed	Mosaic cropland or grassland, Urban	Temperate
Idaho: Boise River Watershed	Closed to open forest, Mosaic cropland or grassland, Urban	Cold
Alaska: Tanana River Watershed	Closed to open forest, Mosaic vegetation Urban	Sub-Polar

The three-phase process of Gathering, Processing and Performing, described in the methods section, was used to test WaVE in order to evaluate its capability and effectiveness in downscaling data from a global, national and regional level to the local level (as close as possible, depending on data availability and spatial resolution of the underlying hydraulic model and DEM), with the goal of transforming this data into a visualized local level flood inundation map. With the goal of eventually incorporating into WaVE other application models that derive discharge for forecasting purposes, two additional models were tested: a machine learning hydrology estimation model and a satellite RS model.

Texas: Colorado River Watershed Basin

This Texas watershed basin has an arid climate with minimal seasonal rainfall, mixed sparse vegetation in the upper watershed, and irrigated crop vegetation. The region is directly impacted by irregular storms and hurricane events that can cause high flash floods in an area with a large population at the base of the watershed, threatening significant property damage and loss of life. To help prevent or mitigate these flood risks, water managers and floodplain managers face the challenge of balancing reservoir storage levels and flood control systems.

When WaVE was tested on the Colorado River watershed, it successfully downscaled the available data and produced a forecasted enhanced inundation map of the national and regional levels, but lacked adequate data to be able to downscale to the local level.

Figure 3.8 depicts an example of the dynamic, interactive and time-sequential WaVE screenshots of the Colorado River watershed. They demonstrate streamflow estimation using 6 hour intervals over a 10-day occurrence highlighting the ability to simulate forecasted streamflow with precipitation impact of national, state, regional, and partial local watershed regions. This same process, generating visual enhanced streamflow models, was also created on each of the other three watersheds with different outcomes.

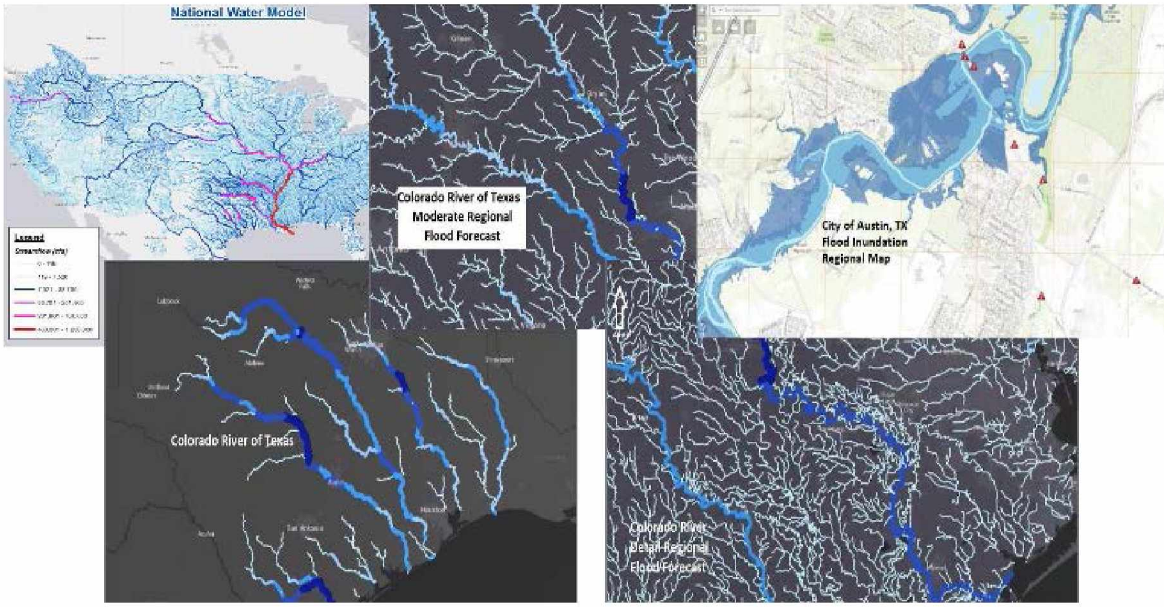

Figure 3.8 Plates created by WaVE demonstrating scaled levels of geospatial streamflow. Forecasted and real-time images courtesy of Esri and designed using ArcGIS 10.3 and Arc Hydro.

Louisiana: Mississippi River, Baton Rouge Regional Watershed

A segment of the Mississippi River within the Baton Rouge regional watershed basin, located in the central-southern U.S., was selected for its temperate climate, mosaic vegetation, and the broad river basin's high flood impact on local populations. Large volume water accumulation during rain runoff can result in high flood inundation, creating a flood hazard potential for the large number of residents, particularly in the Baton Rouge community.

When WaVE was tested on the Mississippi River within the Baton Rouge watershed, the model successfully downscaled the available data and produced an enhanced inundation forecast map at the national and regional levels, but lacked adequate data for downscaling to the local level. The two maps portrayed in Figures 3.9 are historically accurate, localized inundation maps that have been verified by local flood officials at the end of the August 2016 flood event in Baton Rouge. Localized inundation maps like these were used to validate WaVE's prediction of inundation in all four study regions.

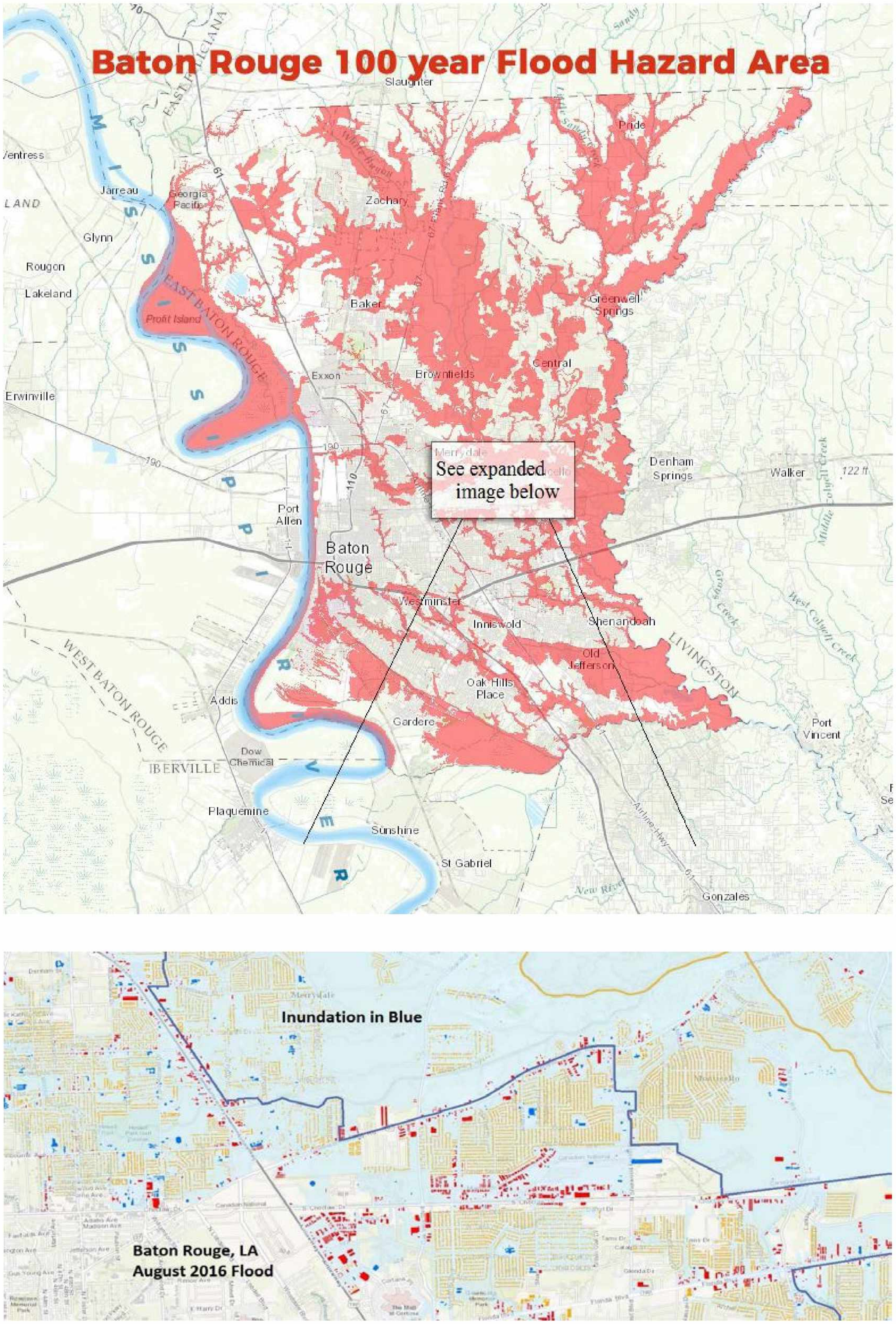

Figure 3.9 Flood inundation map of August 2016 Baton Rouge Regional Area. Images designed using ArcGIS 10.3 and Arc Hydro and the Federal Emergency Management Association (FEMA) datasets.

Idaho: Boise River Watershed

The Boise River basin is located in the Northwest United States, west of the Rocky Mountains, with high mountain ranges and steep slopes east and north of the city of Boise. The land cover is closed-to-open forest and mosaic cropland. This watershed was selected for its combination of high flood inundation events caused by irregular seasonal rainfall that can occur in early spring; the melting of large accumulations of snow in the mountains creates high volumes of spring runoff that can result in flash floods that threaten the state capital's large population and surrounding communities. In this watershed basin, water and floodplain managers have to balance water storage capacity for agriculture and water utilities with necessary flood control precautions and measures.

When WaVE was tested on the Boise River watershed, it successfully downscaled the available data and produced a forecasted enhanced inundation map of the national and regional levels, but lacked adequate data and adequate DEM spatial resolution to be able to downscale to the local level.

Figure 3.10 Forecasted inundation.
Plates demonstrating WaVE forecast and pre and post flood inundation in downtown Boise. Images courtesy of Esri and designed using ArcGIS 10.3 and Arc Hydro and Google Map services.

The images in Figure 3.10 highlight and demonstrate streamflow estimation using 6 hour intervals over a 10 day occurrence, illustrating the ability to simulate forecasted streamflow with precipitation impact on a state and regional level. However, lack of high resolution datasets prevented WaVE from downscaling to the local level with the detail requested by emergency responders for the watershed region. This same process was implemented on each of the other three watersheds with different outcomes.

The Boise River Watershed was specifically selected as part of this case study because of the availability of many years of informationally-rich, well-documented hydrology streamgage data for testing the machine learning methodology. Together with near real-time data, the historical data were measured and applied to acquire historical discharge rates that could be utilized for flooding events like the August, 2016 Baton Rouge flood event when streamgages stopped transmitting and information was lost as a result of the flood.

Although all four watersheds received preliminary testing for the machine learning process, the Boise River watershed provided the most complete data to utilize the methodology. The Texas and Louisiana watersheds demonstrated adequate hydrological *in situ* data to use this methodology in the future. The Alaska Tanana River watershed lacks the necessary *in situ* discharge data at this time to use the machine learning methodology.

Alaska: Tanana River Watershed

The Tanana River watershed is a large, glacially-defined riverine system formed by numerous mountain ranges and arctic streams within the central part of Alaska. The region is characterized by a sub-arctic climate and land cover of closed-to-open forest with mosaic vegetation. This watershed was selected because of the complex flooding events caused by large amounts of snow runoff in the spring that flow into and meet with ice sheets in the Tanana River. Since much of the inland (non-coastal) Alaskan human population is located in the city of Fairbanks and within the Tanana River drainage basin, this frontier city is often threatened with the possibility of extensive riverine flood devastation (see Figure 3.11).

When WaVE was tested on the Tanana River watershed, it successfully used the available data to produce a broad national hydrology water map using both the WRF-Hydro and ECMWF. However, the lack of *in situ* discharge measurement tools prevented the ability to gather the data needed to produce an enhanced inundation forecast map at even the regional level for the Tanana River. Anticipating these limitations, the AMHG remote sensing application was used as another means of forecasting inundation. Testing AMHG (Gleason *et al.*, 2014) parameters and cross-referencing the research on several of the lower latitude watersheds provided tangible research data for further investigation for the WaVE integration model. Analysis results are highlighted in Table 3.5 below. The need still exists to develop tools for gathering discharge data that will operate in this high northern latitude region.

Figure 3.11 Aerial photo and Landsat image of Tanana River.
(1) Aerial photo (provided by U.S. Army Corps of Engineers) of the braided Tanana River outside Fairbanks. (2) Tanana River USGS Landsat imagery used to analyze and test the accuracy of AMHG model's river discharge estimates.

Data analysis methodology and indicator and agreement comparison

Table 3.3 below provides a summary of the assessment of WaVE's methodology for visualization downscaling for each case study flood inundation map analysis at the national, regional and local level.

Table 3.3 WaVE—Forecasted data visualization downscaling analysis (flood inundation map)

Case Study	National	Regional	Local
Texas	Yes	Yes	No
Louisiana	Yes	Yes	No
Idaho	Yes	Yes	No
Alaska	Yes	Partial	No

Applying the WaVE methodology to each case study region, a comparative and contrasting quantitative and qualitative measurement analysis was created by testing available datasets within the full integration framework as a downscaling analysis (see Table 3.4).

The quantitative measurement analysis, that was conducted, compared and correlated the visualized map results of forecasted (pre-) integrated datasets and actual (post-) integrated datasets, and evaluated the available forecasting datasets and the downscaling process for each study region. Using Pearson linear correlation coefficient (r), the formula for testing and analyzing the forecasting (pre-) and actual inundation (post-) event dataset for each watershed basin is as follows:

$$r = \sum_{i=1}^{n}((x_i - \bar{x})(y_i - \bar{y})) \div \sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{3}$$

In this equation, (x) is the forecast dataset collection event, (y) the mean of the actual dataset (post-) collection event, ($\bar{x}$)is the mean of (x), ($\bar{y}$) is the mean of (y), and (n) is the time (in days) of a forecasting time scale event (Equation 3). Note: The forecasting datasets for each tested watershed contain multiple variables and integration processes for each location, measurement, and time, are not evaluated for dataset quantity. Therefore, testing with large quantity data methods, including root mean square, mean absolute error, and R-square error calculations was not performed on this regional case study project at this time.

Table 3.4 WaVE—Forecasted data visualization analysis of (pre-) and (post-) dataset detection

				Qualitative Assessment	Quantitative Assessment
Case Study	Forecasting Downscaled	(pre-) effectiveness	(post-) effectiveness	Time-Series Effectiveness	Correlation Tested
Texas	Partial	Yes	Yes	Yes	0.61/poor
Louisiana	Partial	Yes	Yes	Yes	0.61/poor
Idaho	Partial	Partial	Yes	Yes	0.41/poor
Alaska	Partial	Partial	Yes	Partial	0.10/very poor

Future application models for WaVE framework

All four watersheds received preliminary testing for the hydrology machine learning prediction model for discharge analysis using *in situ* measurement data and the AMHG model for discharge analysis using RS measurement data. During a flooding event, providing estimated forecasting discharge data and integrated WaVE methodology, a new estimated inundation map for first responders on a local level could be assessed. Table 3.5 summarizes the test results of all four watersheds for both the authors' hydrologic machine learning model (previously described) and the AMHG model (Gleason *et al.*, 2014).

Table 3.5 WaVE framework—Forecasted data
Using machine learning & AMHG for gauging river discharge and flood inundation maps.

Case Study	Machine Learning Discharge Value	AMHG Discharge Value	Comments
Texas	Partial	Not tested	More testing required
Louisiana	Partial	Yes - 0.91/very good	Good long term dataset
Idaho	Good	Yes - >0.80/good	Good long term dataset
Alaska	No	Yes - <0.20/poor	Minimal gauges/Braided River

3.5 Discussion

The purpose of WaVE is to provide flood event decision makers with enhanced geoanalytic visualization (common operating picture) and user-customized DS toolsets for contextualizing, making sense of and acting upon accurate and scalable hydrologic and ancillary flood data. The previously described case studies were conducted to test and demonstrate the functionality, reliability, and effectiveness of the WaVE framework and toolsets (including the use of machine learning for estimating proxy streamflow data) under diverse geomorphology, streamflow and flood-related conditions at national, regional and local levels. Results from these case studies highlight some of WaVE's inherent strengths (both existing and potential), limitations, and the need for further development.

3.5.1 Capabilities and functional validation

Framework, downscaling, and visualization

The primary goals of the case studies were to:

- Input, aggregate, and prepare historical, real-time and forecasted data used in baseline analyses, models, estimate comparisons and tools.
- Demonstrate the ability to downscale and utilize national precipitation, flood forecasting, hydrography, and landscape topography datasets to the regional and local scale level (depending on DEM spatial resolution and availability of streamflow and inundation data).
- Demonstrate the use of hydrologic machine learning to produce accurate streamflow estimates that can be integrated into WaVE models.
- Transform this downscaled data into visualized local-level flood inundation forecasts and other useful actionable flood-related knowledge elements of where, when, and what.

- Develop a precipitation, flood forecast visualization map for each of the watersheds and compare their output maps with some form of calibration for pre-, mid-, and post- processing integration of data sets for all technologies into functioning GIS platform characteristics for each of the watershed regions.
- Demonstrate how other models and model results can be integrated into, analyzed and geospatially visualized using WaVE.

Three of the case studies—Texas, Louisiana, and Idaho—provide clear parameters and datasets for a fully integrated test analysis for the WaVE framework as applied to different types of land use and local and regional roles in watershed flooding events. The fourth case study area—Alaska—was used to develop the data requirements. As discussed below, the lack of ground station measurements results in a limited availability of streamflow data and highlights the importance of RS as a source of data.

All six goals of the case studies were achieved to varying degrees according to the availability, quality, and spatial resolution of the data. Overall, the results from the case studies indicate that WaVE can capably and effectively downscale forecast data, as well as transform that data on-the-fly into dynamic streamflow routing and inundation maps. Analysis of forecasted case study map results, compared and contrasted with actual flood inundation maps, demonstrated a medium to high correlation and degree of accuracy.

Ubiquity, flexibility and extensibility

Addressing fundamental limitations of existing flood visualization tools and EMDSS, WaVE was intentionally designed to use a standard and widely available software architecture, together with a flexible and extensible framework that could be easily adapted to users' needs and integrate their existing tools and data. The lack of ubiquitous, interoperable, flexible and extensible systems and standardized data formats are primary reasons why many decision makers and communities either don't acquire flood awareness and EMDSS or are unable to effectively utilize existing programs.

Which flood models and data acquisition methods are selected by users depends on many factors respective to those individual communities (Legleiter *et al.*, 2014). For some floodplain communities, current and traditional flood modeling methods demonstrate tolerable flood analyses, supportable technical complexity, acceptable cost effectiveness, and leverage existing structures for in-place procedures. Acquisition and adoption of new technologies to build flood hazard prediction models may be unacceptable due to perceived costs—additional time and training requirements, the restructuring of old programs, problems associated with the short-term loss of flood programs, accuracy issues of flood prediction tools, or even the increased cost of hiring new staff. Furthermore, for many practitioners, these models and tools simply are not seen as sufficiently accessible or useful to justify acquisition and adoption. This is due to the fact that these models and tools are generally computationally complex, data-intensive, and accessible only to the domain experts who build them, frame the issues, model the results, and design the products they've determined practitioners need (Leskens *et al.*, 2015). Plus, for many users, accessing near real-time data is expensive and often cost-prohibitive.

Other user groups are willing to undertake the transition because they perceive the realized and potential future benefits to be greater than short-term considerations and the cost of acquiring new emergency flood mapping resources or restructuring existing ones. For these groups, however, such a transition is complicated by the variances in user needs, availability of required data and resources, and limitations of satellite-based flood detection systems (Revilla-Romero *et al.*, 2015). The frequent lack of data continuity from one region to another, the lack of historic flood images, and the poor quality of available data often result in poor coverage datasets. Disruptions of datasets often created by the use of different platforms and access points imagery by data providers further complicate flood map development.

To address many of these limiting factors, the authors constructed WaVE to enable potential users to leverage already-owned and familiar building blocks of architecture, platform, framework, mapping and GIS tools. The core WaVE framework is built upon Esri ArcGIS (v. 10.3) and Arc Hydro (v. 10.3) platforms and software architecture for three key reasons: (1) most potential U.S. institutional users are decision makers at the federal, state and local government levels that already have Esri institutional licenses and ArcGIS–Arc Hydro platforms and applications; (2) users' existing programs and datasets can be integrated into the full Esri suite; and (3) many hydrologic models (whether open source or proprietary) in current use or under development (e.g., WRF-Hydro, NHDPlus, RAPID, Tethys, USACE's Hydrologic Engineering Center's River Analysis System, HAND, etc.) are all built on top of Esri's ArcGIS architectural platform. The worldwide GIS market is highly fragmented (Roth, 2013) and consists of a wide spectrum of open source, public and proprietary systems that often use incompatible, non-standardized platforms, data formats, etc. By contrast, ArcGIS, while owned by Esri, is the most common GIS mapping platform worldwide.

WaVE is being designed in collaboration with Esri engineers to seamlessly integrate a suite of mapping, design and analytical tools, as well as to make the WaVE framework sufficiently interoperable and extensible in order to integrate or couple with other open source, public, or proprietary models and data sources. As part of the case study demonstrations, various other models or their resulting datasets were integrated and tested with the WaVE framework.

Additionally, the case studies also show that WaVE's framework accommodates data from newly-developing research models that use hydrologic machine learning and satellite RS imagery. These models interpolate or extrapolate estimated streamflow data in gaged and ungaged rivers, thereby providing valuable datasets of streamflow estimates. This data can then be integrated into WaVE's forecasting and prediction model and downscaled to the local level, expanding the possibility of developing new, accurate and predictive inundation maps. Although WaVE presently uses Microsoft's Azure cloud computing platform, it is also compatible with other cloud services (e.g., Amazon, Google, IBM, Oracle or open source), further illustrating WaVE's flexibility and extensibility.

3.5.2 Limitations

While validating the overall WaVE framework and model, the case studies also highlighted WaVE's inherent dependence on adequate historical streamflow and inundation forecast datasets and sufficiently high spatial resolution DEM and hydraulic model results for downscaling visualized data at the local level.

Testing the WaVE model at different geospatial scales (e.g., regional or local) requires high spatial resolution and detail of elevation and terrain, as well as adequate historical streamflow data. For some areas, there is neither sufficient data nor high enough resolution for adequate regional or local analysis and forecasts.

Inadequate streamflow and inundation data

Another significant limiting factor in the adoption and utility of contemporary hydraulic models and flood inundation maps is the lack of standardized and accurate streamflow and ancillary hydraulic data (Revilla-Romero *et al*., 2015).

Severe climatic conditions or geographic inaccessibility in some regions greatly limit the ability to place and maintain a sufficient number of *in situ* streamgages for measuring and recording quantitative data of river discharge. For example, many rivers in the arctic regions, like the Tanana River, lack evenly-spaced *in situ* streamgages to gather quantitative data of river discharge along the full flow of the watershed, thereby restricting the ability to provide advance warning of a flood event to the surrounding communities.

In order to supply historical or real-time data estimates for gaged streams with non-transmitting gages or for ungaged streams, WaVE utilizes a new hydrologic streamflow estimation model to create proxy datasets by either interpolating missing data for interruptions in streamgage datasets, or to extrapolate forecasted estimates using machine learning and correlation indexing.

Another potential source of gathering critical streamflow data for ungaged rivers is remote sensing. RS is being researched as an alternative for measuring streamflow and forecasting flood inundation, but currently river discharge cannot be directly measured from any known satellite or airborne sensor. Gleason (Gleason *et al.*, 2014) created a systems model of measuring streamflow, highlighted in the case studies, that estimated river discharge using sequenced remotely-sensed images of the river's flow dynamics, physiographic characteristics, and computed geospatial and temporal measurement estimates. Gleason's analysis required no *in situ* measurements, but rather utilized hydraulic geometry that focused on river width, depth and other empirical parameters from remote sensed imagery to estimate measurements of log-linear velocity and discharge. This research process, now referred to as the "at-many-stations hydraulic geometry" (AMHG) model, was evaluated for potential integration into WaVE as an analysis tool.

Challenge for localized data downscaling

A second primary goal of WaVE—effectively scaling flood inundation and streamflow mapping down to a local level, whereby a first responder can accurately determine the extent and depth of inundation at any point along a stream—requires higher spatial resolution and detail of elevation, terrain, and streamflow data than what is currently available in most locations.

While insight at national and regional levels is useful for analyzing trends, it is often of relatively little use to local decision makers who need accurate real-time or nearly real-time information at the local scale to both anticipate and prepare for flood events, as well as tailor mitigation actions and responses.

The focus of research and the availability and spatial scale of data related to RS has shifted from global and national to regional and, increasingly, local. While moderate resolution imaging and passive microwave satellite observation datasets are valuable sources of land surface hydrological information, more frequent and quickly accessed and processed satellite images are needed to evaluate RS as a reliable and effective source of data for analysis and mapping. Combining remotely sensed data with ground-based information provides a more comprehensive overview than just *in situ* streamgage data of the holistic watershed, including landscape topography, geology, watershed drainage, soil moisture, visual history of changes in river water flow drainage, and variables due to weather and seasonal changes (Bjerklie *et al.*, 2005). Of the two RS methods, satellite imagery from SAR platforms is seen as superior for showing and measuring repeatability of land change awareness, whereas lidar technology toolsets are preferred for achieving local ground awareness (Smith *et al.*, 2006).

Currently only a small percentage of the surface elevation of the U.S. (lower 48 states) has been digitally mapped using lidar, and an even smaller percentage of the country (most of that in Alaska) has been digitally mapped using IfSAR (U.S. Geological Survey, 2012). A small percentage of the lidar-mapped surface is mapped at a high enough spatial resolution for effective down-scaling and localization. As higher resolution data becomes available, WaVE will be able to provide localized mapping with greater accuracy and granularity.

3.5.3 Further research and development

The research and testing of WaVE has revealed that in order for this framework to deliver downscaled, localized, predictive, and high resolution inundation maps for emergency responders and flood managers, higher quality streamflow, elevation and remote sensed data are needed.

Additional studies are planned for testing the WaVE model at the local level as higher resolution digital elevation data becomes available. In order to accomplish this, the following research and development will be essential:

- The systematic gathering of more complete elevation data and higher quality topographic data. This will require federal, state and local engagement. One example is the USGS 3DEP initiative currently being developed to systematically collect enhanced elevation data using lidar and IfSAR.
- Further testing and integration of the hydrological machine learning model into WaVE, providing predictive datasets for streams that are ungaged or with gages that have stopped transmitting streamflow data.
- Expanding the testing of AMHG as an integrated model for generating streamflow estimates for ungaged rivers. These estimates can then be processed by WaVE's machine learning correlation indexing to generate water discharge datasets.

3.6 Conclusion

There is a growing consensus among the academic, policy and practitioner communities regarding the need for accurate, scalable, and highly granular geospatial and analytic data at the local level for flood event situation awareness and EMDSS. Furthermore, there is also a general agreement about the need for decision makers to be able to easily access that information in a timely fashion, quickly make sense of all the salient issues related to the flood event, and share that knowledge within a common operating picture with other decision makers in geographically distributed organizations and jurisdictions.

WaVE addresses this need with an integrated support system that provides enhanced geoanalytic visualization (common operating picture) and DS toolsets. To achieve this, WaVE aggregates relevant hydrologic and ancillary data, analyzes that data, and publishes the geoanalytic results using a commonly-shared, yet user-customizable, geovisualization framework and toolsets for flood event situational awareness and EMDSS.

Four case studies were conducted to test and validate the WaVE framework and toolsets under diverse conditions at national, regional and local levels. Results from these case studies highlight some of WaVE's inherent strengths, limitations, and the need for further development. WaVE has the potential for being utilized on a wider basis as data becomes available and models are validated for converting satellite images and data records from RS technologies into accurate streamflow estimates and higher resolution digital elevation models.

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3.8 Abbreviations

3DEP: 3D Elevation Program; ALS: airborne laser scanning; AMHG: At Many-stations Hydraulic Geometry; DEM: digital elevation model; DSS: decision support systems; ECMWF: European Centre for Medium-Range Weather Forecasts; EMDSS: emergency management decision support systems; GFS: Global Forecast System; GIS: geographic information systems; HAND: Height Above Nearest Drainage; IfSAR: interferometric synthetic aperture radar; lidar: light detection and ranging; LS: laser scanning; MLS: mobile laser scanning; NCAR: U.S. National Center for Atmospheric Research; NED: National Elevation Dataset; NHD: National Hydrology Dataset; NHDPlus : National Hydrology Dataset Plus; RAPID: Routing Application for Parallel Computation of Discharge; RFT: Raster Function Template; RS: remote sensing; SAR: synthetic aperture radar; TLS: terrestrial laser scanning; TNM: The National Map; USACE: U.S. Army Corps of Engineers; USGS:

U.S. Geological Survey; WaVE: Water-flow Visualization Enhancement; WBD: Watershed Boundary Dataset; WRF-Hydro: Weather Research and Forecasting Hydrological.

Chapter 4 Bridging Science-Water Policy Action Boundaries: Information influences on U.S. congressional legislative staff decision making[3]

4.1 Abstract

This paper provides a framework to evaluate how policy-makers interact with information, make decisions, and act upon policy-related information. To explore the influence of information in bridging water policy knowledge boundaries and linking policy decision making and action, the authors conducted a grounded theory study of key congressional legislative staff in the U.S. House and Senate involved in federal water policy development and oversight. Federal legislative water policies are largely shaped and developed by senior congressional legislative staff, whose policy priorities, decisions and actions are influenced by policy-related information. Three conceptual themes emerged from the study as common priorities for legislative staff: 1) developing trusted relationship-information networks; 2) prioritizing relevant stakeholder interests; and 3) maximizing efforts to achieve desired results. While the use of policy information is largely determined by the staff's multiple principal-agent roles, competing interests and other constraints, results of this study suggest that information quality criteria can be useful as heuristic tools for both intuitive judgments and reasoning of legislative decision makers and for transferring knowledge across science-policy action boundaries.

4.2 Introduction

This paper explores the degree to which generally-assumed criteria influence policymakers' use of information in decision making and legislative action. To accomplish this, the authors conducted a grounded theory research study of key congressional legislative staff involved in federal water policy development and oversight in the U.S. House and Senate. This study provides an interpretative lens for exploring how policy-makers interact with, make decisions on, and act upon policy-related information.

Traditionally, policymakers have called upon science and other fields of knowledge to produce and disseminate useful information for sound decision making. Such information, it is argued, would

[3] Petty, T. R., J. B. Gongwer, and W.E. Schnabel (2017). Bridging Science-Water Policy Action Boundaries: Information influences on U.S. congressional legislative staff decision making. Manuscript formatted for submission to the Journal of Environmental Science and Policy.

improve the process by clarifying issues and choices and help decision-makers successfully make the rational judgments that lead to desired outcomes (McNie, 2007). However, if decision makers do not perceive the information to be relevant or useful, then simply increasing the supply of accurate scientific information does not help inform policy.

In response to the perception that research has limited influence on policy because it is neither relevant nor useful, considerable discussion has taken place over the last decade or so to identify how best to bridge the so-called divide between science and policy and make information more useful to decision makers. Discussed in a later section, results from a number of studies have indicated that information (e.g., scientific information) must be perceived by decision makers as meeting minimal thresholds of specific quality criteria in order for the information to be considered or to influence policy decisions and actions (Cash *et al.*, 2003).

Refocusing the issue from simply providing "more and better" science to exploring how decision makers perceive the relevance and usefulness of scientific research has led to using this interpretive lens for revisiting issues of research structuring, funding, and results framing. This focus on policy utility has spawned numerous studies, calls for action, research methods, and models for science–policy interaction and decision making. Many, if not most, of these studies were written by or for scientists and specialists and were aimed at improving the shape of research, packaging research results, and crafting more effective communication in order to achieve greater influence of science on policy-making. However, despite the growing body of analytic literature and improvements, the perception persists that science continues to have relatively little impact on policy, regardless of this new focus on receptivity (Meinke *et al.*, 2006; Bauler, 2012; Lemos *et al.*, 2012).

While a few studies have presented the issue from the perspective of policymakers, there has been a relative absence of research or writing on the complex dynamics of how the policymakers themselves process information and make decisions.

4.2.1 Study context—water resources and the legislative process

The water management system in the United States is distributed among different entities and jurisdictions at the federal and state levels. Numerous federal government and independent commissions, from the Gallatin Report of 1808 to the report of the National Drought Policy Commission in 2000, have studied water policy and called for reform of the costly and counterproductive fragmentation and conflict, overlap, duplication, and ultimately the lack of overall accountability for land and water use impacts (Neuman, 2010; Christian-Smith *et al.*, 2011).

Today, at the federal level, water policy related to managing or regulating water resources is created through several mechanisms, most prominently federal agencies and Congress. In the Executive Branch, there are more than 25 federal bureaus and agencies with regulatory authority on water issues, additional boards and commissions with water-related programs and responsibilities, and over 200 separate federal directives, regulations, and laws (Gerlak, 2006; Christian-Smith *et al.*, 2011). Federal water policy, in part, consists of numerous legislative initiatives that deal with a large number of often unrelated issues and funding programs. There are more than a dozen major pieces of federal legislation related to water, and roughly 40 congressional House and Senate committees and subcommittees with various levels of oversight and policy input on diverse and often overlapping water issues (Allin, 2008; Cody *et al.*, 2012).

The legislative process grew significantly following the Legislative Reorganization Acts of 1946 and 1970, and this growing role has been mirrored in the expanding number of committees and committee staff members. Congress currently has twenty-one standing committees in the House and sixteen in the Senate, together with eight other special (or “select” or “joint”) types of committees. While having leveled off in recent years, staff numbers remain comparatively high, and today exceed the 1935 staffing levels by more than 500% (Shobe, 2014).

4.2.2 Role of senior legislative staff

As the legislative process has grown in sophistication over the past several decades, specialized congressional staff—historically often overlooked in literature on policymaking in the legislative process—have played an increasingly dominant role in crafting policy, drafting legislative history and statutory text, and shaping the process and outcome of national legislation (Schultz Bressman and Gluck, 2014).

As of September 2016 there were more than 15,000 staff in Congress. Legislative staff in both the House and Senate are generally defined by where they work and the functions they perform; these definitions roughly correspond with four main types or categories. In 2016 the breakdown of these four staff types were as follows: 1) 73% were legislative staff in the personal offices of individual members in the House and Senate; 2) 16% were staff that work in bipartisan committees (staff members answering to their respective party leadership in their committees); 3) 3% were staff in leadership offices; and 4) 8% were staff working for congressional officers and officials, including approximately eighty nonpartisan professional staff (0.5%) that worked in the Offices of Legislative Counsel (OLC) in the House and Senate (CRS Report No. R43946, 2016; CRS Report No. R43947, 2016).

This paper focuses on a small subset of senior legislative staff in personal offices and committees that work on developing legislation (excluding staff in the leadership offices and OLC staff), since most legislative initiatives and histories originate from personal offices and committees. Staff in the leadership offices are generally not involved in the drafting of legislative histories or bills, and OLC specialists generally take concepts, broad outlines and or rough drafts provided by other sources (e.g., personal offices or committees) and serve as the primary drafters that shape the statutory texts of legislation (Schultz Bressman and Gluck, 2014).

Due to a variety of constraints, members of Congress explicitly or implicitly delegate to their staffs varying degrees of autonomy and responsibility to manage their congressional duties and represent their interests in both daily operations and in critical legislative functions. Elaborated further in the Findings and Discussion section, this relationship of delegated authority has led to a number of studies that evaluate the roles and activities of congressional staff through the lens of agency theory and principal–agent models (Romzek, 2000). In these models, agents are individuals or groups who are authorized and delegated to act on behalf of another party, the principal. While most staff perform multiple principal–agent roles in the course of their duties, a relatively small number of senior or specialist staff perform a variety of complex, often overlapping, and sometimes conflicting roles in legislative development.

Several studies about the key influences on the congressional legislative drafting process confirmed the widely-held view that congressional members rarely draft legislation and or are involved in the actual crafting of legislative texts (Nourse and Schacter, 2002; Gluck and Schultz Bressman, 2014; Shobe, 2014). Instead, it is small groups of congressional staff that influence and draft most or all of the two primary products of the legislative process—legislative history and the bills that become enacted statutory texts. Broad policy concepts may originate from members of Congress, and legislators may initiate, sponsor and vote on the legislation, but modern statutes are largely the product of legislative staff—conceptualized by senior staff from personal offices or committees, researched by professional analysts, and drafted by nonpartisan professional legislative counsels (with initial drafts occasionally prepared by private third parties such as lobbyists), with monitoring and input from hundreds of committee staff and non-government organizations.

For staff in personal offices and committees, task and job functions vary depending on where the staff members work. Only a small percentage of personal office staff are involved in legislative development, with fewer yet involved directly in the statutory drafting process (Gluck and Schultz Bressman, 2014). Many congressional members may have legislative staff who cover water resources policy-related issues, but for most of these staffers these issues are normally only addressed when their member becomes involved in a related issue, floor debates, or votes. However, members who serve on committees related to water issues—particularly those with senior committee positions or those with strong personal or constituent interests—generally have senior legislative staff who have specialty knowledge of relevant water issues and often have experience in drafting legislation, networking, negotiating, and effectively navigating the legislative development process (Romzek and Utter, 1997). In comparison to staff in personal offices, a larger percentage of committee staff are involved in the policy development process—focusing on analyzing policy proposals, drafting legislation and building coalitions in committee, and negotiating on behalf of their committees and chairs (Romzek and Utter, 1996).

4.2.3 Information and decision making

National water policy priorities and decisions of congressional staff are influenced by competing interests, ambiguous or multiple frames of reference, and a variety of policy information sources. This information can be presented to staff from outside organizations and individuals (e.g., lobbyists, nonpartisan policy research organizations, industry groups and other issue stakeholders), generated informally through work relationships and informal networks (friendships with other staffers, social and professional circles, etc.), enlisted upon requests from the staff or members to prepare and present data (e.g., Congressional Research Service), actively solicited (e.g., expert testimony during congressional hearings), or reside in content repositories (e.g., libraries, online data sources). Most of this information and knowledge is explicit, codified, and shared digitally or through impersonal networks and formats, but some knowledge, such as sharing of practical how-to expertise, is tacit and more easily transferred interpersonally.

These information sources (whether institutions or other social entities) often have individually distinct practitioners, practices, values, and attributed characteristics of human information interaction (knowledge generation, processing, decision making and implementation). Together the characteristics act as social boundaries that segment and delineate these entities. Differences in the characteristics can lead to difficulties when these entities attempt to transfer information across boundaries (Guston, 1999).

The content of information transferred across boundaries, as well as the perceptions that senior legislative staff have regarding the sources of that information, not only influence staff priorities (in their principal–agent roles), but ultimately can also have a disproportionate impact on legislative voting behavior. Sabatier and Whiteman's 1985 review of studies on legislative decision making found that the traditional two-stage model of information flow is less applicable in sophisticated legislative environments like the U.S. Congress. In the two-stage model, information flows directly from internal and external legislative information sources to 'specialist legislators' (typically the chairmen and senior members of the committees with jurisdiction over the legislation being considered). Sabatier and Whiteman's alternative three-stage model (an adaptation of which is shown in Figure 4.1) illustrates how information flows first from the legislative environment to personal or committee staff, who then frame and transmit this information to specialist legislators, who in turn communicate this information to 'non-specialist' legislators.

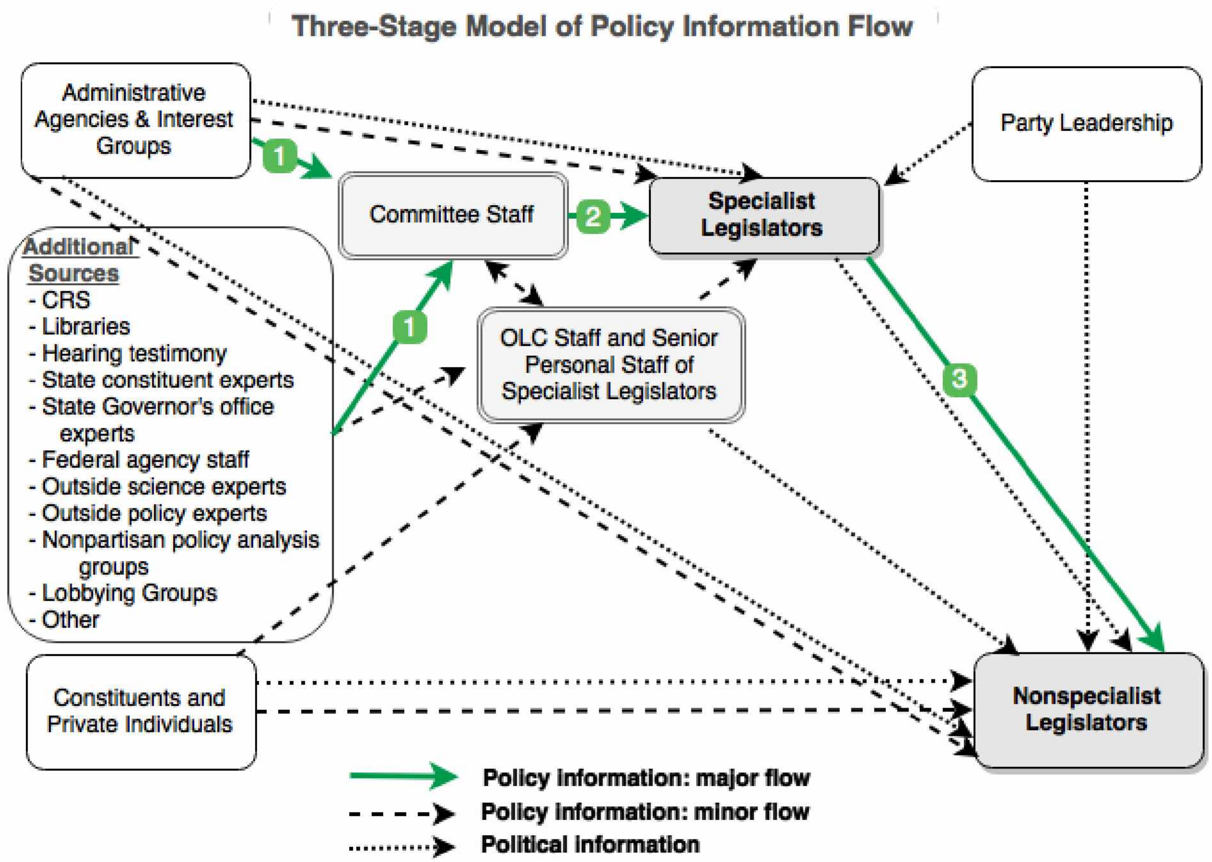

Figure 4.1 Three-stage model of policy information flow.
Adapted from Sabatier & Whiteman (1985), with addition of multiple congressional policy information sources.

Voting choice studies frequently found that non-specialist legislators rely heavily on cues from specialist legislators whom they consider knowledgeable about issues being discussed. These specialist legislators, when working in their areas of expertise, rely heavily upon and have their decision making significantly influenced by their senior legislative staff, whose activities include "monitoring and evaluating information on policy developments, structuring legislative hearings, formulating policy alternatives, and negotiating compromises". For specialist legislators, staff are the most important source of information (Sabatier and Whiteman, 1985).

4.2.4 Framework (RCL) of information choice and utilization for legislative staff

In their exploration of influences on policy decision making and action, a number of researchers have identified three information quality attributes generally considered necessary for bridging the information boundary and utilizing that information in policy decisions and action. These studies indicate that policy makers tend to act on policy-related information when it is perceived as *relevant*, *credible*, and *legitimate* (RCL) (Figure 4.2) with multiple audiences (Cash *et al.*, 2002; Clark *et al.*, 2016). RCL is used in this study as the framework for which to create a contextual understanding.

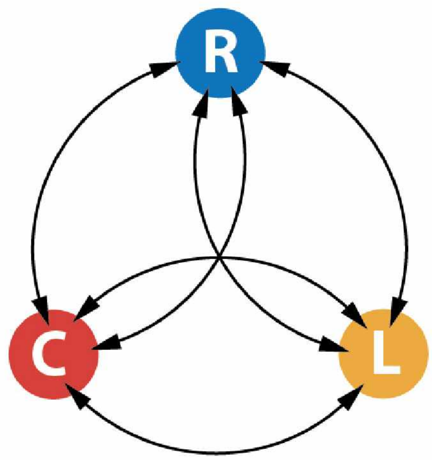

Figure 4.2 The RCL dynamic.
The interrelated dynamic between the information quality criteria of relevancy, credibility and legitimacy in linking policy decisions and action.

Relevance (often referred to as salience or saliency) is understood as the degree of relation to the matter under consideration, or the significance of the information for a decision maker's choices or the choices of a given stakeholder (Heink *et al.*, 2015).

C*redibility* of knowledge, a quality often linked with or equated with the concept of believability (i.e., judgement of logical or scientific soundness), is often the focus of scientists and scholars. Information (theories, beliefs, statistical data, and facts) is perceived as credible if it meets standards and established criteria requirements of scientific plausibility and technical merit. In addition, the source of the information must be perceived or judged as believable or trustworthy. Even if information is relevant, it will tend to be ignored if not considered credible (Cash *et al.*, 2002).

Legitimacy is an ascribed value of information regarding the degree to which the information is produced in an unbiased system that is politically and procedurally fair and is fairly representative of the views, values, and concerns of involved stakeholders, including (and perhaps most importantly) those of the decision makers. If the information is deemed relevant and credible, but is not perceived as having been produced or used in a legitimate way, it has a low probability of being used (Cash *et al.*, 2002). This quality criteria is considered to be essential for information to transfer across science-policy boundaries and be used as “actionable knowledge” that influences policy decision making and action (Meinke *et al.*, 2006).

There are both tensions and complementarities between these three attributes. Efforts to enhance one or more of these attributes may also increase another attribute, or may create a tension and lead to a lessened perception of another attribute. The most successful efforts involve effective balancing and trade-offs where all three attributes exceed their individual thresholds of acceptability.

The remainder of this paper consists of: 1) Methods: research design (theoretical approach and participants), study process, and study limitations; 2) Findings and Discussion; 3) Conclusion; 4) Cited Literature; and 5) Appendices.

4.3 Methods

4.3.1 Research design

This mixed methods study used at its core a "qualitative" grounded theory (GT) methodology (Corbin and Strauss, 2008), with an embedded "quantitative" component for comparison and contextual analysis.

Grounded theory approach

GT was used to: 1) identify participants' main concerns (and behavior in addressing those concerns) related to the use and influence of information in developing legislative water policy; and 2) determine the degree to which specific criteria (RCL) influence the linkage between their decision making and implementation. GT is a qualitative approach that develops theories grounded in the data through systematic processes that follow logic and constant comparisons during analysis (Charmaz, 2014).

Contrasted with positivist research, which can start with a theory to examine data, GT generally uses an inductive approach to construct a theory based on analysis of the evidence of raw data and observations. In this study, the participants were asked to answer both structured and open-ended unstructured questions that were formulated based on numerous notes and memos of interactions with congressional legislative staff over a number of years (Glaser, 2001).

GT helps define related concepts through a multi-stage qualitative process (Figure 4.3) that identifies important ideas and key word relationships (Glaser *et al.*, 1968), together forming an integrated framework (Table 4.1) for explaining human outcomes (Creswell, 2013, Charmaz, 2014). While the staged process is roughly sequential, in practice the researcher is continually forming and refining ideas by comparing and analyzing new data, impressions and conceptual insights together with existing coded keywords, expressions and concepts from memos, notes, questionnaires and interviews.

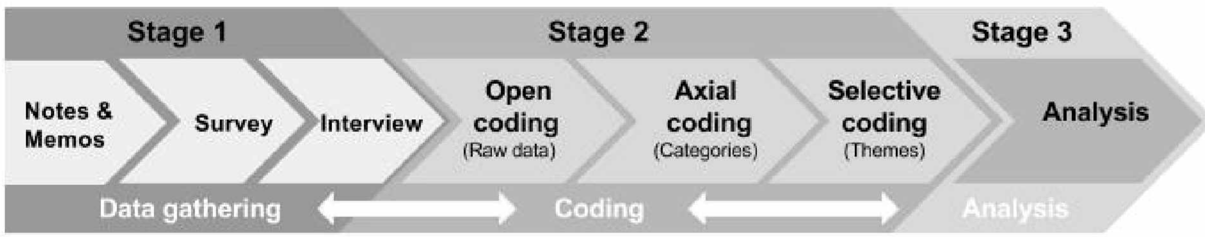

Figure 4.3 Three dynamic stages and fundamental components of GT coding.

Table 4.1 Integrated grounded theory framework.

STAGES	COMPONENTS	DESCRIPTION
Stage 1: **Data gathering**	**Raw data:** 1) Notes & Memos 2) Survey 3) Interview	Collection of the raw data used for analysis. The structured data from the questionnaire are entered into spreadsheet tables, and the unstructured data are collected and formatted for coding in the next stage.
Stage 2: **Coding data**	Analysis using the words, phrases and concepts	The structured table data are aggregated and analyzed, and the collected unstructured data are coded for analysis.
	Open coding	Collected raw data are segmented into conceptual keywords or short meaningful expressions and sequences of words (Strauss & Corbin, 1990; Corbin & Strauss, 2008).
	Axial coding (Identifying Categories)	Keywords and expressions from the open coding process are analyzed and grouped into categories related to the phenomenon under study and associated "conditions, context, actions/interactions strategies and consequences" (Strauss & Corbin, 1990).
	Selective coding (Identifying Themes)	Category data and development concepts from the axial coding stage are analyzed in an inductive process of comparing word sets to reduce individual bias, develop word uniformity, and identify core conceptual patterns and themes (Glaser et al, 1968).
Stage 3: **Analysis & interpretation**	**Interpretation & testing**	Utilizing the identified core themes, a theory is generated about how an aspect of the social world “works”. This theory or explanation emerges from and is connected to the reality that is being explained.

Participants

Considered as policy experts in their fields, congressional water policy legislative staff augment their understanding and knowledge of water policy legislation and inform their policy decision making by drawing on legal assessments, legislative historical context, diverse stakeholders, and policy analysis. As described earlier, while many congressional staff in the House and Senate cover water legislation related issues for their respective members, only a very small number of senior legislative staff are actually involved in drafting and developing water legislation.

In order to gain insight into the role and influence of scientific knowledge and other information and sources on congressional policy decision making and implementation, sixteen senior personal office and committee legislative staff from both political parties in the Senate and House were selected as members of a study group based on their own experiences and their respective congressional members' senior roles in legislative water resource policy. The participants came from diverse backgrounds in engineering, law, environment, history, and political science, and had largely focused on water policy in their congressional positions.

At the time of this study, the first and second authors were both congressional staff in the U.S. Senate with legislative policy and federal agency backgrounds. The first author—a senior legislative specialist with more than a decade of congressional and federal agency water policy and executive management experience—identified and recruited congressional staff colleagues and conducted the individual interviews. The second author—a specialist in innovation and organizational performance—structured the political and decision-making analysis. Both authors' backgrounds contributed to a contextual participant understanding and interpretative perspective in this GT-based research.

4.3.2 Study stages

Stage 1: Data collection—Preliminary observations, survey questionnaire and interview

The first stage of the GT process was to gather "raw" data to analyze. These data took the form of notes and memos, responses to a questionnaire, and personal interviews. An important raw data source for GT, and the initial data collected, were the notes and memos from meetings with many of the key staff over the years.

Each participant was then asked to complete an online survey questionnaire (Appendix A). The questionnaire was prepared and distributed, along with written guidelines, to the survey group. The group members were instructed to answer the questions from the perspective of their positions as legislative aides representing their congressional members and respective constituencies. Their answers were confidential and non-attributable; each respondent was only identified as a senior legislative staffer.

The survey questionnaire included both open-ended, fill-in-the-blank format questions and structured questions consisting of selection lists, multiple choice, priority weighting, and Likert Scale rating (1=Low; 5=High). The survey was divided into three parts: legislative priorities; actionable knowledge criteria; and legislative action. Participants were asked to identify their: 1) top three priorities in the policy issue areas of federal water resources, flood, and drought; and 2) three highest and three lowest federal water resource mission agency priorities. In order to establish a baseline and to weight their other answers, survey participants were asked to determine the degree to which they perceived the information quality factors of relevance, credibility, and legitimacy to be important in the linking of policy-related information and legislative decision making and action. They were then asked to identify their top three information sources and rate each of eleven primary information sources according to how relevant, credible, and legitimate they viewed those sources to be in influencing their policy decision making and implementation. In this manner the framework of RCL was imposed into the data collection.

Personal interviews were then individually conducted on-site in Washington, DC, giving each participant the opportunity to provide any necessary clarification on their answers to the questionnaire and elaborate on their ideas, thoughts, and insights. Before the interview commenced, an introduction to the study was given and consent for the interview confirmed. The basic interview protocol involved first sharing the anonymous aggregated responses from the questionnaire that all participants completed, and then asking each participant a set of common general questions based upon the questionnaire results. These interview questions were open-ended, addressing the participant's policy decision-making and legislative water policy experiences and his or her member's water resource decision-making process. The process of utilizing survey questionnaires and interviews was based on grounded theory research principles. During the interviews, participants were encouraged to speak naturally and unprompted about their water policy work, decision-making process and priorities and share perspectives and insights into their policy decision-making experiences.

The interviews were scheduled over an approximate two-month timeframe, each interview averaging between 30-45 minutes in duration. Roughly half of the interviewed participants consented to being audio recorded, while the remainder preferred to not be recorded for reasons of confidentiality and anonymity. Notes, transcriptions, questionnaire responses, and audio recordings were all consolidated as the "raw data" for processing using the GT qualitative coding analysis. This study was reviewed and deemed to be exempt from human subjects research through an institutional review board (IRB) process, receiving a study waiver IRB - ID#982099-2 from The University of Alaska Fairbanks, Office of Research Integrity.

Stages 2 & 3: Data coding and analysis

After the interviews were completed, the responses were collected, and the results were aggregated and coded from both the questionnaire and the interview process. Structured questionnaire results were aggregated in analytical matrices to generate decision-making characteristics, following a methodology described by Charmaz (2014). Unstructured data were coded through the following three-step process: open, axial, and selective. The procedural framework of the initial coding process and comparison of keywords from the three coding processes were used to create the uniform themes of the study.

Open coding— In the first step, the raw data from the previous notes, memos, survey questionnaire and interviews were analyzed (based on the frequency of occurrences) to identify preliminary keywords and expressions to support the axial and selective coding processes following methods described by Saldaña (2013). The structured questionnaire data were collected and used in an analysis matrix to generate decision-making characteristics. Qualitative data analysis software ATLAS.ti was used to code the responses and analyze the codes. The raw data for coding consisted of approximately 3,000 coded keywords and phrases that then served as the data processed in the next step of categorization.

Axial coding—During the second step, the defined keywords and expressions were aggregated, analyzed and grouped into categories related to the study questions and associated "conditions, context, actions/interactions strategies and consequences" (Strauss and Corbin, 1990). In order to categorize the raw data, the words and phrases were counted, and associations and relationships were identified and grouped into categories of similar meanings. For example, keywords, such as “flood, flooding, rising water, inundation, over the bank” and “relationships, networks, constituents, stakeholders, shareholders”, were grouped into categories of similar meanings.

Selective coding—The third step of the analysis process assimilated and built on results from steps one and two by determining connections between the keywords and phrases from the open coding process, and using the categorization matrix from the axial coding process to identify or describe overall themes. These themes reflected the views, attributed importance, concepts and interests communicated by the participants.

Stage 3 of the process consisted of analyzing the core themes from the selective coding process and generating a theory that explained legislative staff participants' behavior and concerns related to water policy and the decision-making process. This "general, abstract theory of process, action, or interaction [was] grounded in the views of participants in a study", and used an inductive process rendering generalizations from specific observations (Creswell, 2014).

4.3.3 Limitations

With the study group limited to sixteen participants, the authors do not claim that the results represent overall congressional legislative water policy priorities or views, or even those of all senior legislative staff working on water policy issues in the U.S. House and Senate during this time period. However, at the time of this research, these sixteen were considered by the authors to be among the senior staff that were instrumental in the development of federal legislative water policy, and their perspectives provided the insights sought by the study.

As no qualitative research method is completely free from preconceptions and bias in data gathering, interpretation and analysis, there is an inherent individual and contextual subjectivity and bias that the authors brought to the study based on their own experiences in research and policy and professional relationships with the participants. However, this is consistent with the focus of GT—the development and use of an interpretative lens by researchers for thinking about and conceptualizing grounded data, the process resulting in statements about how people think, behave, and resolve their concerns. With this as the objective, proponents argue that GT should be judged by the relevance, fit, workability and flexibility of its methodology and results (Glaser *et al.*, 1968; Glaser, 1978).

4.4 Results and discussion

The analytical process employed both inductive and deductive approaches. Based on their experience with legislative policy, staff decision making, and knowledge of the study participants, the authors identified patterns of information processing within an information quality criteria framework (RCL) describing the transfer of information across science-policy boundaries and the linking of policy decision making to action. In the survey questionnaire, participants were queried as to their assessment of the perceived influence of these criteria on their decision making and policy action, and their responses were analyzed deductively. The interviews, however, utilized an unstructured and open-ended format whereby general questions were posed, and participants were encouraged to talk freely about common issue areas and the role of information in legislative policy decision making and behavior.

GT method coding processes were used to analyze raw data, from which both conceptual categories and core themes emerged. From the raw data, approximately 3000 words were collected and consolidated, producing approximately 936 key coded word concepts or phrases selected from open coding integration. Using axial coding methods, 53 categories were constructed using 278 descriptive keyword concepts or expressions. Described below, selective coding was applied to these axial coded categories, from which three themes emerged.

Both the structured results from the survey and the coded results from the unstructured data were analyzed using an inductive approach. The information quality criteria framework of RCL served as a useful interpretative lens—and was explored as a potential heuristic tool—in identifying potential relational correlations in the patterns, categories and themes that emerged from the participant data.

4.4.1 Themes

Three interrelated conceptual themes (Figure 4.4) emerged, based on percentage of total coded participant keywords and expressions, which reflected interests and priorities of the legislative staff participants: 1) Developing a trusted relationship-information network (DN)—49.6%; 2) Prioritizing relevant stakeholder interests (PI)—33.8%; and 3) Maximizing efforts to achieve desired results (ME)—16.6%.

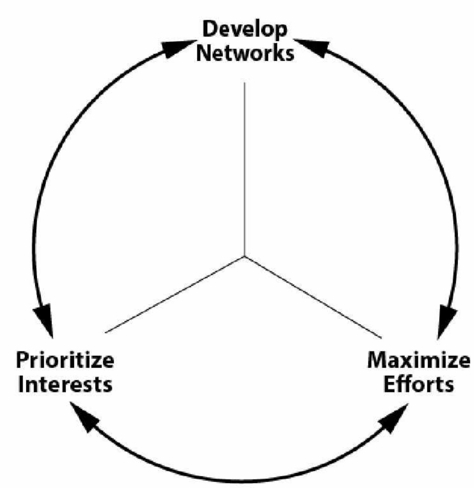

Figure 4.4 Conceptual themes developed from the "selective coding" process

Table 4.2 Illustrated examples from GT coding process.

Open Coding (Raw Data)	⇄ **Axial Coding** ⇄ (Categories)	**Selective Coding** (Themes)
"Finding the right people" "Stakeholders" "Relevant groups" "Partner relationships" "Knowing who to trust" "Constituent relations" "Working groups" "Developing solutions with people"	● Stakeholder buy-in ● Knowledge relationships ● Trusting sources ● Data awareness networks ● Looking at partnerships ● Working with others for solutions ● Improve understanding associations ● Develop participant engagement	**Develop Relationship-Information Networks (DN)** 49.6% of total keywords / expressions
"Create policy mandates" "Select practical outcomes" "Highlight key effects of policies" "Select cost vs. results of polices" "Record areas of gaps/holes" "Place in order" "Pros and Cons"	● Order of affordability & costs ● Imperative criteria of solutions ● Maximize political expectations ● Organize assumptions ● Rank consequences ● Balance needs vs. wants ● Capitalize on policy benefits	**Prioritize Interests (PI)** 33.8% of total keywords / expressions
"Meet w/ state personnel" "Governor's top action items" "local agency responsibilities" "Residential impact of policy" "Capability effort and conclusions " "Make most of policy"	● Apply support outcomes results ● Utilize local development ● Progress in information results ● Advancement in knowledge outcome ● Trusting results and effects ● Improve outcome understanding	**Maximize Efforts (ME)** 16.6% of total keywords / expressions

Table 4.2 depicts results from the phased coding process and highlights the three conceptual themes that emerged from the raw data research analysis. The first column provides several sample raw data keywords and expressions collected during the gathering phase. The middle column lists the categories that were derived from axial coding of the concepts and ideas from the open coding step. Lastly, the third column lists themes that emerged from the categories during the selective coding stage, along with percentage of raw data falling into the respective themes.

Developing Relationship-Information Networks (DN)

While all three conceptual themes were shared by many of the participants, the most commonly shared theme that emerged from participant interviews was the critical importance of developing and cultivating the personal relationship-information networks essential for staff success. Study results confirmed the findings of Romzek and Utter (1997) that information is the primary currency of congressional staff interactions, and that the primary way that staff gather information and develop coalitions and influence is through networks. Staff often receive or solicit information from their work relationships and informal networks (professional friendships with other staffers, second-tier professional circles, and relationships built on long-term community networks, etc.). Establishing knowledge networks with a wide range of congressional and outside sources to obtain relevant policy-related information, together with developing and maintaining a reputation as a credible and trustworthy source, is essential for any staff that wants to be successful in his or her job within the legislative process.

Depending on the degree of trustworthiness of these networks, information received from and shared with network contacts is often as influential, or more so, than information from most other sources. These networks are important not only as direct resources for information, but also indirectly for such purposes as political alliances, collaboration, negotiating partnerships, social and political cohesion, and for advancing personal career interests. These networks are also useful for achieving stakeholder buy-in for policy positions, communicating knowledge, assessing credibility and trust, and developing good working relationships.

Relational-information networks are very diverse, reflecting the personalities and interests of staff members, and can range from highly formal and structured professional relationships to casual or informal trust relationships within personal or social networks. For staff, individual relationships in networks or institutions are generally more important than the actual organization or network to which those individuals belong. At the same time, the attributed value and influence of those organizations with staff members often reflect their personal experiences with specific individuals in those organizations.

Networks are also critical as sources and social interfaces of knowledge. Staff rely heavily upon trusted relationship-information networks for both developing and enhancing their own frames of reference and decisions, and for reducing the equivocality they experience in the face of competing frames of references from multiple credible information sources.

Prioritizing Stakeholder Interests (PI)

The second general conceptual theme that emerged was the goal of effectively prioritizing stakeholder interests and aligning efforts and resources to achieve these priorities. This theme emerged from such recurring concepts (axial coded as "categories") as calculating cost-benefits (both financial, political, social, etc.) of competing interests, determining critical paths to success or failure, weighing political expectations against degrees of fulfillment and their consequences, balancing needs versus wants, capitalizing on policy benefits, etc.

The various roles that legislative staff play influence their perception, balancing, and prioritization of stakeholder interests, as well as the development of their information networks.

Observations and feedback from information networks, in turn, help shape the staff's perception and prioritization of these interests and the actions those interests influence.

Coding analysis of legislative notes, memos, survey answers and interview transcripts indicate that the top five overall water policy priorities of the sixteen participants were: 1) water infrastructure; 2) water policy regulatory reform; 3) water quality; 4) drought; and 5) flooding. Priorities were also listed within the areas of water resources, drought, and flood. As an example, within the area of flood issues, participants listed: 1) flood insurance; 2) floodplain mapping; and 3) flood control (infrastructure) as their top three policy issue priorities. Issue priorities are usually reflections of the legislative staff's cognitive ranking of stakeholder interests in their multiple principal–agent roles.

Staff see themselves as balancing multiple principal–agent roles in which they are either the agent (i.e., to their member or other stakeholders) or the principal (i.e., to science researchers or other information providers). Applying the principal–agent model lens to congressional staff requires consideration of multiple principals and agents and recognition of the risk that staff, as expert agents with their own policy agendas and personal interests, may have interests and agendas that overlap or conflict with those they represent (Romzek, 2000). Staff decisions and behavior are influenced and constrained by relationships of accountability with multiple stakeholders, not only with their respective members of Congress (the primary stakeholder and accountability relationship), but indirectly with any group that potentially affects the primary stakeholder, as well as with their own personal agenda and career interests. Problems can arise from either an unevenness or asymmetry of information—when the agent has more information than the principal—and if and when the agent has different or competing interests.

Maximizing Efforts-Results (ME)

The third conceptual theme that emerged was the commonly shared goal of maximizing personal efforts to achieve desired results. This theme emerged from such recurring concepts as the desire to not waste time, but to efficiently develop stakeholder buy-in, apply support, advance programs, utilize knowledge more effectively, knowing what sources to trust, etc.

Due to multiple competing priorities and many demands on their time, staff often feel that their ability to achieve their objectives and goals is significantly constrained. Many of the projects and tasks they are involved in have many players and levels of complexity and vested interests, often resulting in failure to achieve the desired results. For example, staff expressed frustration at having made many attempts over the years to craft and pass various pieces of water resources legislation, only to successively watch those efforts come to naught as the bills were killed by elements and events outside their control.

4.4.2 Situating the GT results within the RCL framework

In each of the three discussed theme areas, staff intuitively selected and utilized heuristics in determining whether information was relevant to their various principal-agent roles (e.g., matching perceived policy information needs), whether the relevant information was credible enough to be a factor in decision making, and whether relevant and credible information met minimal thresholds of legitimacy in order to influence policy action. Participants confirmed that information quality criteria were important in influencing to what degree they utilized that information in decision making, even though few, if any, of the participants indicated that they were consciously or metacognitively aware of their information relationship roles or the processes they employed in making decisions or taking action. A common participant response was “I've never actually thought about how I make decisions using any type of methodology or what type of structural concept influences them; I just do it.” The arrows in the Figure 5 illustrate the interrelationship of the three themes.

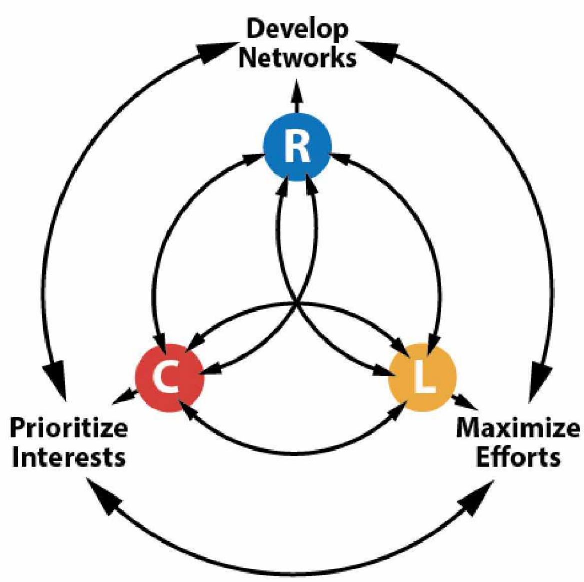

Figure 4.5 RCL dynamic and theme areas.
Dynamic interaction between information heuristic influences (RCL) linking decision making and action in the three conceptual theme areas.

Throughout the various stages of the process, senior staffers are constantly evaluating new and often conflicting pieces of information. The information that they act upon and communicate with their members, or the stakeholder interests the members represent, is largely determined by the staff's assessment of the relevance, credibility and legitimacy of that information. Likert scale results from questionnaire ratings showed that the study participants judged all three quality criteria to be important in determining the degree of influence on their decision making and policy action, with credibility scoring the highest (4.6/5), followed by relevance as a close second (4.3/5) and then legitimacy (3.9/5).

Presented with a list of eleven sources of policy-related information, survey participants were then asked to evaluate each information source, using a Likert scale of 0–5 (0=Not Applicable/Don't know; 1=Very Low; 2=Low; 3=Average; 4=High; 5=Very High), according to how relevant, credible (scientific plausibility and technical adequacy), and legitimate (unbiased and procedurally fair) the participants perceived the sources to be (on average) in forming or changing their water resource policy decisions and taking legislative action on those decisions. The results (Table 4.3) indicate that overall the surveyed staff rated the top three most influential information sources as “committee staff contacts” (avg 4.2/5), “State constituent experts” (4.0/5), and “State governor's office experts” (3.9/5). The three lowest rated sources (based on accumulated averages) were “Think-tanks/nonpartisan policy research groups” (3.2/5), “Lobbying groups” (2.9/5), and “Personal office staff in other congressional offices” (2.6/5).

Table 4.3 Rating of information sources according to influence of quality criteria.

Information Source	Information Quality Criteria	Individual Criteria Avg (1-5)	Individual Criteria Ranking	Cum. Criteria Avg.	Information Quality Ranking
Committee staff contacts	Relevance	4.69	1	4.17	#1
	Credibility	4.06	2		
	Legitimacy	3.75	2		
State constituent experts	Relevance	4.50	4	4.00	#2
	Credibility	3.88	2		
	Legitimacy	3.63	3		
State Governor's office experts	Relevance	4.38	3	3.88	#3
	Credibility	3.81	5		
	Legitimacy	3.44	4		
CRS and LOC briefing summaries/overviews	Legitimacy	4.06	1	3.85	#4
	Credibility	3.94	3		
	Relevance	3.56	8		
Outside source water policy scientist experts	Credibility	4.25	1	3.73	#5
	Relevance	3.50	9		
	Legitimacy	3.44	5		

Table 4.3 continued

Outside source water policy legal experts	Credibility	3.75	6	3.56	#6
	Relevance	3.69	5		
	Legitimacy	3.25	6		
Federal Executive branch staff	Relevance	3.69	7	3.31	#7
	Credibility	3.25	8		
	Legitimacy	3.00	7		
Hearing testimony	Relevance	3.94	4	3.25	#8
	Credibility	3.19	9		
	Legitimacy	2.63	9		
Think-tank briefings, seminars, and workshops	Credibility	3.31	7	3.15	#9
	Relevance	3.25	11		
	Legitimacy	2.88	8		
Lobbying Groups	Relevance	3.69	6	2.94	#10
	Credibility	2.69	10		
	Legitimacy	2.44	10		
Personal office staff contacts	Relevance	3.31	10	2.56	#11
	Credibility	2.31	11		
	Legitimacy	2.06	11		

The results from these individual ratings were compared to the results (Table 4.4) of participants' listing of the top three sources of information (selected from the list of eleven) they considered most important and utilized most often in making and acting upon their legislative policy decisions. The three sources that had the highest aggregate scores in terms of RCL ratings (Table 4.3) were also the three sources rated as the most important and utilized (Table 4.4). One of the three sources that had the lowest aggregate scores in terms of RCL ratings ("Think-tank briefings, seminars, and workshops") (Table 4.3) was also ranked last in the top-three ranking of the eleven sources in terms of being considered important and useful (Table 4.4).

Table 4.4 Information sources ranked by importance and utilization.
Ranking of "top 3" sources considered most important and utilized for decision making and policy action.

Information Source	# Selected as Top 3	Rank
Committee staff	9	1
State Governor's office experts	8	2
State constituent experts	6	3
Personal office staff	5	4
CRS and LOC	5	4
Federal Executive branch staff	4	5
Outside source water policy scientist experts	4	5
Lobbying groups	3	6
Outside source water policy legal experts	2	7
Hearing testimony	1	8
Think-tank briefings, seminars, and workshops	1	8
Other (please specify)	0	–

4.5 Conclusion

This paper seeks to provide insight into the policy priorities of senior legislative staff and their respective congressional members in the U.S. House and Senate, as well as provide an interpretative lens for understanding the content sources, framing and actualization of specific knowledge used both in policy formation and action. The paper discusses the results of a grounded theory research study of senior legislative staff in the area of federal water policy and examines what factors influence the linkages between policy-related information, decision making and legislative action.

Various authors in science-policy literature have argued that science-related information must meet minimum thresholds of the three quality criteria of RCL (as perceived and attributed by the information recipients) in order for that information to transfer across the science-policy boundary and influence policy decision making and behavior. This study used RCL as a framework to discover: 1) to what degree actual decision makers felt these criteria were important in bridging information boundaries to influence policy; and 2) whether or not and/or to what degree these criteria (whether or not the policymakers defined the RCL concepts with those labels) or similar concepts were used by policymakers as intuitive or rational heuristics in judging whether information influenced their decisions.

The information quality criteria framework of RCL can be useful as decision-making tools of legislative policymakers and for transferring knowledge across science-policy action boundaries, but a full understanding of the dynamics of information-processing must take into account the multiple principal–agent roles that staff play. The common priorities for legislative staff of 1) developing trusted relationship-information networks; 2) prioritizing relevant stakeholder interests; and 3) maximizing efforts to achieve desired results can be understood within the RCL framework as a way to bridge the gap between water science and water policy.

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Chapter 5 Conclusion

5.1 Overview

In the introduction to this dissertation, I discuss the common perceptions that 1) local-to-national decision makers do not have as accurate, reliable and actionable data and knowledge as they need to make the best informed flood-related decisions, and 2) because of science–policy disconnects, critical flood and scientific analyses and insights are failing to influence regional and national policymakers in water resource and flood-related decisions that have significant local impact. In response to these real and perceived information gaps and science-policy disconnects, I designed this dissertation to answer the question, "Can flood data be accurately generated and transformed into actionable knowledge for local flood event decision makers, and also be effectively communicated to influence policy?"

5.2 Research summary

5.2.1 Research approach summary

To address this question, I utilized an interdisciplinary three-phase mixed-methods research approach and developed a methodological framework and interpretative lens for each of the three interrelated themes of flood hazard interaction: 1) *Data generation*—using machine learning to estimate streamflow data for flood forecasting (result elements: quantitative data; prediction); 2) *Knowledge development and sharing*—creating a geospatial decision support system for flood events (result elements: quantitative and qualitative data; visualization framework; integrated multiple data sources); and 3) *Knowledge actualization*—using Grounded Theory and heuristic toolsets to identify how policy makers translate scientific knowledge into policy action (result elements: quantitative and qualitative data; informed decision making). Chapters 2 (SHEM), 3 (WaVE), and 4 (Water Policy) of this dissertation describe the research addressing the distinctions of each of these flood hazard themes that focus on developing practical data and methodologies useful to scientists, local flood event decision makers, and policymakers (Figure 5.1).

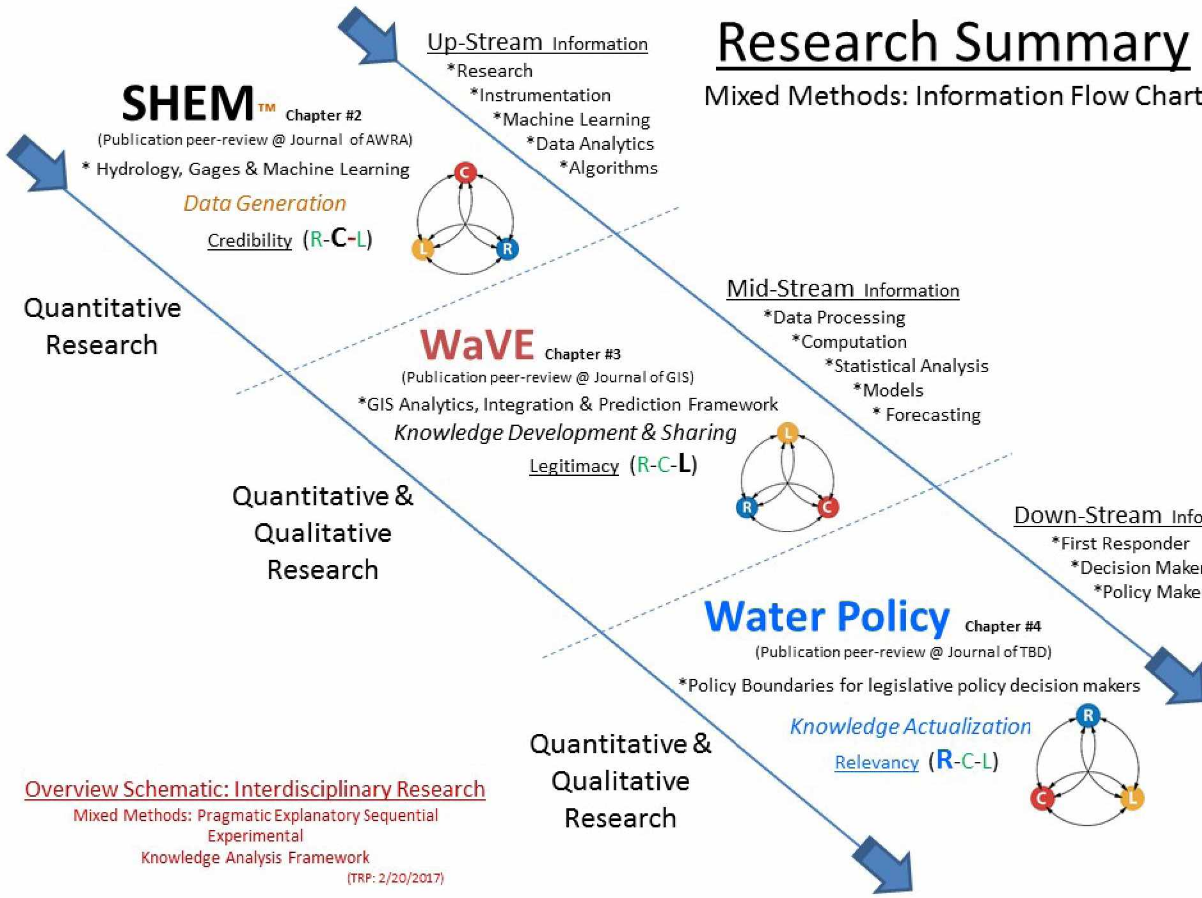

Figure 5.1 Author's research schematic for the interdisciplinary, mixed methods approach

5.2.2. Research outcome summary

Streamflow data from USGS streamgages are critical for flood forecasting, assessing imminent risk, and planning and implementing flood mitigation activities. In answer to the question of whether there is a way to accurately forecast near real-time flood data, even when streamgages are missing or not transmitting, Chapter 2 described the design, testing and results of SHEM, a new methodology that incorporates machine learning and big-data testing to accomplish this goal. The research sought to explain whether a predictive estimate can accurately replicate actual streamflow during a streamgage failure scenario, and do so in a sufficiently timely manner to be useful to decision makers and first responders. The SHEM model was specifically designed to construct accurate and timely proxy streamflow data estimates that can be substituted for missing data when streamgages stop transmitting accurate data. SHEM tested and validated the reliability of the predicted value estimates through rigorous integrated testing methodologies. The accuracy and reliability of the case study results indicated high correlation and predictive factors. The results of the analysis affirm the scientific integrity of the SHEM methodology. When these statistical processes and equations were applied to streamflow hydrology datasets, they effectively produced a result that can be used by first responders and decision makers responding to flooding events. The SHEM construct affirmatively supports the authors' question of whether a predictive estimate can accurately replicate actual streamflow during a streamgage failure scenario, and in a timely manner so as to be useful to decision makers and first responders. In addition, technological advancements are producing multiple new sources of hydrological data from in-situ and remote sensing platforms with flood hazard applications. Building on previous research, this paper reveals that the in-situ and remote sensing data available from these new sources can be used complementarily to provide answers to critical water resource management and flood inundation questions.

There is a growing consensus among the academic, policy and flood forecast practitioner communities regarding the need for decision support toolsets that integrate accurate, scalable and highly granular flood event data. Answering the question of whether forecasted data and relevant ancillary data can be communicated as visualized geoanalytic knowledge that is easily understood by local decision makers and useful in supporting flood event related decisions, Chapter 3 introduced WaVE— a new geospatial visualization framework and decision support toolset designed for first responders, water resource managers, scientists and other decision makers. Four case studies tested and validated the WaVE framework under diverse conditions at national, regional and local levels. Results from these case studies highlighted WaVE's inherent strengths, limitations, and need for further development. Results indicated that WaVE has the potential for being utilized on a wider basis as data become available and models are validated from forecasted machine learning and remote sense technologies into accurate streamflow flood estimates.

Chapter 4 of this dissertation addressed and answered the question of what factors impact the transfer of flood and other scientific knowledge to policy-makers with the result of influencing policy decisions. The interpretative lens of the grounded theory research study provides an understanding of the water policy priorities of the participants, and the content sources, framing and actualization of specific knowledge used in policy formation and action. The study examined the factors that influence the linkages between policy-related information, decision making and knowledgeable action. Science-policy literature have argued that science-related information must meet minimum thresholds of three quality criteria (relevance, credibility, and legitimacy)—as perceived and attributed by the information recipients—in order for that information to transfer across the science-policy boundary and influence policy decision making and behavior. This study explored the use of these criteria as an interpretative framework for understanding how knowledge transfers across science-policy action boundaries, and concluded that a full understanding of the dynamics of information-processing must take into account the multiple principal–agent roles that decision makers play. From the grounded theory analysis of the interview and survey data gathered from study participants, three common themes of interests and priorities emerged within this heuristic interpretative framework: 1) developing trusted relationship-information networks; 2) prioritizing relevant stakeholder interests; and 3) maximizing efforts to achieve desired results.

5.3 Research outcome discussion

Results of this research indicate that, if certain criteria are met, it is possible to generate effective data to forecast and visualize situational awareness during a flood event using machine learning, remote sensing, and geospatial analytical tools. The practical result is that local emergency responders, event decision makers and policy makers are supplied with the useful actionable knowledge they need to make timely and informed decisions.

Building on previous research reflected in the literature review, this research advances new ideas that contribute to the growing body of knowledge of flood hazards. Despite the complexity of forecasting local flood hazard events and building an effective decision support system, this research of flood forecast modeling demonstrated viable forecasting results. The level of accuracy in prediction, however, is directly related to availability of historical and real time local data.

This dissertation explored the information influences linking decision making and policy outcomes given the continued disconnect between policy-related scientific information and the utilization of that information by policymakers, and the difficulty in transferring policy information across knowledge boundaries identified through a literature review. Most of the existing literature is written by or for scientists, without considering the communication factors that influence policy makers. Using an interpretive process, this research formulated a communication bridge that provides insight into the process used by policy makers in responding to and utilizing scientific information in the crafting of public policy. Not only will this more accurate understanding result in better public policy, but it is critical to gain support for future research in flood hazard basic and applied hydrograph science.

5.4 Limitations

As with most research, approaches and methodologies utilized in developing this dissertation are not without limitations.

The overall objective of this dissertation was to answer the question of whether local flood event data could be accurately and reliably generated, transformed into useful actionable knowledge to help local flood event decision makers, and then effectively communicated to influence policy. This question was addressed in three separate parts that centered on developing new concepts, models and analytical frameworks—hydrology estimations for riverine analysis, forecasting flood integration resources, and engaging water policy with science research. Multiple choices of approaches and methodologies exist for each area, but given time and resource constraints, the author selected ones deemed most appropriate for the individual parts and consistent with the dissertation objectives.

Each of the three research sections addressed inherent limitations in approaches, methodologies and analyses in their respective chapters. For chapters 2 and 3, the exploratory design of this dissertation demonstrated limitations resulting from a lack of regional and local data information. Testing the SHEM and WaVE models on a greater number of diverse watersheds and or more data-rich watersheds could have potentially provided a greater amount of conclusive data outcomes related to the studies' objectives. The research framework, scope and testing were constrained by available resources, costs, and time.

Given the uniqueness of any given flood hazard situation, the research in chapters 2 and 3 faced the challenge of extrapolating analytical generalizations based on a few case studies, even if the tests were controlled and results replicable. Individual watershed basins respond to a flood event differently, and any analysis should take into consideration ancillary data and local context. The greater the amount of local data one has for testing, the greater the confidence one can have in generalizing the results.

Additionally, the qualitative research method utilized in chapters 3 and 4 includes the limitation of individual and contextual subjectivity and bias that the author brought to the study. However, this bias, inherent in qualitative research, is consistent with the development and use of exploring, thinking about and conceptualizing data, the process resulting in identifying themes about how people think, behave, and resolve their concerns.

Aside from individual study limitations discussed in chapters 2, 3 and 4, there is also an inherent limitation with the overall three-part approach, considering the basic question that the dissertation set out to answer—i.e., is there a methodological process for reliably generating and using critical and accurate data in local flood event decision support and informing policy decisions and actions? While the three studies indicated promising results (given specific conditions), it is difficult to demonstrate and test that specific local flood event data could directly inform policy using this combined approach.

On the surface, a more straightforward way of approaching this would be to identify existing generated local flood event data, provide an example of that data being integrated into actionable knowledge within a decision support system used by local decision makers, and then identify an example of how that same data/knowledge was integrated into information used by policy makers in their policy decisions and actions. However, examples of such information that can be tracked directly from generation to local situational awareness to policy are not only difficult to find, but the complexity of such examples limits their effectiveness in addressing the underlying essence of the question on which this dissertation focused. This is the more challenging task that this dissertation attempted to tackle.

5.5 Future research

The main conclusion of this research points to the need for further development of flood situational awareness, information and tools in order to support local communities during flood scenarios to save lives and property. This will involve effective communication between the science community and policy makers at the local, regional and national levels.

Scientific research efforts listed below identify ways to continue developing improved knowledge generation, knowledge sharing, and knowledge actualization for flood hazard preparation, better prediction, and effective communication:

- Flood prediction methodologies and geospatial tools that complement real observation providing better data at the local level.
- Further addressing the need for both spatial and temporal downscaling.
- More research in machine learning to increase accuracy, timeliness, and usability of flood forecasting toolsets.
- Further development of quantified and qualified research that can create relevance, credibility, and legitimacy for both science and policy groups.

Building resilience for communities in floodplain areas through better flood hazard plans that identify uncertainty throughout watersheds (upstream, midstream, and downstream), thereby reducing the social and financial impact of floods on lives, communities, and infrastructure.

In conclusion, further research is required to make full use of this interdisciplinary science-policy flood hazards dissertation. The challenge of precise weather forecasting will always be a limitation for the accuracy of flood predictions for vulnerable communities across the United States and the world. This research effort demonstrates how better flood prediction, better usable flood information tools at the local level and better public policy from effective science/policy communication can all contribute to the possibilities of saving lives and property through enhancing our techniques, communication and policies.

Chapter 6 Appendix – UAF IRB Exemption

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November 9, 2016

To:	William Schnabel, PhD Principal Investigator
From:	University of Alaska Fairbanks IRB
Re:	[982099-2] Water Resource Policy Survey

Thank you for submitting the Amendment/Modification referenced below. The submission was handled by Exempt Review. The Office of Research Integrity has determined that the proposed research qualifies for exemption from the requirements of 45 CFR 46. This exemption does not waive the researchers' responsibility to adhere to basic ethical principles for the responsible conduct of research and discipline specific professional standards.

Title:	Water Resource Policy Survey
Received:	November 3, 2016
Exemption Category:	2
Effective Date:	November 9, 2016

This action is included on the December 14, 2016 IRB Agenda.

Prior to making substantive changes to the scope of research, research tools, or personnel involved on the project, please contact the Office of Research Integrity to determine whether or not additional review is required. Additional review is not required for small editorial changes to improve the clarity or readability of the research tools or other documents.