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Integrated Systems Modeling to Improve Watershed Habitat Management and Decision Making

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INTEGRATED SYSTEMS MODELING TO IMPROVE WATERSHED HABITAT

MANAGEMENT AND DECISION MAKING

by

Ayman H. Alafifi

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ABSTRACT

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Management and Decision Making

by

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Utah State University, 2018

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Regulated rivers provide opportunities to improve habitat quality by managing the times, locations, and magnitudes of reservoir releases and diversions across the watershed. To identify these opportunities, managers select priority species and determine when, where, and how to allocate water between competing human and environmental users in the basin. Systems models have been used to recommend allocation of water between species. However, many models consider species' water needs as constraints on instream flow that is managed to maximize human beneficial uses. Many models also incorporate uncertainty in the system and report an overwhelmingly large number of management alternatives. This dissertation presents three new novel models to recommend the allocation of water and money to improve habitat quality. The new models also facilitate communicating model results to managers and to the public. First, a new measurable and observable habitat metric quantifies habitat area and quality for priority aquatic, floodplain, and wetland habitat species. The metric is embedded in a systems model as an ecological objective to maximize. The systems model helps managers to identify times and locations at which to apply scarce water to most improve habitat area and quality for multiple competing species. Second, a cluster analysis approach is introduced to reduce large dimensional uncertainty problems in habitat models and focus management efforts on the important parameters to measure and monitor more carefully. The approach includes manager preferences in the search for clusters. It identifies a few, easy-to-interpret management options from a large multivariate space of possible alternatives. Third, an open-access web tool helps water resources modelers display model outputs on an interactive web map. The tool allows modelers to construct node-link networks on a web map and facilitates sharing and visualizing spatial and temporal model outputs. The dissertation applies all three studies to the Lower Bear River, Utah, to guide ongoing habitat conservation efforts, recommend water allocation strategies, and provide important insights on ways to improve overall habitat quality and area.

(161 Pages)

PUBLIC ABSTRACT

Integrated Systems Modeling to Improve Watershed Habitat

Management and Decision Making

Ayman Hashim Alafifi

Existing river management tools prioritize human uses and provide for ecosystem water needs as minimum instream flow requirements. Management efforts to provide water for multiple human and ecological needs can be improved by tools that recommend when, where, and how to allocate water between competing users across a river basin. This dissertation presents a set of tools in three studies to help managers make decisions on the allocation of water and money to improve habitat quality and area. The first study develops a new metric to measure habitat quality and area for priority river, riparian, and wetland species. The second study presents a new approach to address uncertainty in habitat models and focus management efforts on important factors to measure and monitor more carefully. The third study develops a tool to help water resources modelers share and display model results with policy makers and the public on web maps. These studies are applied to real-world problems in collaborations with river managers to provide insights and recommendation and help protect threatened species in the Lower Bear River, Utah. Results of the three studies show opportunities to most improve habitat area and quality while meeting human water needs. For example, releasing more water from Porcupine and Hyrum Reservoirs in winter months and reducing late spring spills can support brown trout spawning and Fremont cottonwood restoration efforts.

To my parents Hashim and Nawal, my wife Maram,
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CHAPTER 1

INTRODUCTION

Rivers and their riparian and wetland areas provide numerous services for humans, including domestic and agricultural water supply, recreation, power generation, and flood control. They also provide ecological services, such as food and habitat, that contribute to sustaining ecosystem health (Delisle and Eliason, 1961; Frisell and Ralph, 1998). While policy makers acknowledge the need to allocate water to maintain a healthy and functioning riverine ecosystem, human beneficial water uses typically receive the highest priority (Bunn and Arthington, 2002; Petts, 2009). Regulated rivers provide an opportunity for managers to improve habitat conditions for valuable species while meeting human needs by managing the magnitudes, locations, times, and durations of reservoir releases and diversions (Jager and Smith, 2008; Tharme, 2003). To make these water allocation decisions across a watershed, managers can use models that consider the competing demands for water between multiple river habitat species, ecological response of species at different life stages to changes in flow regimes, and temporal and spatial dependency between flow control infrastructure in the basin. The effects of these decisions on habitat quality can be quantified using measurable and observable metrics that have a physical meaning that managers can relate to (e.g. area). Habitat models should also consider the inevitable uncertainty in river hydrology and ecology and quantify how multiple sources of uncertainty affect management decisions to improve habitat quality and area. In addition, managers can better communicate these decisions with the public using user-friendly web maps. These maps allow policy-makers and the public to visualize and interact with model outputs and recommendations.

Previous work to recommend management actions to improve river habitat quality has modeled ecological needs of species as constraints on water and money allocations (Cioffi and Gallerano, 2012; Porse et al., 2015). In addition, previous work to quantify uncertainty in habitat models found that large uncertain ranges of input parameters propagate and generate an overwhelmingly large number of management alternatives (Groves and Lempert, 2007; Pappenberger and Beven, 2006). Also, previous work has found it challenging to build web maps for water allocation models because it is difficult to describe and include node-link data in GIS structure and format (McKinney and Cai, 2002; Sui and Maggio, 1999). To address these challenges, this dissertation develops a measureable metric for habitat quality, quantify multiple sources of uncertainty, embed the metric in a systems model, and effectively communicate recommendations to managers and the public. Three tools (1) identify times and locations at which to apply scarce water to most improve habitat quality, (2) reduce a large uncertain space of possible habitat model alternatives and identify a few, easy-to-interpret management scenarios to improve overall habitat quality, and (3) provide a web-accessible tool to interactively describe and display spatial and temporal water resources model outputs.

The tools of this dissertation are applied to Lower Bear River (LBR), Utah, basin which is the downstream sub-basin of the 491-mile Bear River that runs through Wyoming, Idaho, and Utah. The LBR is a snowmelt driven system that receives 60% of its water from runoff in April, May, and June. The river and its tributaries are used to irrigate over 300,000 acres of agricultural land, supply water to numerous cities and counties, and generate electricity at run-of-river hydroelectric plants. The river is central to future development and growth debate for many counties in Northern Utah and the Wasatch Front (UDWR, 2004; UDWRe, 2000). In addition, the river is vital to maintain critical wildlife habitat for many native and threatened aquatic, floodplain, and wetland species (Bio-West, 2015). The Bear River is also the largest water source for the Great Salt Lake and the 30,000 acre-Bear River Migratory Bear Refuge, which is located in the Bear River delta at the northern part of the Great Salt Lake (Downard and Endter-Wada, 2013). The Refuge is home to over 250 migrating bird species that use 25 impounded wetlands for feeding, resting, nesting, and breeding every year (Alminagorta et al., 2016).

Land disturbances, water development, fish barriers, and intensive agricultural and grazing activities along the LBR led to degrading habitat conditions for many native and threatened species. The Nature Conservancy, Trout Unlimited, state, federal agencies, and landowners identified low flow regimes and reduced floodplain connectivity as major threats (Bear River CAP, 2008).

This dissertation presents three sets of decision-support tools to improve habitat which are presented in three chapters:

1. Systems Modeling to Improve River, Riparian, and Wetland Habitat Quality and Area

Problems with allocation of scarce water and money between competing river, riparian, and wetland habitat species while meeting human needs in the basin are addressed by developing a new systems optimization model. The main contributions of this work include:

- Develop a habitat area metric, measured in acres, to quantify habitat quality and area across aquatic, floodplain, and wetland habitats,
- Embed the metric in a new systems optimization model as an objective to maximize, and
- Apply the systems model to the Lower Bear River as a case study and identify where and when to apply scarce water and money to most improve habitat quality and area

2. Cluster Analysis to Improve Communicating Uncertainties in River Habitat Models

Problems with communicating uncertainty in habitat models are addressed by applying cluster analysis to explore the large space of plausible alternatives and identify a smaller set of management actions to improve habitat quality and area. The main contributions of this work are to:

- Identify the main sources of uncertainty in river, riparian, and wetland habitat models and quantify how multiple sources propagate to affect habitat model outputs and recommendations,
- Use semi-supervised cluster analysis to include management preferences to explore a large multivariate space of possible management alternatives and search for clusters,
- Identify a few management scenarios and define key uncertain parameters to monitor, and

- Apply this approach to a stochastic water and habitat optimization model for the Lower Bear River to infer management implications and tradeoffs between management scenarios and highlight opportunities to improve overall habitat quality and area

3. Interactive Web GIS Applications to Visualize Water Resources Model Outputs

Problems with describing node-link schema of water resources models as GIS layers are addressed with a web tool that facilitates developing user-friendly and interactive interfaces to communicate spatially and temporally-distributed water resources model outputs. The main contributions are:

- Develop an open-access web tool that allows users to interactively create web GIS layers of water resources nodes and links,
- Use the tool to create web maps that display water resources model outputs on a publically-available web GIS platform, and
- Demonstrate use of the tool to build two web maps for optimization and simulation water allocation models in the Bear River basin and facilitate collaborative model development and communication of results.

References

Alminagorta, O., Rosenberg, D.E., Kettenring, K.M., 2016. Systems modeling to improve the hydro-ecological performance of diked wetlands. Water Resources Research 52(9) 7070-7085.

Bear River CAP, 2008. The Bear River, A conservation priority. The Nature Conservnacy: Utah.

Bio-West, 2015. Little Bear and Blacksmith Fork Rivers Environmental Flows: Background Report. Bio-West Inc.: Logan, UT.

Bunn, S.E., Arthington, A.H., 2002. Basic Principles and Ecological Consequences of Altered Flow Regimes for Aquatic Biodiversity. Environmental Management 30(4) 492-507.

Cioffi, F., Gallerano, F., 2012. Multi-objective analysis of dam release flows in rivers downstream from hydropower reservoirs. Applied Mathematical Modelling 36(7) 2868-2889.

Delisle, G.E., Eliason, B.E., 1961. Stream flows required to maintain trout propulations in the Middle Fork Feather River Canyon, Water Project Branch. Californai Department of Fish and Game, p. 19 pp.

Downard, R., Endter-Wada, J., 2013. Keeping wetlands wet in the western United States: Adaptations to drought in agriculture-dominated human-natural systems. Journal of Environmental Management 131(0) 394-406.

Frisell, C., Ralph, S., 1998. Stream and watershed restoration, In: R.J. Naiman and R.E. Bilby (Ed.), River Ecology and Management: Lessons from the Pacific Coastal Ecoregion. Springer-Verlag: New York, pp. 599-624.

Groves, D.G., Lempert, R.J., 2007. A new analytic method for finding policy-relevant scenarios. Global Environmental Change 17(1) 73-85.

Jager, H.I., Smith, B.T., 2008. Sustainable reservoir operation: can we generate hydropower and preserve ecosystem values? River Research and Applications 24(3) 340-352.

McKinney, D.C., Cai, X., 2002. Linking GIS and water resources management models: an object-oriented method. Environmental Modelling & Software 17(5) 413-425.

Pappenberger, F., Beven, K.J., 2006. Ignorance is bliss: Or seven reasons not to use uncertainty analysis. Water Resources Research 42(5) n/a-n/a.

Petts, G.E., 2009. Instream Flow Science For Sustainable River Management1. JAWRA Journal of the American Water Resources Association 45(5) 1071-1086.

Porse, E.C., Sandoval-Solis, S., Lane, B.A., 2015. Integrating Environmental Flows into Multi-Objective Reservoir Management for a Transboundary, Water-Scarce River Basin: Rio Grande/Bravo. Water Resources Management 29(8) 2471-2484.

Sui, D.Z., Maggio, R.C., 1999. Integrating GIS with hydrological modeling: practices, problems, and prospects. Computers, Environment and Urban Systems 23(1) 33-51.

Tharme, R.E., 2003. A global perspective on environmental flow assessment: emerging trends in the development and application of environmental flow methodologies for rivers. River Research and Applications 19(5-6) 397-441.

UDWR, 2004. Utah Division of Water Resources, Bear River Basin, Planning for the Future: Utah.

UDWRe, 2000. Bear River Development, Utah Divion of Water Resources: Salt Lake City, UT.

CHAPTER 2

SYSTEMS MODELING TO IMPROVE RIVER, RIPARIAN, AND WETLAND HABITAT QUALITY AND AREA[1]

Abstract

Improving river habitat is challenging because managers must identify priority species and determine when, where, and how to allocate water between competing ecosystem and other users in the basin. While prior systems modeling efforts to manage stream flow include ecological objectives as constraints on flow or to minimize deviations from natural flow regimes, we present a new systems optimization model that formulates and maximizes an ecological objective as the sum of aquatic, floodplain, and wetland habitat areas and quality. Embedding this measurable ecosystem objective in a systems model allows managers to identify when, where, and how to allocate scarce water and financial resources to improve habitat area and quality. We followed a participatory approach to apply our model to the Lower Bear River watershed, UT. Results show that increasing winter releases from reservoirs on the Little Bear River, a tributary to the Bear River, and minimizing spring spill volumes can create additional suitable habitat area without compromising urban and agricultural water demands. Further, additional flow on the Little Bear River between August and December will most increase habitat area and quality compared to other locations. We display results on an open-access web map that allows stakeholders to visualize tradeoffs between habitats, identify opportunities to manage reservoirs that improve habitat, and validate results.

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[1] Co-authored by David E. Rosenberg

Highlights

- A new measurable ecological objective for habitat area identifies when and where managers can most improve habitat quality and area in a watershed
- A collaborative systems modeling approach that maximizes the new ecological objective and recommends the allocation of water between multiple competing aquatic, floodplain, and wetland habitat species
- A case study in a snowmelt-driver river basin shows that reducing spring reservoir spills and increasing winter releases can increase habitat area and quality.
- An open-access web map helps communicate opportunities to improve habitat area and quality to stakeholders.

Software and Data Availability

Name of software:	Watershed Area of Suitable Habitat (WASH) optimization model
Developers:	Ayman H. Alafifi and David E. Rosenberg
Contact:	aafifi@aggiemail.usu.edu
Year first available:	2016
Hardware required:	A personal computer
Software required:	General Algebraic Modeling System software (GAMS) with non-linear global solver such as Branch-And-Reduce Optimization Navigator (BARON), MS Excel 2016, R 3.3.0, and a web browser
Software availability:	All source code, input data, post-processing file, and documentation are available on Alafifi (2017). The application of WASH to the Lower Bear River, Utah, for one year (2003) is displayed on an open-access web map at: https://www.WASHmap.usu.edu
Cost:	The source code is released under the BSD 3-Clause, which allows for reuse of the code.

2.1 Introduction

Rivers and their riparian and wetland areas are managed to supply domestic and agricultural water users, generate hydropower , reduce flood damages, and support habitat for flora and fauna (Bernhardt et al., 2005). Although managers often prioritize human beneficial uses, regulated rivers also provide opportunities to improve habitat (Jager and Smith, 2008; Tharme, 2003). Improving river habitat requires defining measureable ecological objectives and determining the timing, magnitude, and locations of reservoir releases, diversions, and restoration efforts to advance the objectives.

Determining timings, magnitudes, and locations often requires navigating a complex set of considerations. First, managers must identify and locate the aquatic, floodplain, and wetland habitat areas in the basin that need improvement. Second, they should select indicator species from among the numerous species available in each habitat. The presense of indicator species denotes a healthy ecosystem and that can be monitored for abundance and are impacted by flow conditions. Third, managers may use models to mathematically quantify each species' response to changes in flow regimes. And finally, managers may collaborate with watershed stakeholders to identify when, where, and how to allocate water to meet other basin uses and improve habitat over observed conditions (Barbour et al., 2016).

Some quantification and modeling approaches such as the natural flow paradigm define species hydrologic requirements to mimic important timing, duration, magnitude, and frequency features of the natural flow regime (Poff et al., 1997). These approaches assume that historical natural flows are known and adequate to create desired ecosystem functions (Baron et al., 2002). Other approaches, such as Habitat suitability indices (HSI; U.S. Fish and Wildlife Service 1981) and dervatives (Hickey and Fields, 2013), use empirical relationships to describe the suitability of habitat to support the survival and productivity of a single species as a function of single or multiple habitat attributes such as instream water depth, water temperature, substrate, or flow duration. HSI values range from 0 (poor) to 1 (excellent) (Hemker et al., 2008; Hooper, 2010; Pinto et al., 2009). The Weighted Usable Area (WUA) method multiplies the HSI reach surface area by a unitless habitat suitability index and divides by reach length (Stalnaker, 1995). WUA can be used to describe habitat quality for a particular species at a specific site and time under prior or proposed flow regimes (Garcia-Rodriguez et al., 2008; Moir et al., 2005; Souchon and Capra, 2004). These approaches cannot determine whether a flow regime is feasible nor do they recommend locations, timings, or magnitudes of water allocations to improve multiple habitat types and species across a watershed.

Water resources systems models include multiple ecosystem assets as part of a connected network of reservoir, river, tributary, diversion, demand, and return flow components and can determine the feasibility of proposed flow regimes. Models typically include habitat considerations as constraints, such as to meet a minimum required instream flow (see, for example, Cioffi and Gallerano, 2012; Harman and Stewardson, 2005; Porse et al., 2015; Ryu et al., 2003). In other cases, a suitability index is maximized or minimized as a single objective or tradeoff with water delivery, hydropower generation, or other objectives (Null et al., 2014; Simonović and Nirupama, 2005; Yang, 2011). Or the model tries to minimize deviations from a pre-defined target value. For example, Higgins et al.

(2011) developed a heuristic nonlinear integer optimization model to minimize the difference between managed and natural flow regimes in the Murray River, Australia. Steinschneider et al. (2014) used linear programming to minimize the deviation between model recommended reservoir releases and estimated natural flows in the Connecticut River basin. Szemis et al. (2012, 2014) developed a heuristic ant colony nonlinear model for the Murray River to minimize the inverse of an ecological index plus constraint violations. Minimizing deviations from an ecosystem target poses challenges because managers need to subjectively define the target, such as natural flow regime or species-required flow (Barbour et al., 2016). Additionally, deviations and indices may not have physical meaning and are difficult to measure, validate, and communicate. Further, the habitat improvement to move a set number of units closer to the target depends on how close the current system state is to the ecological target. The above reasons make it difficult for managers to use deviation objectives to identify opportunities to improve habitat and compare potential improvements across watershed sites.

This paper develops the Watershed Area of Suitable Habitat (WASH) systems model, which formulates and embeds a measureable and observable suitable habitat area metric as an ecological objective to maximize. Suitable habitat area represents the combination of habitat quality and area, is measured in acres, and indicates the area of good quality habitat with physical characteristics that can support the life needs of priority species. Suitable habitat area is the sum of suitable aquatic, floodplain, and wetland habitat areas. WASH recommends flow regimes that improve suitable habitat area for priority species. The WASH model and habitat area objective allow managers to (i) compare ecological measures across sites; (ii) identify where and when to apply scarce water, money, and planting efforts to most improve habitat quality and area; (iii) involve stakeholders to help define ecological objectives, view, and validate results; and (iv) adapt the method to other basins, sites, habitat types, and species. Section 2 introduces the study area for the Lower Bear River, Utah. Section 3 describes the model formulation and system components. The remaining sections present results, management implications, and conclusions.

2.2 Study Area

The Lower Bear River (LBR) is part of the longer 491-mile Bear River that starts in Utah, flows north through Wyoming and Idaho, then returns south to Utah. The study area is the LBR basin, which includes the Bear River from the Utah-Idaho state line to the river's terminus at the Great Salt Lake and tributaries (Figure 2.1). The Utah Division of Water Resources (2004) estimates that approximately 60% of LBR flow comes from snowmelt runoff in April, May, and June. The river and its tributaries irrigate over 300,000 acres of agricultural land and supply water to numerous cities and communities, as well as run-of-river hydroelectric plants (UDWR, 2004; UDWRe, 2000). The river is central to the growth and development planning debate for several counties within the basin such as Cache and Box Elder Counties, Utah in addition to the off-basin Wasatch Front metropolitan region (UDWR, 2004; UDWRe, 2000).

The LBR is also vital to maintaining critical wildlife habitat for many native and threatened fish, riparian plants, and migratory bird species (Bio-West, 2015). Intensive urbanization, water development, fish barriers, and grazing have led to distributed flow regimes for native and game fish species, reduced floodplain connectivity, and altered native plant community composition (Bear River CAP, 2008; Bio-West, 2015). At the river's terminus at the Great Salt Lake, the U.S. Fish and Wildlife Service (FWS) manages the Bear River Migratory Bird Refuge (hereafter the Bird Refuge), comprising 300 km^2 of impounded wetlands that provide feeding, resting, and breeding grounds for over 250 globally significant populations of migratory birds (Alminagorta et al., 2016a).

According to the western U.S. prior appropriation doctrine, the Bird Refuge holds a more recent water right that is junior to more senior upstream agricultural users (Downard et al., 2014). Thus, senior irrigators take their entire water rights before the Refuge receives any water. Most other land in the LBR is privately owned and few formal or legal mechanisms exist to provide water to improve fish, riparian plant, and migratory bird habitats throughout the basin. The Nature Conservancy, Trout Unlimited, landowners, and local, state, and federal agencies have identified low flow as a major threat to fish populations, riparian plants, and migratory birds in the watershed (Bear River CAP, 2008). Thus, we selected the LBR because management efforts are already underway to restore valuable habitat and study results could allow managers to determine the amount of water needed to sustain ecosystem health for priority species.

2.3 Model Development

Improving river habitat quality and area requires a collective effort among researchers and managers to identify habitat types, priority sites, indicator species, habitat attributes, suitability of habitat attributes for species, and the network of water system components. Here, we demonstrate a participatory approach to develop a systems model

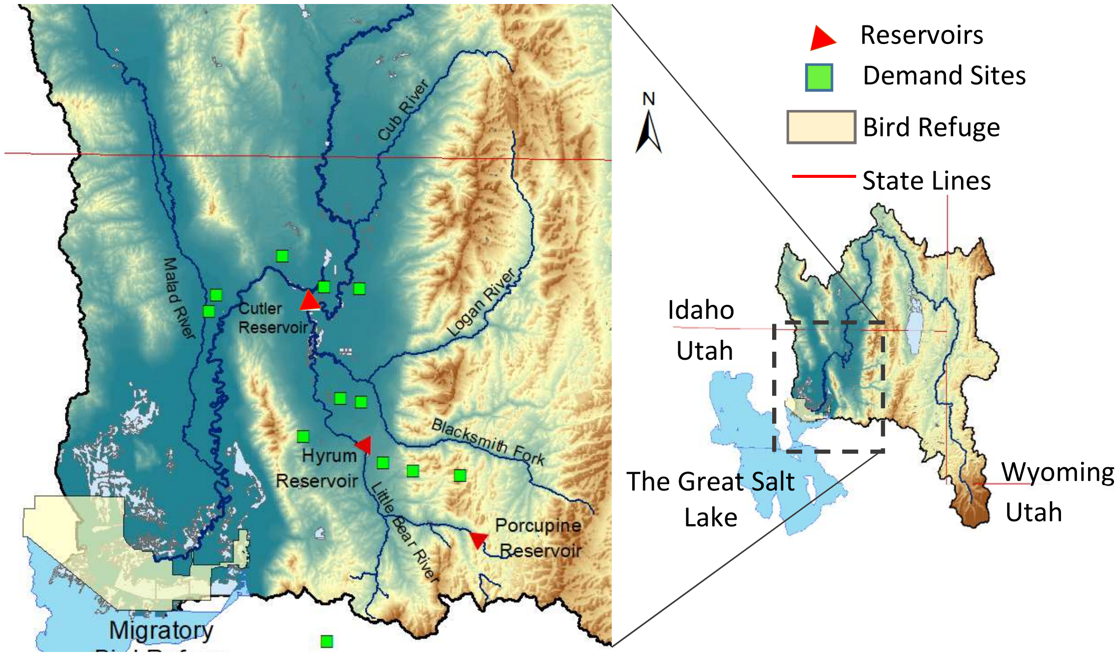

Figure 2.1: The Lower Bear River, Utah including major tributaries, demand sites, and reservoirs

that maximizes the suitable habitat area, addresses multiple habitat management goals, and identifies promising management strategies to improve habitat area and quality.

We began by soliciting support from river managers and stakeholders working to implement the Bear River Conservation Action Plan (Bear River CAP, 2008). The CAP team identified a management target to improve aquatic, floodplain, and wetland habitat quality for key species in the basin. Improving habitat quality requires determining where, when, and how to allocate water between priority species at multiple habitats across the watershed to improve overall habitat quality. Therefore, a systems model approach to guide management decisions needs to have a physically measureable and observable objective function that considers habitat quality and area so managers can compare habitat across diverse ecological sites, communicate results, and show implications of actions over time.

2.3.1 Selection of indicator species

The presence and abundance of indicator species is a strong signal of ecosystem response to alterations in flow regimes (Carignan and Villard, 2002). We identified key native and game fish, riparian plants, and wetland migratory bird species in the LBR watershed based on their abundance in the watershed and sensitivity to changes in flow regimes. For each species, we defined suitable ranges of habitat attributes such as water depth and flood recurrence. We considered seasonal variations in habitat attributes for species different life stages (Table 2.1). We derived habitat attribute ranges from literature, empirical studies, and other models and verified them with project stakeholders.

Fish spawning, seed recruitment, and migratory bird feeding, nesting, and breeding occur on a seasonal (multi-month) time scale. We selected a monthly time step (t) for WASH because watershed managers plan and schedule flow management actions at monthly intervals.

Below we describe the general model formulation of decision variables, objective function, and constraints. In the formulation, capitalized terms represent variables, lower case indicates parameters and model inputs, and lettered subscripts denote indices for space, time, species, and habitat types (bottom of Figure 2.2).

2.3.2 Decision Variables

To improve habitat quality, managers can adjust reservoir releases $RR_{v,\mathrm{t}}$ [million cubic meters per month, Mm^3] at each reservoir v in month t. They also control diversion volumes $Q_{\mathrm{j,dem,t}}$ [Mm^3/month] from the river at node j to each demand site *dem* in each month t to satisfy urban and agricultural demand. Managers can also plant $RV_{j,\mathrm{k,t,n}}$ [Mm^2]

in the floodplain adjacent to the river reach from node j to node k during month t by seeding or planting species n. These variables control a group of state variables that include reservoir storage volume $STOR_{v,t}$ [Mm^3], reservoir surface area $RA_{v,t}$ [Mm^2], river flow $Q_{j,k,t}$ [Mm^3/month] from node j to node k in month t, river water depth $D_{j,k,t}$ [m/month], channel surface area $A_{j,k,t,}$ [Mm^2], channel width $WD_{j,k,t}$ [m], and floodplain plant cover $C_{j,k,t,n}$ [Mm^2].

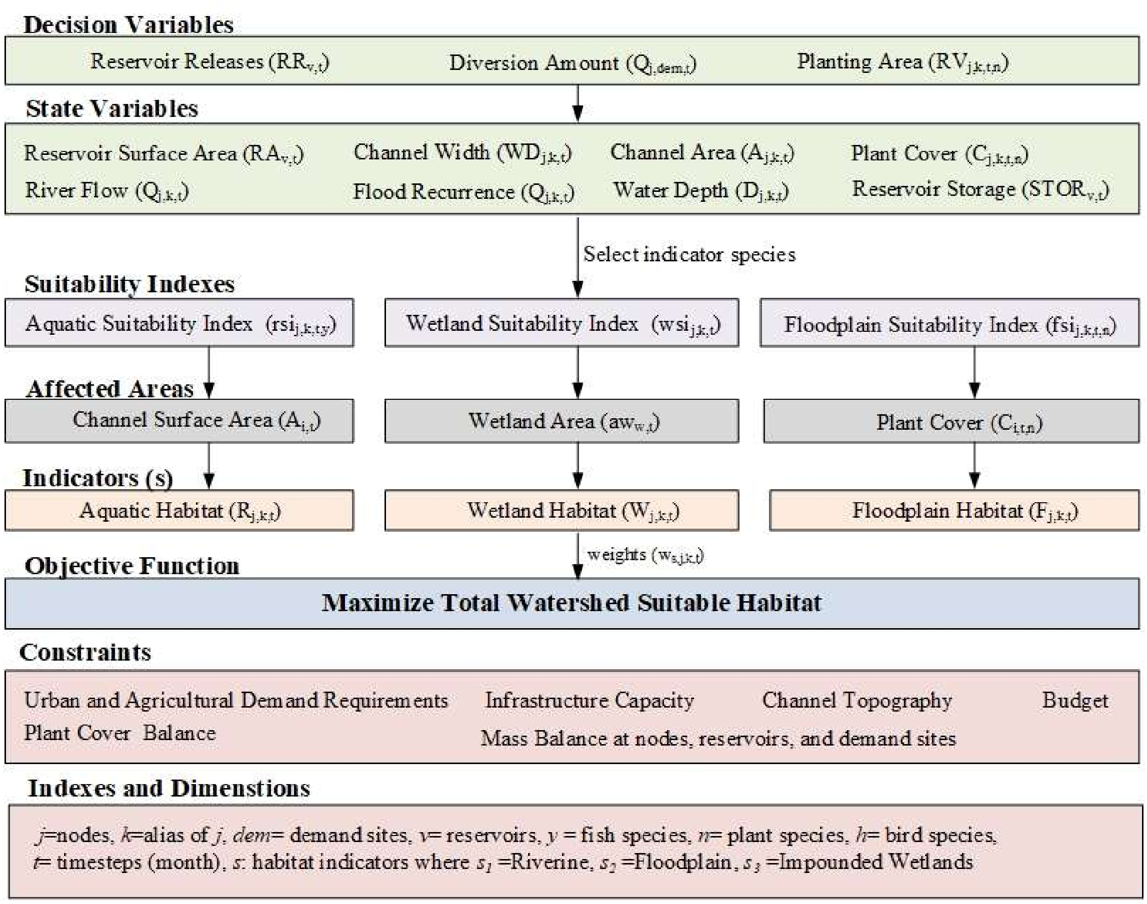

Figure 2.2 The WASH model connects decision variables, state variables, parameters, and suitability indices to an objective function measured as suitable habitat area. Physical, management, and plant constraints limit decisions

Table 2.1 Habitat indicator components by habitat type, species, species life stage, seasons, and ecosystem function

Habitat	**Indicator Species**	**Life Stage**	**Aspects of life stage supported and (timing)**	**Habitat Attribute**	**Suitable Range of Habitat Attribute**	**Affected Area**	**Data Source(s)**
Aquatic	Bonneville cutthroat trout (*Oncorhynchus clarki utah*)	Adult	Native spawning (Sep. – Mar.)	Water depth (m)	0.30 - 0.75	Channel surface area	Hickman and Raleigh (1982), Braithwaite (2011), Gosse et al. (1977) and Gosse (1981)
		Fry	Native maturing (Apr. – Aug.)		0.10 - 0.45		
	Brown trout (*Salmo trytta*)	Adult	Game fish spawning (Sep. – Mar)		0.10 - 0.80		
		Fry	Game fish maturing (Apr. – Aug.)		0.10 - 0.50m		
Flood-plain	Cottonwoods (*Populus fremontii)*	Germinate & disperse seeds	Native recruitment (Apr. – Aug)	Flood recurrence	> Bank-full flow	Floodplain area	Meier and Hauer (2010) Mahoney and Rood (1998)
Wetland	Black-necked stilt (*Himantopus mexicanus*)	Adult	Feeding, resting, and breeding (Apr. – Sep.)	Water depth (m)	0.15–0.25m	Impounded wetland area	Alminagorta et al. (2016)
				Invasive plant cover (%)	< 10%		
	American avocet (*Recurvirostra Americana)*		Feeding, resting, and breeding (Mar. – Oct.)	Water depth (m)	0.35-0.45m		
				Invasive plant cover (%)	< 10%		
	Tundra swan (*Cygnus columbianus*)		Feeding and resting (Nov.– Mar.)	Water depth (m)	> 0.55m		
				Invasive plant cover (%)	< 10%		

2.3.3 Objective Function

The objective function maximizes the weighted sum of the suitable areas of aquatic [$IND_{aquatic,j,k,t}$], floodplain [$IND_{floodplain,j,k,t}$], and wetland [$IND_{wetland,j,k,t}$] habitats [Mm^2] in reach *j* to *k* in month *t* where $wght_{s,j,k,t}$ are stakeholder-decided weights for habitat indictor *s* in reach *j* to *k* at month *t.* Weight values range from 0 (not important) to 1 (important).

$$Max\ \ Z = \sum_{s,j,k,t} wght_{s,\mathrm{j},\mathrm{k},t} \ \cdot \ IND_{s,j,k,t} \qquad [1]$$

The value of each habitat indicator is the product of a suitability index representing habit quality and an affected area. Using the habitat suitability ranges in Table 1, we designed suitability indices (SIs) [unitless] for aquatic, floodplain, and impounded wetland habitats as functions of hydrologic and ecological habitat attributes that influence priority species survival and abundance, such as water depth, flood recurrence, and plant cover. Functions defining SIs are specific to the reach, species, species life stage, and habitat attribute. The SIs approach 1 (excellent conditions) when values for the habitat attribute support densities for the priority species that exceed a certain threshold. In contrast, *SIs* approach 0 (poor conditions) when the density of a priority species is below a threshold (Roloff and Kernohan, 1999). SIs are constructed using empirical data, literature, and expert opinion.

Affected areas are the reach-specific habitat areas in the watershed at which each suitability index applies (Figure 2.1). Affected areas are also functions of flow and plant cover habitat attributes. We aggregate habitat indicators using spatial and temporal weights to express the overall WASH area for the watershed in area units (m^2). Therefore, suitable habitat areas are the fraction of the total affected areas that are characterized by the good habitat attributes to support the life needs of priority species.

a. Aquatic Habitat

Managers can improve fish habitat in the LBR by improving flow regimes that shape physical habitat health and determine biotic composition of riverine species (Bunn and Arthington, 2002). Here, we use water depth and temperature as two primary abiotic factors that define aquatic habitat quality and suitability for fish (Jackson et al., 2001). We designed water depth suitability curves and adjusted them to fish species tolerance for water temperature.

The Bonneville cutthroat trout (BCT; *Oncorhynchus clarki utah*) is a critical native fish species in the Blacksmith Fork and Little Bear rivers, two Bear River tributaries, and is the target of many restoration efforts because of declining numbers in recent decades (Bio-West, 2015). Brown trout (*Salmo trytta*) is a popular non-native game fish species that has high tolerance to low summer flows, warmer lower-elevation reaches, and parasites causing whirling disease compared to other members of the trout family (UtahFishingInfo Website, 2016).

The lower elevation Bear River main stem has warm summer water temperatures that reach 26° C. The higher elevation Little Bear and Blacksmith Fork rivers have cooler water temperatures that do not exceed 22.5° C (Watershed Sciences, 2007). Johnstone and Rahel (2003) report that water temperature at or above 25° C could be lethal for BCT, while Raleigh et al. (1984) reported that brown trout can tolerate water temperature up to 27.2° C. Currently, BCT is only abundant in the headwaters of the Blacksmith and Little Bear rivers (DeRito, pers. comm., 2016). Thus, we assigned BCT as the indicator fish species in

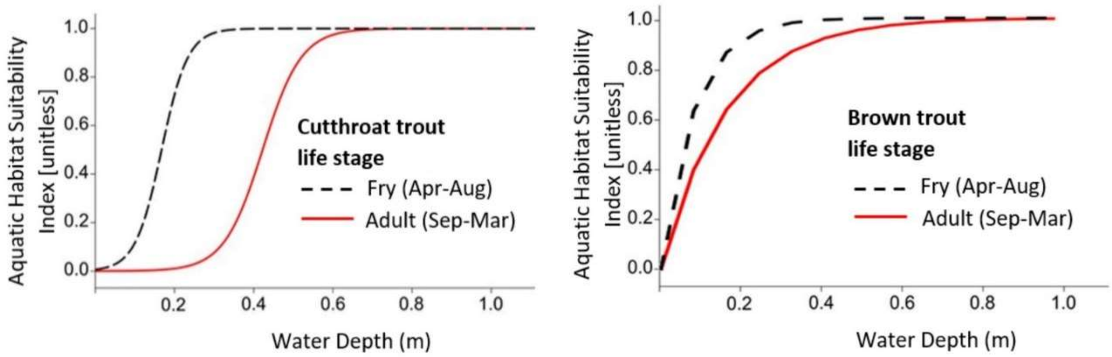

Figure 2.3 Aquatic Suitability Index values for water depth for Bonneville cutthroat trout (left) and brown trout (right).

colder headwater reaches and brown trout in remaining warmer reaches.

We developed the aquatic suitability index (*rsi;* unitless) as a function of water depth $D_{j,k,t}$. The rsi curves vary between 0 at water depths in LBR reaches where empirical studies found no fish to 1 at water depths where fish (or redd counts) were abundant. The corresponding water depth ranges for BCT were obtained from a 2-year study in the nearby Strawberry River by Braithwaite (2011) and for brown trout from Gosse et al. (1977) and Gosse (1981) on the Logan and Provo rivers in northern Utah. Water depth ranges were also verified by the project stakeholders. For brown trout, we assigned a poor suitability index value of 0 at 10 cm water depth because brown trout can tolerate very shallow depths (Raleigh et al., 1984). We used Boltzmann and exponential decay functions to specify the shapes of suitability index curves for BCT and brown trout (Figure 2.3) based on similar FWS HSI curves for water depth (Hickman and Raleigh, 1982; Raleigh et al., 1984).

The aquatic habitat indicator is the product of *rsi* for each reach (*j,k*), month (*t*) and fish species (*y*) and the corresponding channel surface area (Eq. 2). With multiple fish species (*y*), we multiply suitability indices together to emphasize the concurrent need for suitable water depths for all species at the same time and location.

$$IND_{aquatic,j,k,t} = \prod_y rsi_{j,k,t,y}(D_{j,k,t}) \cdot A_{j,k,t}\,, \qquad \forall\, j,k,t \qquad [2]$$

Other methods to combine multiple species use arithmetic or geometric averages to aggregate multiple indices and assume that good habitat for one species compensates for poor condition for another species (Ahmadi-Nedushan et al., 2006).

b. Floodplain Habitat

Floodplain areas are adjacent to streams and are periodically inundated with water. Seasonally high water levels in these areas inundate riparian plant roots and keep soil moist (Meier and Hauer, 2010). The lateral connectivity between the river channel and its floodplain area is a primary factor shaping plant community composition, abundance, and survival (Merritt et al., 2010; Poff et al., 1997; Rivaes et al., 2013; Rood et al., 2005). In connected floodplains, plant recruitment and seed germination coincide with flood events that occur when discharge exceeds the bankfull flood level (Meier and Hauer, 2010; Yarnell et al., 2010). This level is defined as the visible break in slope between the un-vegetated bank and the adjacent vegetated floodplain surface (Li et al., 2015; Parker et al., 2007). Bankfull discharge is often associated with the 1.5 year flood recurrence interval (Kilpatrick and Barnes, 1964; NOAA, 2015; Rosgen, 1994). Therefore, to restore lateral connectivity, managers need to determine the proximity of priority floodplain plants to riverbanks and manage streamflow to exceed bankfull discharge and inundate target plants during their seed germination season.

We selected cottonwood trees (*Populus fremontii*) as an indicator native plant species in the LBR because it predominates in the basin's floodplains and provides shade, food, and habitat for mammals, birds, and insects (Bio-West, 2015). Cottonwoods release seeds just after peak flows in snowmelt-driven rivers (Bhattacharjee et al., 2006; Mahoney and Rood, 1998). Thus, lateral connectivity between the channel and floodplains is most important between April and June for successful seed dispersal and through August for the continued soil moisture needed to establish dispersed seeds (Bhattacharjee et al., 2008; Mahoney and Rood, 1998). Cottonwood trees grow adjacent to river channels and are likely to be inundated by flow magnitudes over bankfull flow (1.5-year flood recurrence value). Therefore, we designed the floodplain suitability index (fsi; unitless) as a function of streamflow $Q_{j,k,t}$. The index curves transition from 0 (poor lateral connectivity), when flow is at or below the 1-year recurrence value, to 1 (excellent connectivity) when the instream flow equals or exceeds the 2-year recurrence flow (Figure 2.4). The 1- and 2-year recurrence flow thresholds at different reaches in the basin are determined from historical flow records using the Log Pearson Type III distribution with mean and standard deviation of the log-transformed annual flow series. We measured initial existing cottonwood tree cover alongside every reach from NAIP Imagery.

The floodplain connectivity indicator is calculated by multiplying fsi for reach, month, and riparian plant species by the area of plant cover (C) and then summing the values for each plant species n [eq. 3]. The summation across plant species in eq. [3] emphasizes that individual plant species can coexist at lateral different distances from the riverbank and these different lateral distances require different flood magnitudes to establish connectivity. For example, cottonwood trees lives adjacent to river banks and requires flood recurrence of 2-year for lateral connectivity (Richter and Richter, 2000).

Other riparian trees such as Pacific willow *(Salix lasiandra)* live further upslope in the floodplain and could require a higher flood frequency interval for lateral connectivity (Dettenmaier and Howe, 2015; Rood et al., 2003).

$$IND_{floodplains,j,k,t} = \sum_n fci_{j,k,t,n}(Q_{j,k,t}) \cdot C_{j,k,t,n} \qquad \forall\, j,k,t \qquad [3]$$

c. Impounded Wetlands

Wetlands are recognized as one of the most productive ecosystems for a variety of wildlife species, particularly water birds (Nikouei et al., 2012). Impounded wetlands have dikes, gates, weirs, canals, or other hydraulic structures that allow managers to control flows into and out of wetlands. The Bird Refuge comprises 25 impounded wetland units that draw water from the Bear River (Downard et al., 2014). Maintaining wetland

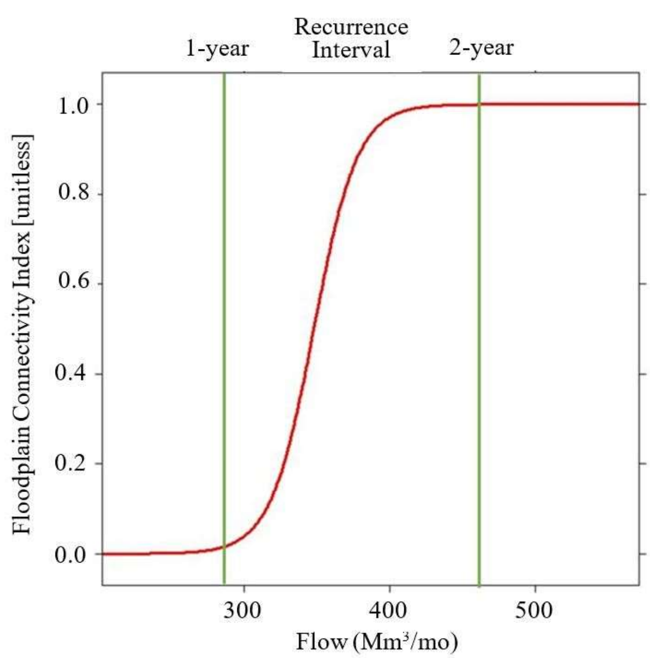

Figure 2.4 Floodplain suitability index as a function of flow at the Bear River Corinne site. Floodplain suitability transitions from 0 to 1 between flow values with recurrence interval of 1- and 2-years

ecological services at the Bird Refuge requires managing water depth and plant cover habitat characteristics necessary for different bird species to feed, nest, rest, and breed (Downard and Endter-Wada, 2013; Faulkner et al., 2010; Rogers and Ralph, 2011).

Prior work by Alminagorta et al. (2016b) developed a composite Usable Area for Wetland (WU) metric for the Bird Refuge (measured in km^2) and embedded the WU metric in a systems model as an objective to maximize. The WU metric quantified the wetland surface area with water depth and plant cover habitat characteristics that support Black-necked stilt, American avocet, and Tundra swan (Table 2.2). These three priority bird species were selected because they use a range of shallow, medium, and deep water depths that encompass depths used by 20 other priority bird species at the Refuge.

We built on the WU work of Alminagorta et al. (2016a) at the Bird Refuge to develop a Wetland Suitability Index (*wsi*) for WASH. The *wsi* represents the suitability of impounded wetlands to improve water depth and native plant cover for priority bird species. Here, we estimated monthly wetland suitability index values by dividing Alminagorta's monthly WU areas, generated for various water availability scenarios between 1992 to 2011, by the total Refuge area. Then we developed monthly relationships between the suitaibilty index values and monthly river flows measured just upstream of the Bird Refuge at the Corinne, UT USGS station (one example shown in Figure 2.5).

The impounded wetland indicator is calculated by multiplying a *wsi* index (as a function of streamflow) by the total wetland surface area *aw* [Mm^2]. In Eq. [4], the *wsi* defines an aggregate suitability index for multiple wetland bird species.

$$IND_{wetlands,j,k,t} = wsi_{j,k,t}(Q_{j,k,t}) \cdot aw_{j,k,t}, \qquad \forall\, j,k,t \qquad [4]$$

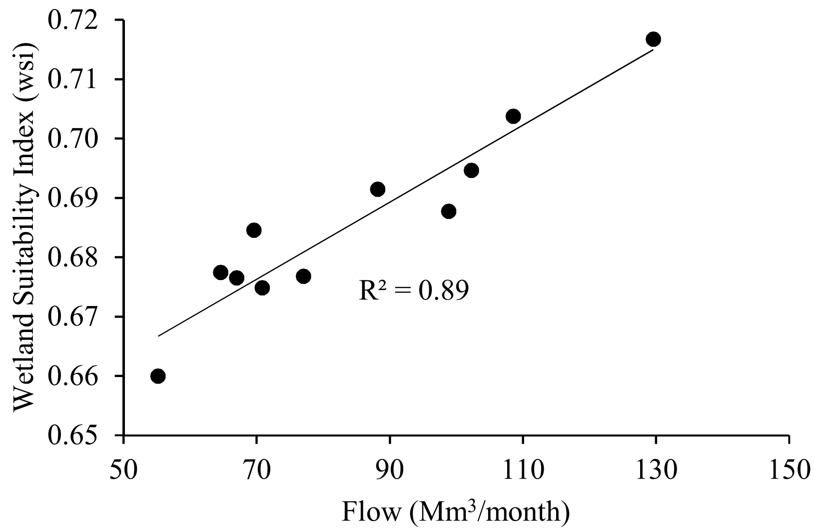

Figure 2.5 Example WASH wetland suitability index for February

2.3.4 Constraints

Reservoir releases, diversions, planting, and other decisions are bound by physical, infrastructure, and management constraints (Appendix B, eqs.5-18). Physical constraints include low-order, finite-difference approximation to conservation of water mass balance at each reservoir, node, and demand site. They also include equations to constrain plant cover growth over time and define channel topography. Infrastructure constraints place minimum and maximum limits on reservoir and diversion canals capacity. Management constraints include urban and agricultural demand requirements and available budget. Nonlinear objective and constraint functions in WASH formulation are all continuous and smooth to avoid numerical difficulties in the optimization.

2.3.5 Model Input Data

WASH requires hydrologic, ecological, topological, and management data (Table 2.1). We collected the required data from sources including the Utah Division of Water

Resources (DWRe) water supply/demand simulation model for the Lower Bear River (Adams et al., 1992). We also established two monitoring sites on the Bear River mainstem and one site on the Cub River to collect and ground truth hydrologic and ecological data between August 2012 and November 2016. We assumed a budget of $650,000 to plant native riparian trees based on the Cache County Water Masterplan estimated budget for

Table 2.2 Data required for WASH model components

Model Component	**Data Item**	**Source(s)**	**Component Type**
Aquatic Habitat	Reach lengths	NHDPlus V2 (2016), USGS (2012), field measurements	Link
	Water depth-ecological suitability curves	FWS, stakeholders, and literature	Link
Floodplain Habitat	Plant cover and distance from banks	USDA (2014) NAIP Imagery, field measurements	Link
	Floodplain area	NAIP Imagery, field measurements	Link
	Flow-ecological suitability curves	FWS, stakeholders, and literature	Link
Wetland Habitat	Wetland unit water level-storage curves	LiDAR, field measurements	Link
	Invasive plant cover	Landsat satellite imagery	Link
	Evaporation rates	Western Regional Climate Center	Link
	Flow-ecological suitability curves	FWS, stakeholders, and literature	Link
Physical Constraints	Reservoirs storage-elevation-area, evaporation, and capacity	Adams et al. (1992), U.S. BoR	Node
	Diversions capacity	Adams et al. (1992)	Link
Natural Constraints	Headwater and local inflows	USGS, NHDPlus V2, UWRL (2009)	Node
	Water level and channel cross section	Field measurements	Link
	Evaporative losses on reaches	NHDPlus V2	Link
	Natural growth of riparian plants	Stakeholders	Link
Management Constraints	Urban and agricultural demand	GenRes	Node
	Consumptive use of flow	GenRes	Node
	Instream flow requirements	Stakeholders	Link
	Budget and unit costs	Stakeholders	Link
Model Formulation	Weights	Stakeholders	Link

future ecosystem projects (JUB, 2013). Processed hydrologic and ecological data are available at the Bear River Fellows website (http://bearriverfellows.usu.edu). WASH model input data and code are available at the WASH GitHub repository (Alafifi, 2017).

2.3.6 Model Scenarios

We implemented the model on a monthly time scale for one calendar year (2003) to represent an average year, based on monthly headflows observed over the last 15 years. We selected a single year to run the model because most reservoir and watershed managers in the basin plan operations at monthly intervals for a one-year cycle. Also, spring snowmelt runoffs typically fills reservoirs in April, May, or June. We first ran the model in simulation mode for the base case year (2003) by fixing flows on all river segments to observed historical gaged values. We then compared WASH habitat area under observed flows to a second scenario with flow limits relaxed. This scenario showed potential habitat gains if water was managed as the model recommends. Two other scenarios with different headflows for a wetter (2005) and drier (2004) year allowed us to examine model response to changes in headflows. Additional scenarios multiplied each urban and agricultural demand in the basin by a fraction of total demand to explore the tradeoffs between WASH habitat area and water supply objectives. We also ran the model for 5 years (2003 to 2007) to identify the effects of annual flow variability.

In a final scenario, we substituted habitat suitability curves for the bluehead sucker *(Catostomus discobolus)* aquatic fish species for brown trout downstream of Cutler reservoir to identify the effect of indicator species on habitat quality and area. Bluehead sucker is a non-game fish and is listed as a sensitive species by state and federal agencies.

Declining bluehead sucker numbers in the Utah Bonneville Basin might warrant listing bluehead sucker as a threatened or endangered species (UDNR, 2006; Webber et al., 2012). Based on the suggestion of project stakeholders, we designed bluehead sucker suitability index curves using the empirical study of Anderson and Stewart (2003). These functions are Blotzmann curves that transition from 0 at a water depth of 100 cm to 1 at 150 cm for both adults and fry.

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2.3.7 Model Implementation

We segmented the Bear River and its main tributaries into a network of 43 nodes and 56 links, with 3 reservoirs, 12 municipal and agricultural demand sites, and 26 environmental sites where species of concern live (Figure A.1; Appendix A). We ran the model with the same weight value of 1 for all indicators to equally favor all locations, species, and months.

We coded the WASH model [equations 1–17] using the General Algebraic Modeling System software (GAMS; Hozlar, 1990) and solved the model using the non-linear global solver Branch-And-Reduce Optimization Navigator (BARON; Sahinidis, 1996). The GAMS code uses GDX (GAMS Data Exchange format) to read all input data from an MS Excel spreadsheet and pass it to the model. The 1-year implementation of the model for the Lower Bear River system has approximately 27,000 variables and 5,300 equations and takes 2 hours and 15 minutes to find a global optimal solution on a Dell XPS Windows10 64-bit computer.

2.3.8 Model Outputs and Visualization

WASH results include recommended flows, reservoir releases, storage volumes, and temporal and spatial variations of suitable aquatic, floodplain, and impounded wetland habitat area. We display model results in an open-access, interactive web map application (http://WASHmap.usu.edu). With the web map, users can compare modeled and simulated results, add base maps and data layers, and customize the tool. The WASH map displays results in US Customary Units to better communicate with local stakeholders. All WASH model input data, code, and post-processing files are available at the WASH GitHub repository (Alafifi, 2017).

2.4 Results

The model run that simulated 2003 flows shows nearly 100 thousand acres of suitable aquatic, floodplain, and wetland habitat in the watershed. The WASH global optimal solution shows a potential to increase the overall suitable habitat area by 25 thousand acres (25%). This overall increase is achieved with 3-, 10-, and 7-fold increases, respectively, of the suitable areas of aquatic, floodplain, and wetland habitats over 2003 modeled historical conditions in several months (Figure 2.6). The largest aquatic habitat increases for fish occur in May, June, and November and help BCT and brown trout fry to mature and adults to spawn. The largest floodplain habitat increases for plants occur in July and August and help cottonwood to reestablish on the Bear River reaches above Cutler reservoir. Wetland habitat increases occur from June to August at the Bird Refuge and help stilts, avocets, and swans to nest, breed, and feed. These suitable areas approach 53%, 3%, and 40% of the total aquatic, floodplain, and wetland habitat areas in the basin.

The WASH model improves suitable habitat area by increasing winter and early spring releases at Hyrum Reservoir and minimizing late spring spills at Hyrum and Porcupine reservoirs in May (Figure 2.7). The model increases habitat area while continuing to meet human water uses at all demand sites during all months. This recommended release pattern supports brown trout spawning in late fall, and maintains the eggs in gravel redds until they hatch in spring.

Although wetland suitable area at the Bird Refuge increases to only 40% of the total suitable area, improvements occur during critical summer months when Bear River flows at Corrine typically did not satisfy the Bird Refuge's junior water rights (Figure 2.8). Overall, the model recommended habitat area approaches 18% of the total available habitat area in the watershed if all suitability index values are at 1. Additional river flow, habitat suitability, reservoir release, and demand site results are available on an interactive webmap at http://WASHmap.usu.edu.

Running the model for 2005 (wet year) increased the suitable habitat area by 18 thousand acres (Figure 2.9, red circle), while using 2004 flows (dry year) decreased the suitable habitat area by 15 thousand acres (orange triangle). Reducing urban and agricultural demand in 10% increments increased habitat suitability area by approximately 4,000 acres per 10% reduction in demand, with most of the initial increases in habitat area occurring at the Bird Refuge and in aquatic habitat on the Little Bear River. The model becomes infeasible when human demands in the 2003 base case scenario exceed 110% of existing demand.

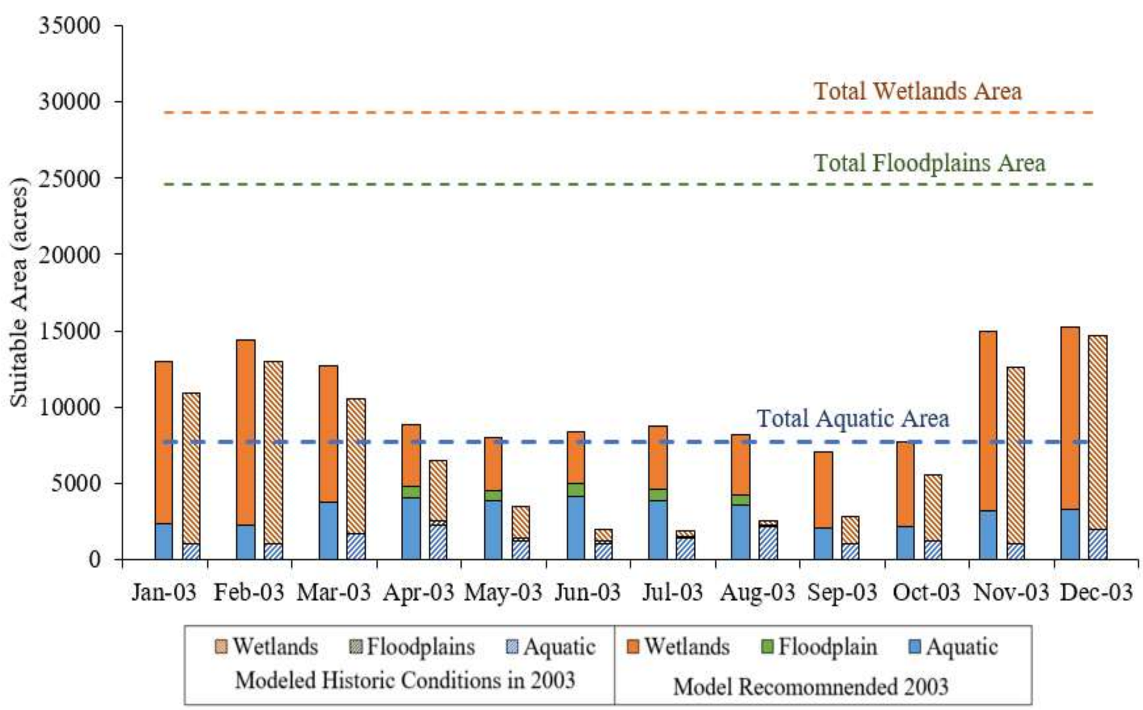


Figure 2.6 Monthly suitable aquatic, floodplain, and wetland habitat areas in the Bear River watershed compared to total available areas (dashed, horizontal lines)

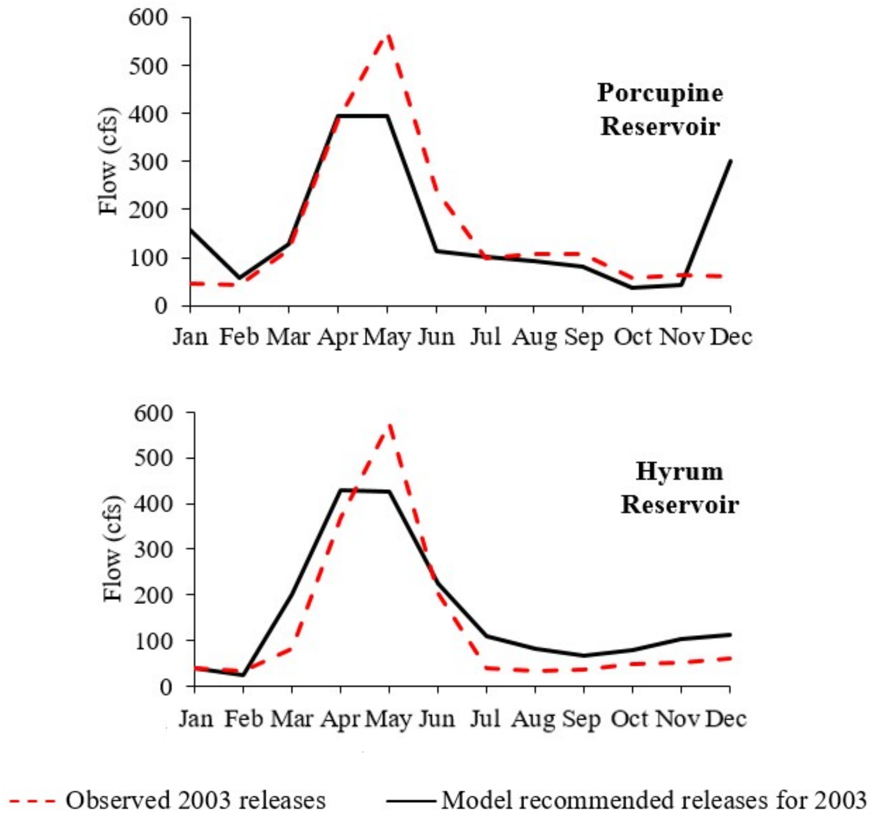
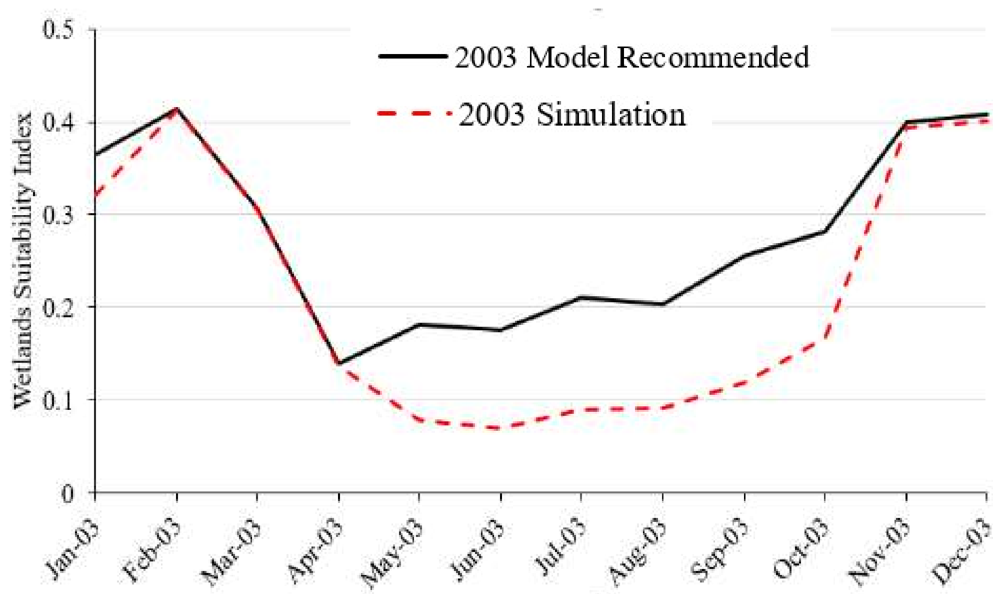


Figure 2.7 Comparison between model recommended and current reservoir releases for 2003 for (top) Porcupine and (bottom) Hyrum reservoirs

Running the model for 5 years, from January 2003 to September 2007, shows that the model can sustain habitat increases across seasonal and annual variations in flows compared to modeled historic conditions (Figure 2.10). For instance, aquatic habitat suitability for spawning and maturing dropped in 2004 but remains higher than in the modeled historic conditions case. Monthly flows and reservoir storage volumes minimize late spring spills, increase winter releases, and conform to storage and release patterns seen in the single-year run (Figure 2.8).

A. Wetland habitat suitability index at the Refuge



B. River flow at the Refuge

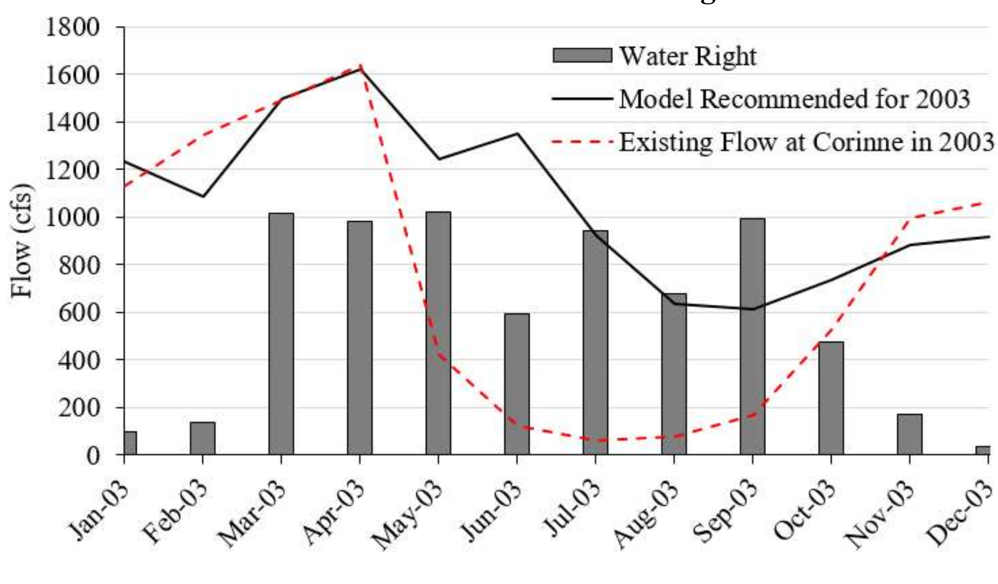


Figure 2.8 Model recommended improvements at the Bird Refuge compared with simulated historic conditions in (A) wetland suitability index and (B) flows

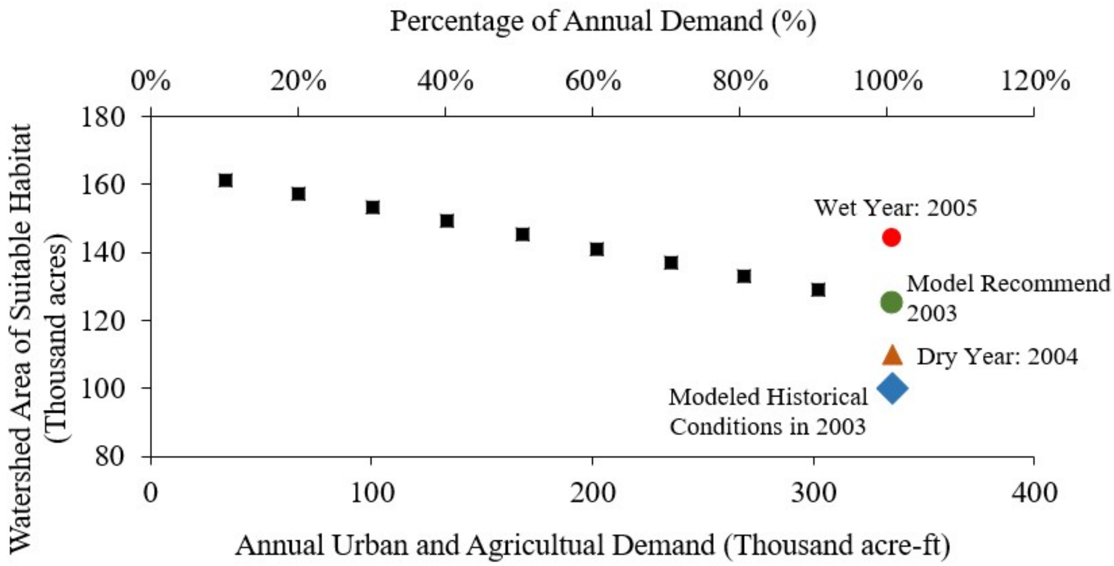


Figure 2.9 Tradeoff between WASH suitable area and annual demand delivery targets

Using bluehead sucker to define aquatic habitat suitability downstream of Cutler reservoir decreased the overall WASH habitat area by 6 thousand acres, as compared to the base case with two trout species. This decrease occurs because adult Suckers use deeper water depths (3.3–5 ft) to spawn. Also, the model has a difficult time allocating water downstream of Cutler reservoir in summer months because most upstream water is diverted to the Bear River Canal Company, the largest and most senior agricultural water user in the watershed.

To identify when and where the greatest ecological benefits for each additional unit of flow will occur in the system, we examined the shadow values (Lagrange multipliers) associated with the water mass balance constraints for nodes with headwater flow [Appendix B Eq. 7]. Shadow values report the increase in the WASH objective function value—acres of suitable habitat—per one additional flow unit (cfs) (Table 2.3). The largest shadow values occur on the East Fork of the Little Bear River for most months of the year. There are also increases greater than 2.5 acres/cfs on the Bear River in August, Blacksmith Fork from April to October, and South Fork of the Little Bear in August and September. Similarly, we examined shadow values for the budget constraint [Appendix B Eq. 18] and found that the objective function value increases by 30 acres per additional $10,000 available for planting floodplains.

2.5 Discussion

Formulating the WASH model objective function as a habitat area to maximize allowed us to examine ways to manage water and plants in the Lower Bear River to increase aquatic, floodplain, and wetland habitat area for priority species in the watershed while satisfying water demands of existing human users. Managing river flow, water depth, flood recurrence, and vegetation cover in the Lower Bear River supports ecosystem functions of aquatic, floodplain, and wetland species and improves habitat quality, which in turn increases the area of suitable habitat.

Table 2.3 Shadow values of additional water by location and month (acres/cfs)

Shadow Values/ Month	**Jan**	**Feb**	**Mar**	**Apr**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
Bear River	2.19	1.54	1.54	1.54	2.40	2.44	7.62	1.73	1.09	0.73	1.09
Cub River	1.35	0.75	0.53	2.26	0.66	2.09	0.95	0.86	1.07	0.97	0.98
Blacksmith Fork River	1.80	1.20	1.10	2.87	3.29	3.25	3.32	2.43	2.50	1.41	1.42
Little Bear River at East Fork	4.36	3.36	4.73	2.73	3.73	4.27	7.80	12.15	3.99	3.81	3.81
Little Bear River at South Fork	1.80	1.20	1.10	2.87	1.29	1.25	3.32	3.43	2.50	2.41	1.42
Malad River	0.80	0.20	0.12	0.15	0.11	0.12	0.15	0.18	0.43	0.32	0.39

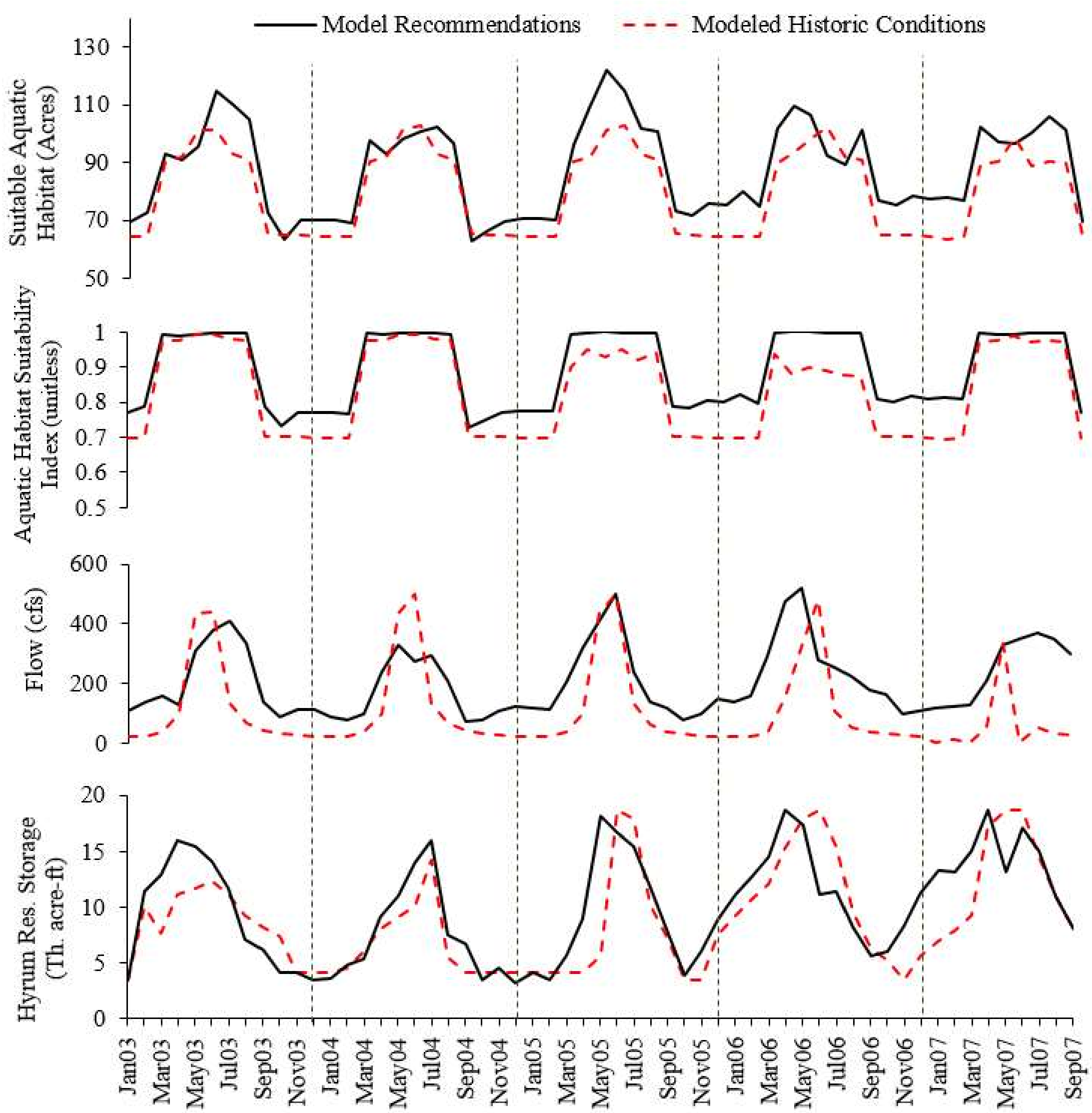


Figure 2.10 Comparison of suitable aquatic habitat area (acres), habitat index (unitless), flow (cfs), and reservoir releases (acre-ft) between model recommendation and modeled historical conditions for 5 years (2003 – 2007) on the Little Bear River downstream of Hyrum Reservoir and just before Cutler dam

To increase habitat area in the Lower Bear River, the model recommends releasing more water from Porcupine and Hyrum reservoirs in winter months and reducing late spring spills. These changes in reservoir releases would support brown trout spawning in late fall. The gradual release of water from reservoirs also protects trout eggs from winter and spring flood events that could scour or kill incubated eggs and newly emerged fry (George et al., 2015). These changes in reservoir releases would likely result in small improvements in floodplain habitat area relative to aquatic habitat because several summertime diversions lower the instream flows and decrease lateral connectivity to adjacent floodplains. Also, many watershed reaches border private agricultural fields and grazing lands and have narrow riparian corridors. Improving floodplain habitat area will require water and managers to set up agreements and easements with riparian landowners to return lands to floodplain functions. Changing reservoir operations, diversions, and other management actions higher up in the basin can also increase impounded wetland habitat during summer months. These results support Bird Refuge managers' recent efforts to actively communicate with upstream users and establish conservation easements, and suggest that these managers should acquire upstream storage rights, forecast supply and demand, and plan for droughts.

Formulating the WASH objective function as a habitat area to maximize also shows where and when to direct scarce water, money, and planting efforts to most improve habitat. Water is scarce during summer months, but WASH results suggest managers can create 2.5 to 12 acres of additional suitable habitat per additional cfs of flow acquired during summer, fall, or winter on the East Fork of the Little Bear River or during late summer and fall months on the Blacksmith Fork and South Fork of the Little Bear. These increases contrast with increases of 30 acres per additional 10,000 dollars available to plant floodplains and can help managers prioritize where to focus restoration and habitat improvement efforts.

In the scenario for bluehead sucker, the modeled aquatic habitat area for the fish decreased compared to the base case with brown trout, and improving habitat quality and area will require managers to release more water below Cutler Reservoir. This flow is not currently available because of upstream diversions. Thus, future conservation efforts for bluehead sucker will likely need to include innovative water procurement plans.

WASH recommends flow regimes that increase flood recurrence to improve floodplain connectivity. Most of the land adjacent to the Bear River is privately owned by PacifiCorp, which operates several run-of-river hydroelectric plants, or private individuals. Therefore, managers need to consider the effects of increasing flood flows to encourage seed recruitment and growth in floodplains on neighboring farmers, ranchers, and hunters. Recent conservation easements made by PacifiCorp illustrate one way to co-manage for multiple objectives. These easements are used for riparian plant restoration projects or as flood buffer zones. WASH results can help identify promising location to procure additional conservation easements to improve habitat quality for multiple aquatic and floodplain priority species.

WASH results were corroborated using an end use validation approach (Bockstaller and Girardin, 2003) and the results were used as a benchmark for habitat management decision making. We presented the results to the project stakeholders using WASH interactive web map (http://washmap.usu.edu) that the authors developed and used to communicate WASH outputs with basin stakeholders. For example, during an August 2016 model workshop, we presented key reservoir release and habitat area results (earlier versions of Figures 2.6, 2.7, and 2.8) while stakeholders simultaneously explored results in real time on their phones, tablets, and laptops. Their explorations identified a problematic aspect of reservoir releases for BCT and motivated us to update aquatic suitability indices to reflect temperature-water depth relationships, base water depth ranges on recent fish ecology studies, and differentiate BCT and brown trout distributions.

Because WASH multiplies habitat suitability indices by affected areas, the model structure is flexible and can be extended to explicitly include additional water quality parameters such as dissolved oxygen or turbidity. This requires describing relationships between model decision variables and additional indices. Similarly, one can add other species, habitat attributes, or habitat types such as natural, oxbow, seasonal, or other wetlands in the watershed that were not included in the Lower Bear River study.

The WASH model quantifies some habitat quality conditions that are necessary for the survival and productivity of priority species. However, it does not predict or model species distribution across the watershed. While we have validated habitat quality conditions with available and collected cutthroat trout and cottonwood tree sightings, the authors see value to couple WASH with a predictive species distribution model. This coupling will permit managers to more accurately locate ecological functions in need of improvements across different sites.

The WASH model assumes that measured and modeled water depths and channel widths are uniform along reaches that are few miles long. This assumption was made using the best available, measured data and does not capture the dynamics of stream habitat ecology. A finer spatial resolution could improve our findings. At the same time, more spatially resolved ecological data can help determine where finer and coarser data is appropriate for modeling. Including other water quality constituents such as dissolved oxygen and ecological variables such as competition could improve estimates of habitat quality. We also assume that inundating the floodplains during seed germination and dispersal will help riparian plants to reestablish. This assumption neglects seedling survival, which requires other biotic and abiotic conditions such as groundwater level, soil salinity, and other plants' competition for water (Bhattacharjee et al., 2008).

As a first cut effort to examine the effects of uncertainties in the empirically established habitat suitability curves, we substituted the bluehead sucker indicator fish species for brown trout. Bluehead sucker use deeper water to spawn and a different SI curve form. The scenario showed less flow available for environmental purpose and less bluehead sucker habitat area available. We recognize that suitability indices (SI) carry along statistical errors that result from measurement error, spatial and temporal variability, and function form (Van der Lee et al., 2006). In ongoing research, we are evaluating and quantifying uncertainties in SI curves and their implications for water management.

The WASH model allocates water using perfect foresight of future water availability. Managers never have perfect information about future flows. However, Bear River flows are snowmelt driven, and managers use snowpack measurements throughout the winter to forecast spring, summer, and fall water availability. Forecast reliability decreases in successive years; thus multi-year scenario results are more appropriately interpreted as the upper bound on potential habitat gains (when future flows are known perfectly).

Implementing WASH recommendations to improve habitat will also require recognizing and protecting environmental flows in the water permitting and planning process. Although Utah water law does not currently allow new appropriations of water for instream flow, more restrictive temporary or permanent transfers of existing rights to environmental users are possible (Szeptycki et al., 2015). Transfer mechanisms may include donation, lease, or purchase but must go to either the Utah Division of Wildlife Resources, the Division of Parks and Recreation, or a nonprofit fishing group such as Trout Unlimited. The State Engineer must approve all transfers (Szeptycki et al., 2015). Even if approved, the next downstream water right holder may file on and withdraw the instream flow for their beneficial use.

Despite these limitations, the WASH model objective to maximize habitat area helps to identify and quantify the habitat benefits of environmental flows. The approach also helps identify within a watershed the locations and times where water, money, and staff effort can most improve habitat quality and area. The approach can be extended to other regulated river systems by defining species of concern, habitat attributes, and sites and then establishing relationships between river flow and habitat attributes of the species of concern. Quantifying results as an observable habitat area allows managers to compare model recommendations to current conditions and could motivate changes to state water law that allow more flexibility to transfer existing water rights or appropriate new water for aquatic, floodplain, wetland, or other ecological purposes.

2.6 Conclusions

Improving habitat in a watershed requires determining when, where, and how to allocate water between competing users in the basin. Prior systems models that manage stream flow to improve habitat quality have focused on maximizing human benefits of water and have included habitat quality as constraints on flow. Other models tried to minimize deviations from natural or species-required flow regimes. Here, we developed a measurable and observable suitable habitat area metric measured in acres and embedded the metric in a systems optimization model named WASH. The WASH model maximizes habitat area, which allows comparison of locations, times, and species to identify opportunities in the basin to most improve overall habitat quality. WASH recommends reservoir releases, river flows, and planting efforts to maximize habitat area subject to physical, infrastructure, and management constraints.

We applied WASH to the Lower Bear River, UT using stakeholder-verified species- and site-specific habitat suitability curves for cutthroat trout, brown trout, cottonwood, black-necked stilt, American avocet, and tundra swan. WASH identified opportunities to increase aquatic, floodplain, and impounded wetland habitat area by 25 thousand acres over existing conditions. This increase could be realized by releasing more water from Porcupine and Hyrum reservoirs in winter months and reducing late spring spills. Further, procuring additional flow in the East Fork of the Little Bear River during summer, fall, and winter months would most increase habitat area per cfs of new flow. Other scenarios showed WASH results are sensitive to hydrologic conditions, length of the simulation period, and consideration of additional species. The WASH web map application provided managers with direct access to model results, helped us validate results, and motivated further model development to make scenarios and results more relevant to managers. Overall, developing and embedding a measurable and observable habitat area metric in a systems model as an ecological objective to maximize has allowed us to compare habitats across watershed sites and identify sites and times where managers can apply scarce water, money, and planting efforts to most improve habitat quality and area. This approach allowed us to involve stakeholders in the process and adapt the method to other basins, sites, habitat types, and species.

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2.8 References

Adams, T.D., Cole, D.B., Miller, C.W., Stauffer, N.E., 1992. GENRES A Computer Program System for Reservoir Operation with Hydropower, In: Resources, U.D.o.W. (Ed.).

Ahmadi-Nedushan, B., St-Hilaire, A., Berube, M., Robichaud, E., Thiemonge, N., Bobee, B., 2006. A review of statistical methods for the evaluation of aquatic habitat suitability for instream flow assessment. River Research and Applications 22(5) 503-523.

Alafifi, A., 2017. ayman510/WASH: First release of WASH code. doi:10.5281/zenodo.801509. URL: https://github.com/ayman510/WASH

Alminagorta, O., Rosenberg, D.E., Kettenring, K.M., 2016a. Systems modeling to improve the hydro-ecological performance of diked wetlands. Water Resources Research 52(9) 7070-7085.

Alminagorta, O., Rosenberg, D.E., Kettenring, K.M., 2016b. Systems modeling to improve the hydro-ecological performance of diked wetlands. Water Resources Research n/a-n/a.

Anderson, R., Stewart, G., 2003. Riverine Fish Flow Investigations, In: F-289-R6, F.A.P. (Ed.), Federal Aid in Fish and Wildlife Restoration - Job Progress Report Colorado Division of Wildlife Fort Collins, Colorado.

Barbour, E.J., Holz, L., Kuczera, G., Pollino, C.A., Jakeman, A.J., Loucks, D.P., 2016. Optimisation as a process for understanding and managing river ecosystems. Environmental Modelling & Software 83 167-178.

Baron, J.S., Poff, N.L., Angermeier, P.L., Dahm, C.N., Gleick, P.H., Hairston, N.G., Jackson, R.B., Johnston, C.A., Richter, B.D., Steinman, A.D., 2002. Meeting Ecological and Societal Needs for Freshwater. Ecological Applications 12(5) 1247-1260.

Bear River CAP, 2008. The Bear River, A conservation priority. The Nature Conservnacy: Utah.

Bernhardt, E.S., Palmer, M.A., Allan, J.D., Alexander, G., Barnas, K., Brooks, S., Carr, J., Clayton, S., Dahm, C., Follstad-Shah, J., Galat, D., Gloss, S., Goodwin, P., Hart, D., Hassett, B., Jenkinson, R., Katz, S., Kondolf, G.M., Lake, P.S., Lave, R., Meyer, J.L., O'Donnell, T.K., Pagano, L., Powell, B., Sudduth, E., 2005. Ecology - Synthesizing US river restoration efforts. Science 308(5722) 636-637.

Bhattacharjee, J., Taylor, J., Smith, L., 2006. Controlled flooding and staged drawdown for restoration of native cottonwoods in the Middle Rio Grande Valley, New Mexico, USA. Wetlands 26(3) 691-702.

Bhattacharjee, J., Taylor, J.P., Smith, L.M., Spence, L.E., 2008. The Importance of Soil Characteristics in Determining Survival of First-Year Cottonwood Seedlings in Altered Riparian Habitats. Restoration Ecology 16(4) 563-571.

Bio-West, 2015. Little Bear and Blacksmith Fork Rivers Environmental Flows: Background Report. Bio-West Inc.: Logan, UT.

Bockstaller, C., Girardin, P., 2003. How to validate environmental indicators. Agricultural Systems 76(2) 639-653.

Braithwaite, N.R., 2011. The Effect of Stream Restoration on Preferred Cutthroat Trout Habitat in the Strawberry River, Utah, Watershed Sciences. Utah State Univeristy: Logan, UT, p. 950.

Bunn, S.E., Arthington, A.H., 2002. Basic Principles and Ecological Consequences of Altered Flow Regimes for Aquatic Biodiversity. Environmental Management 30(4) 492-507.

Carignan, V., Villard, M.-A., 2002. Selecting Indicator Species to Monitor Ecological Integrity: A Review. Environmental Monitoring and Assessment 78(1) 45-61.

Cioffi, F., Gallerano, F., 2012. Multi-objective analysis of dam release flows in rivers downstream from hydropower reservoirs. Applied Mathematical Modelling 36(7) 2868-2889.

Dettenmaier, M., Howe, F.P., 2015. Taking Care of Streams and Rivers in Cache Valley, USU Extension. Utah State University: Logan, Utah.

Downard, R., Endter-Wada, J., 2013. Keeping wetlands wet in the western United States: Adaptations to drought in agriculture-dominated human-natural systems. Journal of Environmental Management 131(0) 394-406.

Downard, R., Endter-Wada, J., Kettenring, K.M., 2014. Adaptive wetland management in an uncertain and changing arid environment. Ecology and Society 19(2).

Faulkner, S., Barrow, W., Keeland, B., Walls, S., Telesco, D., 2010. Effects of conservation practices on wetland ecosystem services in the Mississippi Alluvial Valley. Ecological Applications 21(sp1) S31-S48.

Garcia-Rodriguez, E., Martinez-Austria, P.F., de Jalon-Lastra, D.M.G., Martinez-Capel, F., 2008. Physical habitat simulation in a stretch of the Lozoya River using the PHABSIM system. Ingenieria Hidraulica En Mexico 23(4) 41-52.

George, S.D., Baldigo, B.P., Smith, A.J., Robinson, G.R., 2015. Effects of extreme floods on trout populations and fish communities in a Catskill Mountain river. Freshwater Biology 60(12) 2511-2522.

Gosse, R. S. Wydoski, Helm, W.T., 1977. Microhabitat of fish in intermountain rivers. Utah State University, Logan, UT: Utah Coop. Fish. Res. Unit.

Gosse, J.C., 1981. Brown trout (Salmo trutta) responses to stream channel alterations, their microhabitat requirements, and a method for determining microhabitat in lotic systems. Utah State University: Logan, UT, p. 138 pp.

Harman, C., Stewardson, M., 2005. Optimizing dam release rules to meet environmental flow targets. River Research and Applications 21(2-3) 113-129.

Hemker, T., Fowler, K.R., Farthing, M.W., von Stryk, O., 2008. A mixed-integer simulation-based optimization approach with surrogate functions in water resources management. Optimization and Engineering 9(4) 341-360.

Hickey, J., Fields, W., 2013. HEC-EFM Ecosystem Functions Model. US Army Corps of Engineers - Hydrologic Engineering Center.

Hickman, T., Raleigh, R., 1982. Habitat Suitability Index Models: Cutthroat Trout, Biological Services Program. Fish and Wildlife Service.

Higgins, A.J., Bryan, B.A., Overton, I.C., Holland, K., Lester, R.E., King, D., Nolan, M., Connor, J.D., 2011. Integrated modelling of cost-effective siting and operation of flow-control infrastructure for river ecosystem conservation. Water Resources Research 47(5) W05519.

Hooper, B., 2010. River basin organization performance indicators: application to the Delaware River basin commission. Water Policy 12(4) 461-478.

Hozlar, E., 1990. Gams - General Algebraic Modeling System for Mathematical-Modeling. Ekonomicko-Matematicky Obzor 26(1) 96-99.

Jackson, D.A., Peres-Neto, P.R., Olden, J.D., 2001. What controls who is where in freshwater fish communities - the roles of biotic, abiotic, and spatial factors. Canadian Journal of Fisheries and Aquatic Sciences 58(1) 157-170.

Jager, H.I., Smith, B.T., 2008. Sustainable reservoir operation: can we generate hydropower and preserve ecosystem values? River Research and Applications 24(3) 340-352.

Johnstone, H.C., Rahel, F.J., 2003. Assessing Temperature Tolerance of Bonneville Cutthroat Trout Based on Constant and Cycling Thermal Regimes. Transactions of the American Fisheries Society 132(1) 92-99.

JUB, 2013. Cache County Water Master Plan. Cache County, UT, p. 375 pp.

Kilpatrick, F.A., Barnes, H.H., 1964. Channel Geometry of Piedmont Streams as Related to Frequency of Floods, In: Interior, U.S.D.o.t. (Ed.), Physiographic and Hydraulic Studies of Rivers: Washington D.C.

Li, C., Czapiga, M.J., Eke, E.C., Viparelli, E., Parker, G., 2015. Variable Shields number model for river bankfull geometry: bankfull shear velocity is viscosity-dependent but grain size-independent. Journal of Hydraulic Research 53(1) 36-48.

Mahoney, J., Rood, S., 1998. Streamflow requirements for cottonwood seedling recruitment—An integrative model. Wetlands 18(4) 634-645.

Meier, C.I., Hauer, F.R., 2010. Strong effect of coarse surface layer on moisture within gravel bars: Results from an outdoor experiment. Water Resources Research 46.

Merritt, D.M., Scott, M.L., Poff, N.L., Auble, G.T., Lytle, D.A., 2010. Theory, methods and tools for determining environmental flows for riparian vegetation: riparian vegetation-flow response guilds. Freshwater Biology 55(1) 206-225.

Moir, H.J., Gibbins, C.N., Soulsby, C., Youngson, A.F., 2005. PHABSIM modelling of Atlantic salmon spawning habitat in an upland stream: testing the influence of habitat suitability indices on model output. River Research and Applications 21(9) 1021-1034.

NHDPlus V2, 2016. NHD Plus V2 Attribute Extensions, In: Systems, H. (Ed.), Great Basin (Vector Processing Unit 16). Esri.

Nikouei, A., Zibaei, M., Ward, F.A., 2012. Incentives to adopt irrigation water saving measures for wetlands preservation: An integrated basin scale analysis. Journal of Hydrology 464–465(0) 216-232.

NOAA, 2015. High Water Level Terminology: Alaska - pacific River Forecast Center.

Null, S.E., Medellín-Azuara, J., Escriva-Bou, A., Lent, M., Lund, J.R., 2014. Optimizing the dammed: Water supply losses and fish habitat gains from dam removal in California. Journal of Environmental Management 136(0) 121-131.

Parker, G., Wilcock, P.R., Paola, C., Dietrich, W.E., Pitlick, J., 2007. Physical basis for quasi-universal relations describing bankfull hydraulic geometry of single-thread gravel bed rivers. Journal of Geophysical Research-Earth Surface 112(F4).

Pinto, R., Patricio, J., Baeta, A., Fath, B.D., Neto, J.M., Marques, J.C., 2009. Review and evaluation of estuarine biotic indices to assess benthic condition. Ecological Indicators 9(1) 1-25.

Poff, N.L., Allan, J.D., Bain, M.B., Karr, J.R., Prestegaard, K.L., Richter, B.D., Sparks, R.E., Stromberg, J.C., 1997. The natural flow regime. Bioscience 47(11) 769-784.

Porse, E.C., Sandoval-Solis, S., Lane, B.A., 2015. Integrating Environmental Flows into Multi-Objective Reservoir Management for a Transboundary, Water-Scarce River Basin: Rio Grande/Bravo. Water Resources Management 29(8) 2471-2484.

Raleigh, R.F., Zuckerman, L.D., Nelson, P.C., 1984. Habitat suitability index models and instream flow suitability curves: Brown trout, Biological Report, 10.24 ed. U.S. Fish and Wildlife Service, p. 65.

Richter, B.D., Richter, H.E., 2000. Prescribing Flood Regimes to Sustain Riparian Ecosystems along Meandering Rivers
Prescripción de Regímenes de Inundación para Mantener Ecosistemas Riparios a lo Largo de Ríos Sinuosos. Conservation Biology 14(5) 1467-1478.

Rivaes, R., Rodríguez-González, P.M., Albuquerque, A., Pinheiro, A.N., Egger, G., Ferreira, M.T., 2013. Riparian vegetation responses to altered flow regimes driven by climate change in Mediterranean rivers. Ecohydrology 6(3) 413-424.

Rogers, K., Ralph, T.J., 2011. Floodplain Wetland Biota in the Murray-Darling Basin: Water and Habitat Requirements. CSIRO Publishing.

Roloff, G.J., Kernohan, B.J., 1999. Evaluating Reliability of Habitat Suitability Index Models. Wildlife Society Bulletin (1973-2006) 27(4) 973-985.

Rood, S.B., Braatne, J.H., Hughes, F.M.R., 2003. Ecophysiology of riparian cottonwoods: stream flow dependency, water relations and restoration†. Tree Physiology 23(16) 1113-1124.

Rood, S.B., Samuelson, G.M., Braatne, J.H., Gourley, C.R., Hughes, F.M.R., Mahoney, J.M., 2005. Managing river flows to restore floodplain forests. Frontiers in Ecology and the Environment 3(4) 193-201.

Rosgen, D.L., 1994. A classification of natural rivers, In: Catena (Ed.), pp. 169-199.

Ryu, J., Palmer, R., Jeong, S., Lee, J., 2003. An Optimization Model to Mitigate Conflicts in the Geum River Basin, Korea, World Water & Environmental Resources Congress 2003. American Society of Civil Engineers, pp. 1-10.

Sahinidis, N.V., 1996. BARON: A general purpose global optimization software package. Journal of Global Optimization 8 201-205.

Simonović, S.P., Nirupama, 2005. A spatial multi-objective decision-making under uncertainty for water resources management. Journal of Hydroinformatics 7(2) 117-133.

Souchon, Y., Capra, H., 2004. Aquatic habitat modelling: biological validations of IFIM/Phabsim methodology and new perspectives. Hydroécol. Appl. 14 9-25.

Stalnaker, C.B., B.L. Lamb, J. Henriksen, K. Bovee, and J. Bartholow, 1995. The Instream Flow Incremental Methodology: A Primer for IFIM. . Washington, DC: US Geological Survey Biological Report 29 45.

Steinschneider, S., Bernstein, A., Palmer, R., Polebitski, A., 2014. Reservoir Management Optimization for Basin-Wide Ecological Restoration in the Connecticut River. Journal of Water Resources Planning and Management 140(9) 04014023.

Szemis, J.M., Maier, H.R., Dandy, G.C., 2012. A framework for using ant colony optimization to schedule environmental flow management alternatives for rivers, wetlands, and floodplains. Water Resources Research 48.

Szemis, J.M., Maier, H.R., Dandy, G.C., 2014. An adaptive ant colony optimization framework for scheduling environmental flow management alternatives under varied environmental water availability conditions. Water Resources Research 50(10) 7606-7625.

Szeptycki, L.F., Forgie, J., Hook, E., Lorick, K., Womble, P., 2015. Environmental Water Rights Transfers: A Review of State Laws. Water in the West for The National Fish and Wildlife Foundation: Stanford, CA.

Tharme, R.E., 2003. A global perspective on environmental flow assessment: emerging trends in the development and application of environmental flow methodologies for rivers. River Research and Applications 19(5-6) 397-441.

UDNR, 2006. Range-Wide Conservation Agreement and Strategy for Roundtail Chub (*Gila robusta),* Bluehead sucker (*Catostomus discobolus*), and Flannelmouth sucker (*Catostomus latipinnis*). Utah Divison of Natural Resources.

UDWR, 2004. Utah Division of Water Resources, Bear River Basin, Planning for the Future: Utah.

UDWRe, 2000. Bear River Development, Utah Divion of Water Resources: Salt Lake City, UT.

USDA, 2014. USA NAIP Imagery: NDVI, Esri Living Atlas of the World.

USGS, 2012. USA NHDPlusV2, Esri Living Atlas of the World.

UtahFishingInfo Website, 2016. Brown Trout.

UWRL, 2009. Little Bear River WATERS Test Bed. Utah Water Research Laboratory, Utah State University: Logan, UT.

Van der Lee, G.E.M., Van der Molen, D.T., Van den Boogaard, H.F.P., Van der Klis, H., 2006. Uncertainty analysis of a spatial habitat suitability model and implications for ecological management of water bodies. Landscape Ecology 21(7) 1019-1032.

Watershed Sciences, 2007. Airborne Thermal Infrared Remote Sensing Bear River Basin, ID/WY/UT Pacificorp and Trout Unlimited: Corvallis, OR.

Webber, P.A., Thompson, P., Budy, P., 2012. Status and Structure of Two Populations of the Bluehead sucker (*Catostomus discoblus*) in the Weber River, Utah. The Southwestern Naturalist, 75(3) 267–276

Yang, W., 2011. A multi-objective optimization approach to allocate environmental flows to the artificially restored wetlands of China's Yellow River Delta. Ecological Modelling 222(2) 261-267.

Yarnell, S.M., Viers, J.H., Mount, J.F., 2010. Ecology and Management of the Spring Snowmelt Recession. Bioscience 60(2) 114-127.

CHAPTER 3

CLUSTER ANALYSIS TO IMPROVE COMMUNICATING UNCERTAINTIES IN RIVER HABITAT MODELS[2]

Abstract

River habitat models are useful to recommend management actions to improve habitat conditions for priority species. However, these models have multiple hydrologic, ecological, and management input data that are uncertain. These uncertainties are often not communicated to highlight risks of water management decisions. Prior work to quantify uncertainty in habitat models found that large uncertain ranges propagate and produce an overwhelmingly large number of management alternatives. Here, we apply semi-supervised cluster analysis to reduce a large dimensional space of plausible alternatives and identify a few, easy-to-interpret management scenarios that consider multiple sources of uncertainties. We apply this approach to a large watershed-scale nonlinear optimization model for the Lower Bear River, Utah to recommend water and money allocation to improve valuable habitat quality and area for selected river, floodplain, and wetland species. We include management preferences to subset uncertain parameters into two groups. One improves habitat quality under 3 uncertain input parameters and the other improves quality under 7 uncertain ecological parameters. Results identified four possible management scenarios to operate reservoirs and enhance habitat quality based on modeled uncertainties. Budget to plant riparian trees in addition to indicator species and their conditions defining habitat quality are the main factors in guiding management decisions.

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[2] Co-authored by James H. Stagge, Sarah E. Null, and David E. Rosenberg

These key parameters define possible future scenarios. Examining variability within each cluster help highlighting tradeoffs and identifying more desirable alternatives than cluster centroids. Our approach helps focus efforts on identifying few management actions to improve overall habitat quality. Our approach helps identify a few management actions to improve overall habitat quality, guides resource allocation, quantifies tradeoffs, and highlights promising management alternatives.

3.1 Introduction

Managing river systems to improve habitat requires allocating water between multiple human and environmental uses. Habitat models recommend management actions to operate reservoirs, restore floodplain connectivity, and prioritize restoration to improve habitat conditions for river, floodplain, and wetland species (e.g. Null and Lund, 2012; Shiau and Wu, 2013). However, the inherent fluctuations of hydrologic and hydraulic conditions, our incomplete understanding of the complexity of the ecosystem, and lack of sufficient empirical data to validate results mean that habitat models are almost always uncertain (Lek, 2007; Wilhere, 2012). Characterizing uncertainties in habitat models generates more informative and reliable management strategies that improves model credibility (Ahmadi-Nedushan et al., 2006; Pinto et al., 2009; Vucetic and Simonović, 2011). However, there are limited applications of uncertainty analysis to ecology and water resources decision-oriented habitat models (Hamel and Bryant, 2017; Pappenberger and Beven, 2006). One of the main reasons for not conducting uncertainty analyses for habitat models is that the propagation of multiple uncertainties through model components makes it challenging to communicate results and identify a clear set of management actions

(Groves and Lempert, 2007; Pappenberger and Beven, 2006).

Uncertainties in habitat models exhibit multiple sources of uncertainty and are derived from the input data, model structure and formulation, and lack of understanding of complex ecosystem (Hughes et al., 2005; Lek, 2007; Li and Wu, 2006a). Input data include hydrologic, hydraulic, habitat conditions and quality, and management inputs to a model and may have errors deriving from sampling quality, errors in measurements, or incomplete and missing information (Katz, 2002; Li and Wu, 2006b). Habitat model structure can introduce error when numerical formulas do not adequately represent ecological complexities (Cao and Carling, 2002; Clifford et al., 2008). For example, habitat models often assume non-linear processes to simplify the response of a species to changes in habitat conditions. Also multiple processes operate at different or varying spatial and temporal scales. This is evident, for example, in selecting parameters to describe the shape of numerical equations that mathematically describe species response to alterations in flow regime (Rivaes et al., 2013).

Uncertainty analysis in habitat models is often conducted by defining upper and lower bounds on one or multiple uncertain input data or parameters, selecting representative probability distributions, and sampling from each distribution (Li and Wu, 2006b; Pianosi et al., 2016b). Probability distributions define a range and likelihood of values representing variations around mean estimates that the value of a certain parameter is likely to have within a specified probability (Bender et al., 1996). Often, bounds on input parameters and their corresponding probability distributions are constructed using triangular and uniform distributions using empirical data or expert opinion (O’Hagan, 2012; Van der Lee et al., 2006). Different Monte Carlo (Mooney, 1997), bootstrap (Williams, 1996), Bayesian networks (Douglas and Newton, 2014), and fuzzy numbers (Burgman et al., 2001) can sample values from the distributions. The outcomes of sampling are confidence intervals for model results and recommendations. For example, Burgman et al. (2001) used fuzzy numbers to bound habitat suitability index (HSI) curves for Florida scrub-jay based on uncertain measurements of canopy and shrub cover and other ecological attributes. Similarly, Ayllon et al. (2012) used bootstrap sampling to measure the effects of uncertain channel hydraulic variables on HSI curves for brown trout and developed 95% confidence intervals for uncertain curves. Van der Lee et al. (2006) used Monte Carlo simulation to sample uncertainties from channel hydraulics and quality parameters for pondweed and developed ranges for HSI curves based on standard deviations. The common approach of developing ranges for uncertain parameters and input data propagates uncertainty through models and affects results (Di Baldassarre and Montanari, 2009; Janssen et al., 2010).

The propagation of uncertainty through model components makes it difficult to identify the factors that contribute to producing uncertain results (Cressie et al., 2009; Saltelli et al., 2008). Zajac et al. (2015) analyzed the propagation of uncertain input data and model structure on the results of HSI models using Sobol's global sensitivity analysis (Sobol, 1993) to determine the relative importance of uncertain input factors. Sobol's method generates sensitivity indices to explore which inputs contribute to the total variance of the model outputs. However, drawbacks of applying variance-based methods to ecological models include high computational costs that grow exponentially with the number of uncertain parameters, a large number of possible management alternatives, and difficulty of interpreting results as management decisions (Harper et al., 2011; Poudyal et al., 2009). Communicating a large number of model alternatives creates a challenge to decision makers to select a clear path forward with management actions (Hamel and Bryant, 2017 ; Pappenberger and Beven, 2006).

Well-developed methods exist to select a small number of scenarios to summarize a large set of management alternatives. Scenarios are often selected to explore different combinations of the forces driving decisions in large multivariate spaces where each scenario describes a distinct possible future (Schwartz, 2012). Cluster Analysis (CA) is a data-mining technique that groups (i.e. clusters) observations or results that are more similar to each other. It can be applied to decision making to represent plausible management scenarios that might otherwise be overlooked in large multivariate spaces of possible futures (Groves and Lempert, 2007). Each cluster can be represented by its centroid or medoid. The medoid is most centrally located member in the cluster (Sarstedt and Mooi, 2014). CA can also identify the most important parameters that drive dissimilarities between clusters and that characterize key sources of uncertainty in habitat models.

Clustering is traditionally considered a type of unsupervised learning method that considers all of the dimensions of a large dataset and find similarities with no knowledge about expected outcomes or relationships between observations (Romesburg, 2004; Sarstedt and Mooi, 2014). A semi-supervised approach can improve the clustering outcomes and serve explicit management preferences by providing clustering algorithm with information about data (Bair, 2013). This approach groups dataset dimensions into subsets that have common attributes. Then, it performs clustering on observations using each subset of dimensions, which helps localize the search for clusters and uncover clusters that might be overlooked by unsupervised clustering (Parsons et al., 2004). A semi-supervised clustering can be useful in cases where some dimensions in the dataset are more dominant than others, which means unsupervised clustering algorithms will always consider some dimensions to be irrelevant (Basu et al., 2002). It is also useful in high dimensional datasets where distance measures become meaningless as the number of dimensions increase and observations become more sparse (Parsons et al., 2004).

Applications of CA data mining to water resources problems have primarily explored historical patterns and forecasted future water demand functions by clustering consumption data among household connections or cities (e.g. Candelieri and Archetti, 2014; Noiva et al., 2016; Veerender, 2007). For example, Groves and Lempert (2007) used unsupervised CA to define two possible future scenarios from a robust decision making space (Lempert et al., 2010) that is described by 16 supply and demand uncertainties for California's south coast region. They concluded that their two clusters (i.e. scenarios) were defined by three parameters: population growth, rate of exogenous conservation, and cost of efficiency programs. More recently, Chen et al. (2017) applied unsupervised CA on the results of an evolutionary algorithm optimization model to identify promising re-operation of multiple reservoirs on the Columbia River with multiple inflow scenarios. They used the centroid to represent the mean recommended reservoir elevations of each cluster. They also concluded that temporal distribution of the inflow is the main driver to select reservoir operations. These applications of CA algorithms to water resources models are promising and suggest that the technique may also quantify and communicate uncertainties in habitat models. In habitat models, these techniques could be improved by applying semi-supervised clustering to localize the search for clusters within a large number of uncertain parameters. In addition, quantifying variability within each cluster could help find better alternatives to represent each cluster other than the medoids.

This paper demonstrates a method to effectively communicate uncertainty in habitat models and improve water and habitat management decision making capability using data-mining techniques. Here, we use a semi-supervised CA approach to (1) perform localized search for clusters within a large multivariate space of possible management alternatives, (2) identify key driving forces that form dissimilarities between alternatives, (3) compare management implications and tradeoffs within and between clusters, and (4) define a few easily-interpretable management scenarios to allocate resources to improve habitat quality. We apply this approach to a study area in the Lower Bear River, Utah where efforts are underway to restore valuable habitat (Bear River CAP, 2008) using a watershed-scale nonlinear deterministic optimization model that recommends reservoir releases and riparian planting to improve aquatic, floodplain, and wetland habitat quality (Alafifi and Rosenberg, In Review). The following sections of this paper describe the study area, present the model framework and sources of uncertainty, describe results, discussion, and conclusions.

3.2 Study Area

The Lower Bear River (LBR), Utah is a snowmelt driven system that receives most runoff in April, May, and June (Figure 1). The LBR provides vital wildlife habitat for native and game fish including Bonneville cutthroat trout (*Oncorhynchus clarki utah*), brown trout (*Salmo trutta*), and native riparian plant species such as cottonwood trees (*Populus spp.)* (UDWR, 2004). The river is the largest water source to the Great Salt Lake and to the 30,000 acre-Bear River Migratory Bird Refuge. The Refuge's impounded wetlands provide feeding, resting, and breeding habitat for over 250 migratory bird species every year (Alminagorta et al., 2016). The LBR and its tributaries irrigate over 300,000 acres of agricultural land with a total annual consumptive water use of approximately 535,000 acre-feet (UDWRe, 2000). Intensive agricultural and grazing activities along the river triggered habitat conservation efforts to identify critical areas and species for restoration. Efforts are underway to allocate water and management resources between human and environmental

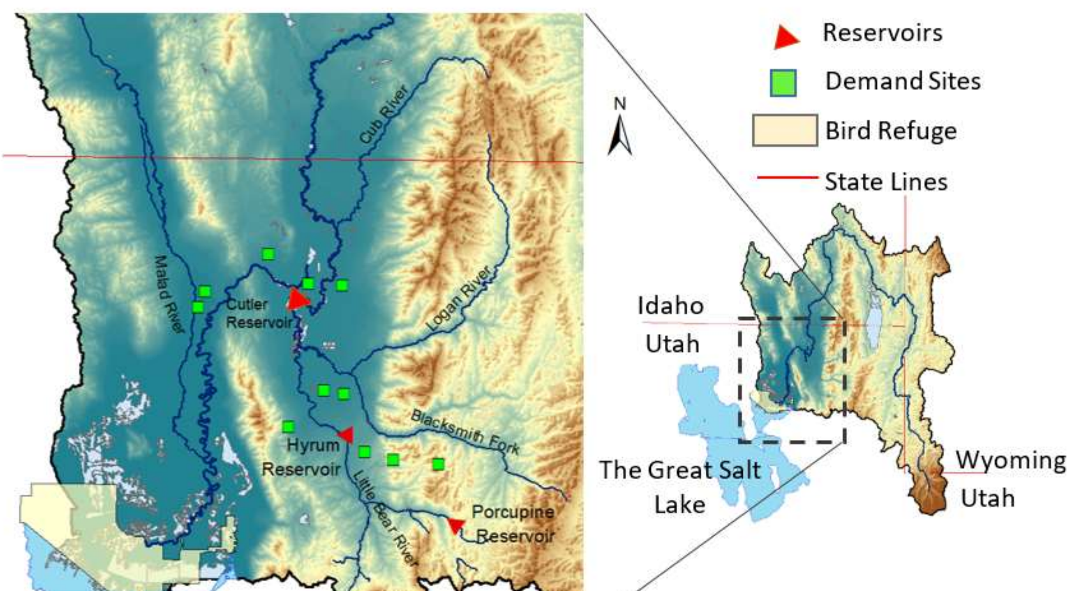

Figure 3.1 The Lower Bear River, Utah including major tributaries, demand sites, and reservoirs

users in the watershed (Bear River CAP, 2008). Understanding and quantifying uncertainties in such a large watershed with multiple habitats and key species is important to prioritize management efforts to restore and improve valuable habitat.

3.3 Optimization Framework

The Watershed Area of Suitable Habitat (WASH) model is a generic nonlinear systems optimization approach that was applied to the LBR to guide the allocation of money and water to increase aquatic, floodplain, and wetland habitat area for priority species in the watershed while satisfying agricultural and urban demands for human users (Alafifi and Rosenberg, In Review). WASH formulates ecological objectives based on habitat areas weighted by habitat suitability, which allows managers to identify when and where to allocate scarce money for planting and water to most improve habitat quality and area. WASH was applied to the LBR for a single year (2003 as a representative year between 1990 and 2010) of measured or modeled flows. Urban and agricultural demand requirements and other hydrologic, habitat, infrastructure, water management data were collected from a variety of sources including several U.S. Geological Survey (USGS) gage stations along the LBR and its tributaries, the Utah Division of Water Resources GenRes simulation model (Adams et al., 1992), and other flow monitoring sites.

We segmented the LBR basin (Figure 3.1) into a network of 43 nodes and 56 links with 12 urban and agricultural demand sites. The 1-year implementation of the model for the LBR system has approximately 27,000 variables and 5,300 equations. The full model formulation is available in appendix B. Next, we highlight the main components of WASH optimization model including decision variables, objective function, and constraints and discuss sources of uncertainties in WASH that were not considered in the original deterministic analysis.

3.3.1 Decision variables

The optimization model has three main decision variables: (1) volume of reservoir releases, (2) diversion volumes, and (3) floodplain plant cover that is controlled by seeding or planting species. These decision variables affect reservoir storage, river flow, river water depth, and other model state variables.

3.3.2 Objective function

The WASH objective function *(Z)* maximizes the weighted sum of the suitable areas of aquatic [$IND_{aquatic,j,k,t}$], floodplain [$IND_{floodplain,j,k,t}$], and wetland [$IND_{wetland,j,k,t}$] habitats in reach *j* to *k* in month *t* [eq.1]. *s* is the habitat indicator (aquatic, floodplains, or wetlands) and $wght_{s,j,k,t}$ are the stakeholders-decided weights for habitat indictor *s* in reach *j* to *k* at month *t.* Weights take values from 0 (not important) to 1 (important).

$$Max\ Z = \sum_{s,j,k,t} wght_{s,\mathrm{j},\mathrm{k},t} \cdot IND_{s,j,k,t} \qquad \text{-- [1]}$$

$$\text{Where } IND_{s,j,k,t} = \sum_{n,j,k,t} SI_{s,\mathrm{n},\mathrm{j},\mathrm{k},t} \cdot A_{s,j,k,t} \qquad \forall s \qquad \text{-- [2]}$$

The value of each habitat indicator $IND_{s,j,k,t}$ is the product of a suitability index $SI_{s,\mathrm{n},\mathrm{j},\mathrm{k},t}$ and an affected area $A_{s,j,k,t}$. Each suitability index *SI* is specified for species *n* at life stage *t* along the reach between nodes *j* and *k*. Alafifi and Rosenberg (In Review) collaborated with river managers and local stakeholders to identify important native and game fish, riparian plants, and wetland bird species in the LBR watershed. They designed SI curves for cutthroat trout (*Oncorhynchus clarki utah*), brown trout (*Salmo trytta*), cottonwood (*Populus fremontii)*, black-necked stilt (*Himantopus mexicanus*), American avocet (*Recurvirostra Americana)*, and tundra swan (*Cygnus columbianus*). Each SI is a function of a measureable habitat attribute that influences priority species' survival and abundance. For fish species, water depth and water temperature determine the ability of fish to spawn and mature (Braithwaite, 2011). For cottonwoods, the flood recurrence interval influences seedling recruitment and germination and defines connectivity between the river and floodplain (Kauffman et al., 1997; Mahoney and Rood, 1998). For wetland bird species, water depth and plant cover allow birds to rest, nest, and breed (Downard and Endter-Wada, 2013). The relationships between SIs and habitat attributes were estimated using empirical data (Alminagorta et al., 2016; Braithwaite, 2011; Hickman and Raleigh, 1982; Mahoney and Rood, 1998), or where data was not available, they were assigned based on expert opinion and described in WASH by nonlinear curves (Table 1).

3.3.3 Constraints

Reservoir releases and riparian planting are bound by physical, infrastructure, and management constraints. Physical constraints include mass balance for reservoirs, rivers, and demand sites that account for reservoir storage volume and water availability from upstream reaches, diversions, and return flows from demand sites. They also include equations to constrain plant cover growth over time and define channel topography. Infrastructure constraints place minimum and maximum limits on reservoir and diversion canals capacity. Management constraints include urban and agricultural demand requirements and available budget to plant floodplain species.

3.4 Sources of Uncertainty in WASH

The WASH model has multiple sources of uncertainty in the hydrologic and management input data in addition to ecological uncertainties which we described as follows.

1. **Input data:** Uncertainty in input data surrounds inflow supply, water demands, and budget to plant cottonwood trees. Although managers have control over water from upstream reaches and human demands within the watershed, water inflow and demand requirements are almost always uncertain and challenging to project in the future (Loucks et al., 2005). Another uncertain management input was the budget of $650,000 to plant cottonwood trees and restore floodplain habitat. This budget value was based on expected costs for future ecosystem projects listed in the Cache County Water Masterplan (JUB, 2013) which could change based on the County's future priorities.
2. **Ecological parameters:** Our incomplete understanding of natural variability and species' response to changes in habitat conditions mean that suitable habitat attributes and SI curve parameters are uncertain (Wilhere, 2012). Suitable habitat attributes (e.g. water depth range) that define SI curves were primarily driven from empirical studies of similar streams and relevant literature, and were only verified by the project stakeholders. Measuring these habitat attributes is another source of uncertainty. For example, water depth was calculated based on stage-flow rating curves. Curve parameters are uncertain because they are based on field measurements of flow and channel cross sections. Another source of uncertainty is the shape of SI curves. WASH primarily uses Boltzmann sigmoidal function, which is most common in the Fish and Wildlife Service habitat suitability estimates for water depth-habitat suitability indices.

3.5 Methods

To identify and characterize a few management options from a large multivariate space of alternatives, we follow a five-step approach to propagate and reduce uncertainties (Figure 3.2). First, we run a conventional one-at-a-time sensitivity analysis (Pianosi et al., 2016a) to identify the uncertain parameters that have the largest effects on system outputs. Second, we run Monte Carlo simulations to sample from the main uncertain parameters. Third, we group uncertain parameters together based on management goals and priorities to improve habitat quality under multiple sources of uncertainty. Fourth, we apply a semi-supervised cluster algorithm to each group. And fifth, we develop scenarios and infer management implications from each resultant cluster.

3.5.1 Sensitivity Analysis

We first do a one-at-a-time sensitivity analysis for the 28 uncertain WASH input data and parameters to identify the uncertain parameters that most affect the variance of the objective function (Saltelli et al., 2008). In the one-at-a-time sensitivity analysis, we vary each parameter value while keeping all other parameters fixed and recorded the objective function value.

3.5.2 Monte Carlo Simulations

Next, we run Monte Carlo simulations to sample from the probability distributions of all main uncertain parameters and pass sampled values to the WASH optimization model. The outputs of each Monte Carlo simulation consist of the objective function value (the weighted sum of suitable habitat areas in all reaches and months, km^2), suitable aquatic, floodplain, and wetland habitat areas (km^2), time series of reservoir releases for

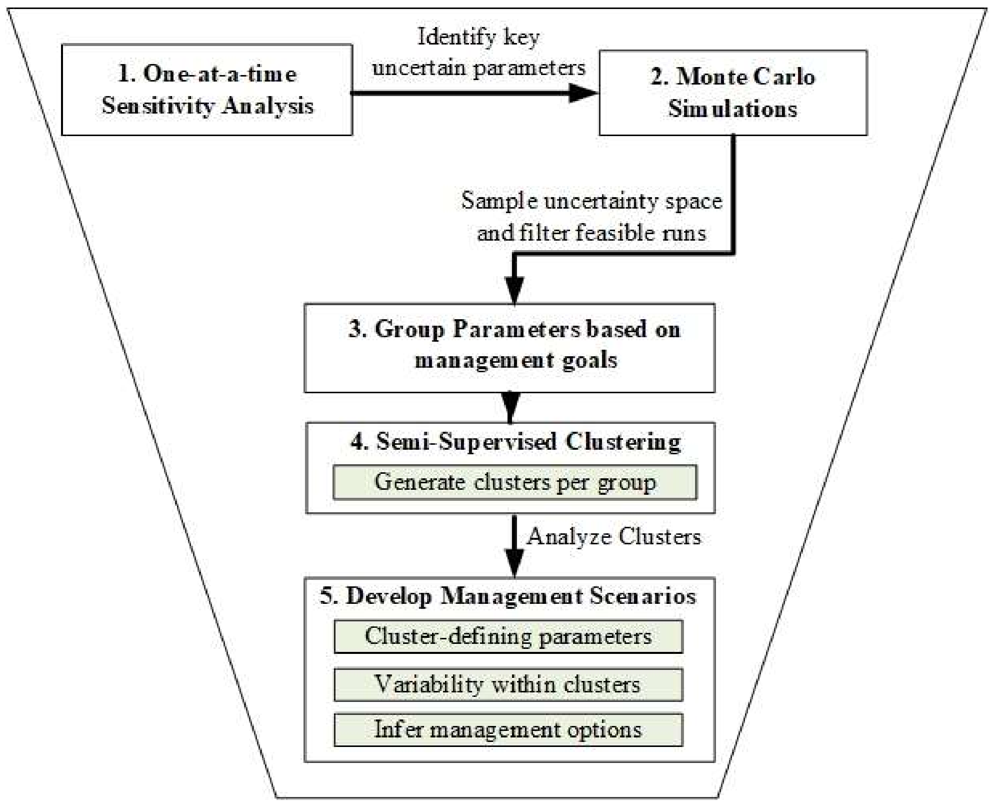

Figure 3.2 Methods to generate a few management options from large uncertainty space

each reservoir (Mm^3/mo), and planted area for every reach (km^2). We filter out all infeasible runs and record the inputs and outputs for each feasible run. We continue sampling to 800 runs until the variance of the objective function value for the feasible runs does not change by more than 10% with additional runs. Filtering out infeasibilities result in nearly 200 feasible runs. Each run represents a possible management alternative and is defined by a combination of uncertain parameters.

3.5.3 Group Parameters

Exploring a large multi-dimensional space of Monte Carlo runs can be improved by performing a localized search for clusters. This search is performed on subsets of model parameters that managers want to consider together. For example, in a multi-habitat model, managers could group uncertain parameters together by habitat type. In a reservoir operation model, managers could group parameters based on uncertainty sources such as inflows and water delivery target uncertainties. Grouping parameters could reduce uncertainty problems and help focus efforts on finding important parameters to measure.

Here, we group parameters based on uncertainty sources which allows managers to explore the effects of certain parameters on specific system functions. In particular, we formulate two groups of parameters based on the two groups of uncertainty sources in section 3.4 to reflect two management goals. These groups are:

1. Parameters that describe the human system: (1) boundary flows into the river system from upstream reservoirs releases and diversions, (2) urban and agricultural demands, and (3) budget to plant riparian trees. This group uncertainties in more-readily measured conventional water management system components and ignores uncertainties in harder to measure ecological and habitat system components.
2. Parameters that describe ecological and habitat system components including SI curve parameters and habitat attributes for aquatic, floodplain, and wetland habitats. This group also considers uncertainties in selecting indicator species to denote healthy ecosystem in addition to assumptions of available floodplain area and impounded wetlands area. These ecosystem parameters are more difficult to measure, less frequently included in uncertainty analyses for habitat models, and showcase a way to approach systems with multiple habitats and multiple uncertain ecological parameters.

3.5.4 Cluster Analysis

Next, we apply semi-supervised cluster analysis for each parameter group clustering feasible Monte Carlo runs on both the uncertain input parameters and outputs (objective function and three habitat areas). Clustering using both inputs and outputs helps to understand relationships between model components and tradeoffs between the three habitats. However, highly correlated parameters with a Pearson correlation coefficient of more than 0.9 are excluded because they could skew clustering (Sarstedt and Mooi, 2014). We use semi-supervised clustering to reduce the number of alternatives and identify a few manageable and interpretable scenarios. The semi-supervised approach is appropriate because we subset the large multivariate space of uncertain parameters into groups and apply the clustering algorithm separately for each group using the selected parameters within each group.

Two common clustering methods are applied in water resources applications: hierarchical and k-means partitioning (Chen et al., 2017). Hierarchical agglomerative clustering uses the Euclidean (or straight line) distance between members. All member attribute values are standardized. In contrast, k-means partitioning minimizes within-cluster variation and is less sensitive to outliers (Sarstedt and Mooi, 2014). Here we applied hierarchical clustering using the ‘gower’ distance method (Gower and Ross, 1969) because k-means partitioning cannot handle nominal and categorical data. To select number of clusters, we plotted the Silhouette index, which indicates dissimilarity between clusters (Rousseeuw, 1987).

3.5.5 Management Scenarios

The CA yields a small number of clusters. Each cluster consists of similar Monte Carlo runs representing a possible future scenario, where the likelihood of a scenario happening is proportional to the number of members in the cluster. To characterize each cluster, we perform a one-way ANOVA (ANalysis Of VAriance) with post-hoc Tukey HSD (Honestly Significant Difference) test and examine the p-value for each parameter to determine the statistical significance in the difference of means between clusters. We use the p-value to identify the most important parameters for clustering. We label each cluster by these parameters to facilitate communicating future scenarios.

Finally, we compare clusters based on their clustering parameters and select model outputs. We compare select model outputs for each run in each cluster with the deterministic model solution to infer management options that improve the model objective function value. We show results for Hyrum Reservoir, one the two active reservoirs in the system. We also examine the tradeoffs between the three aquatic, floodplain, and wetland habitat areas for each cluster. In addition, we explore the variability within each cluster in parallel coordinate plots to infer management options that improve overall habitat quality.

3.5.6 Stochastic WASH Model

In our case study, we modify the deterministic version of WASH to include uncertain parameters. WASH was coded using the General Algebraic Modeling System software (GAMS; Hozlar, 1990) and solved using the non-linear global solver Branch-And-Reduce Optimization Navigator (BARON; Sahinidis, 1996). The solve took 2 hours and 15 minutes to find a global optimal solution on a Dell XPS Windows10 64-bit. We update the original code to add Monte Carlo sampling for all 28 uncertain parameters of WASH (Table 3.1). The large size of the problem and number of Monte Carlo runs require that we use CONOPT solver (Drud, 1996) to find a local optimum for each run. The optimization code uses GAMS Data Exchange (GDX) format to read all deterministic and stochastic input data and their ranges from both MS Excel spreadsheet and R scripts and pass them to the model. The model outputs for each run are stored in an output GDX file and passed to R for analysis. We used the R 'cluster' package (Maechler et al., 2016; R Core Team, 2016) for cluster analysis and the 'parcoords' package for parallel plots (Bostock et al., 2016). The model code and post-processing scripts and data are available on a GitHub repository (Alafifi, 2017).

3.6 Results

3.6.1 Sensitivity Analyses

We adjusted boundary flows by a percentage and sampled from a discrete distribution to capture variability in the last 10 years based on historical data (Table 3.1). In the absence of data to inform the selection of a probability distribution for ecological and management parameters, a uniform distribution with assumed upper and lower bounds were assumed appropriate (Fox et al., 2010). For example, we varied demand requirements and available budget by a percentage and used uniform distributions assuming equal probability of any value within selected ranges (Table 3.1). For ecological parameters, we varied available floodplain areas and wetland area to reflect errors in measurements. We tested the objective function sensitivity to two water depth ranges for Bonneville cutthroat trout (*Oncorhynchus clarki utah*) and brown trout (*Salmo trytta*) based on literature. We discretely generated 80 habitat suitability curves for each fish species by varying the slope and centroid parameters to sample the curve region (Figure 3.3). We also tested the sensitivity to two riparian plants (Figure 3.4). First, Fremont cottonwood (*Populus fremontii)* which largely lives adjacent to river banks and requires flood recurrence of 2-year for lateral connectivity (Richter and Richter, 2000). Second, Pacific willow *(Salix lasiandra)* which lives further upslope in the floodplain and requires 5-year flood frequency interval (Dettenmaier and Howe, 2015; Rood et al., 2003). Some values reported in Table 3.2 (marked with asterisk) show examples of reach-and time-specific data values. Full ranges of uncertain parameters are available on the GitHub repository (Alafifi, 2017). We selected 10 key parameters that the variance of the objective function value was most sensitive to (Figure 3.5).

3.6.2 Cluster analysis for two management objectives

3.6.2.1 Improve habitat under uncertain parameters describing human system

We performed cluster analysis on three uncertain input data parameters: boundary flows, demand requirements, and budget, in addition to the four model outputs: the objective function maximizing total habitat, and aquatic, floodplain, and wetland habitat areas. We explored a range of two to six clusters and two distinct clusters were identified based on the Silhouette index. The first cluster contained 87 (44%) of the feasible runs that had relatively lower mean total habitat area objective function of 501 km^2 and low mean suitable floodplain area of 12.4 km^2 that was driven by a lower mean budget of nearly $562,000 to plant riparian trees. Cluster 2 contained 111 (56%) of feasible runs that had higher mean total habitat area objective function of nearly 504 km^2, higher mean suitable floodplain area of 15.7 km^2, and higher mean budget of nearly $689,000.

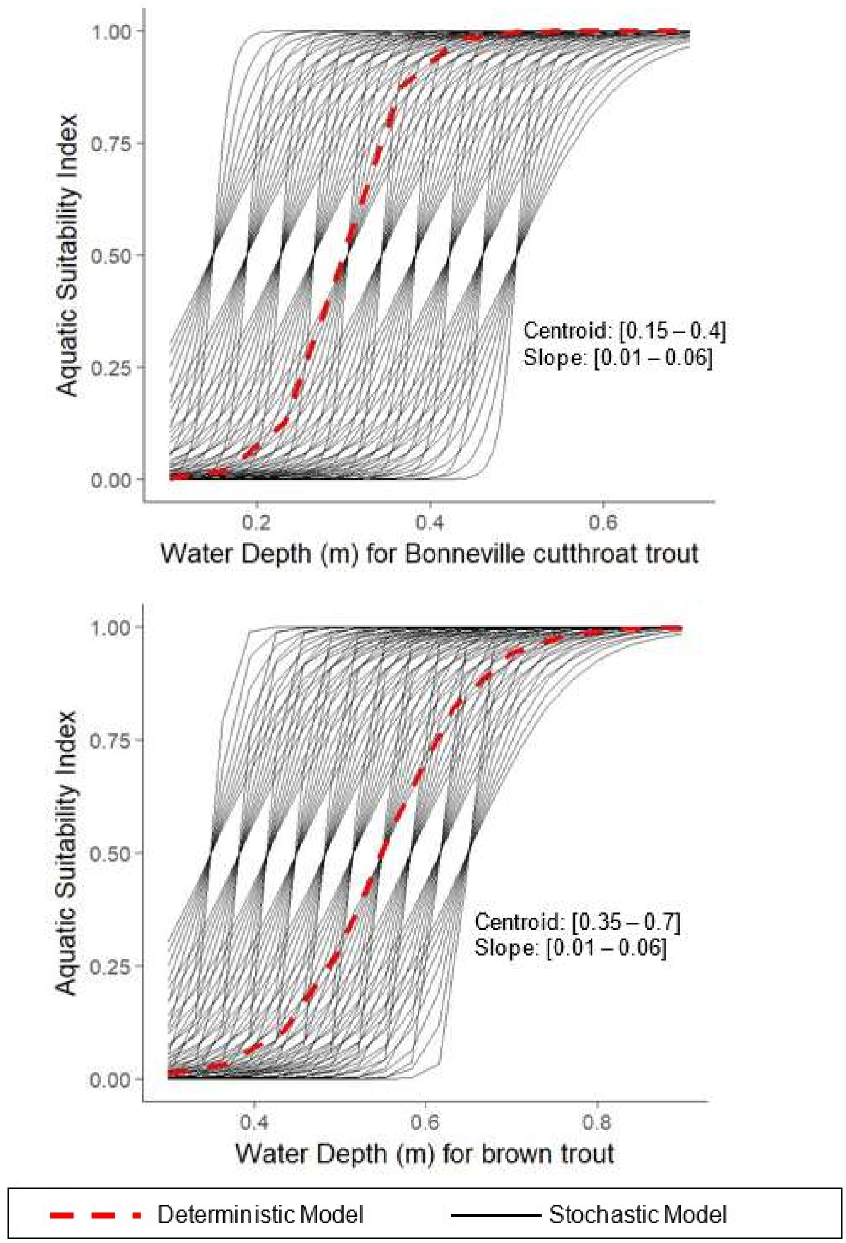

Figure 3.3 Habitat suitability curves for cutthroat trout (right) and brown trout (left). Red dashed lines are the curve used in the deterministic model. Black curves are alternative curves with varying slopes and centroids of Boltzmann sigmoidal for the water depth range used in the uncertainty analysis

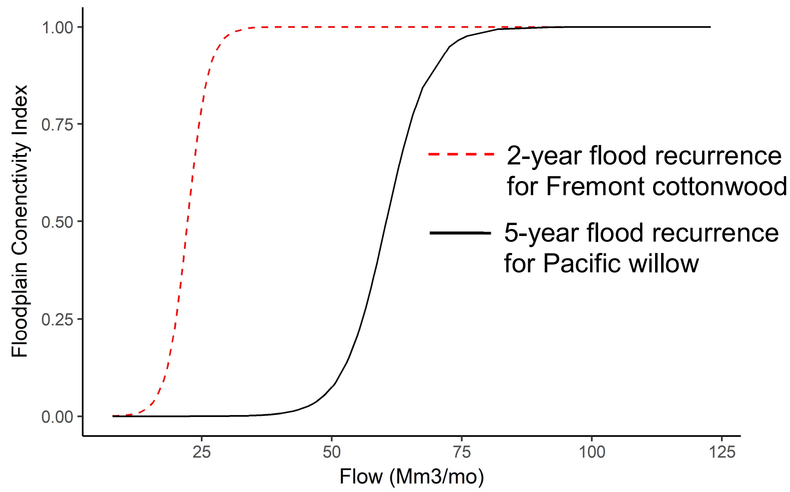

Figure 3.4 Flood recurrence curves at the Blacksmith fork river headwater for two riparian plants with two different flood recurrence needs

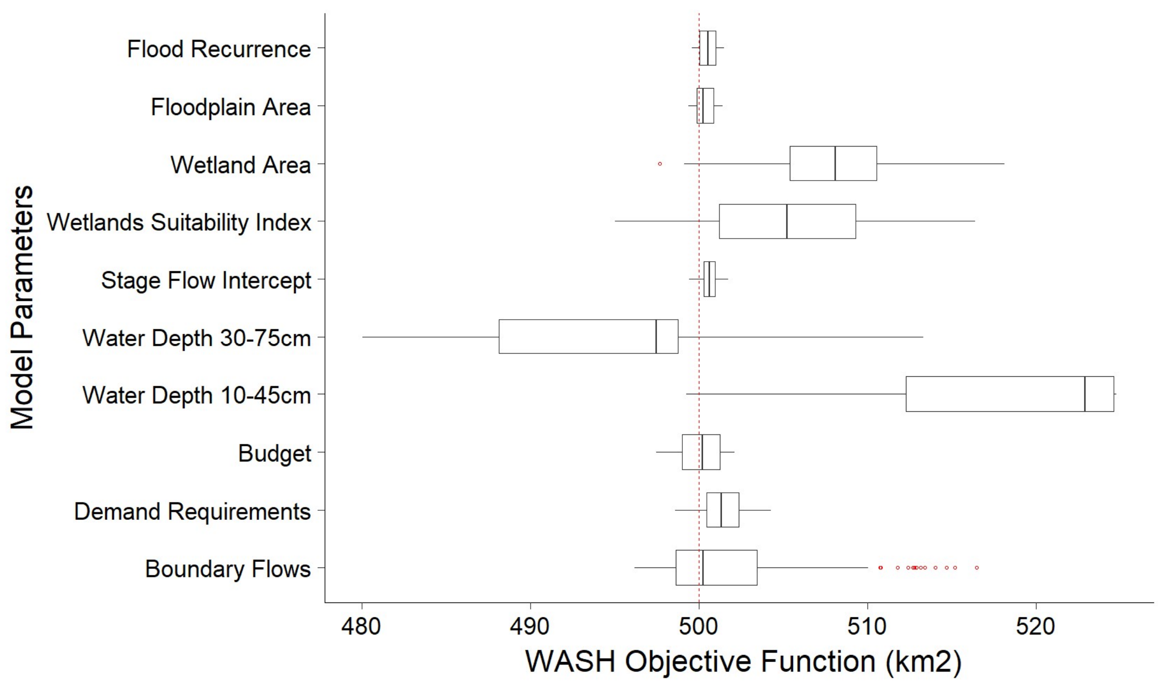

Figure 3.5 Sensitivity analyses results for 10 key parameters against the objective function value. Vertical red dashed line is the objective function value for the deterministic model. Boxplots right and left edges are the 25th and 75th percentile and vertical black lines are the 50th percentile. Red circles are outliers

The one-way ANOVA test in Table 3.1 shows that there is a statistically significant difference between the two cluster means which was determined by the budget at the $p<0.05$ value. Therefore, the model was insensitive to changes in boundary flows and demands and within the group's 7-dimensional variate space, the two clusters are primarily separated by the budget parameter. Thus, model runs with a budget below \$628,000 are members of the first cluster, labelled *Low Budget.* Conversely, model runs with a budget of over \$628,000 are members of the *High Budget* cluster.

To identify and characterize the management implications of low and high budget clusters, we compared recommended releases from Hyrum Reservoir for each cluster with the deterministic model solution and historical releases. Figure 3.6 shows that the high budget scenario increased releases in spring to benefit riparian plants. In contrast, the low budget scenario increased releases in late summer and early fall to benefit trout species and the aquatic habitat area.

The tradeoffs between the two budget clusters and their three habitat area objectives can further characterize the variability within each cluster. Figure 3.7 shows that, in high budget cluster, suitable floodplain habitat area (purple circle for medoid) increased by 25% compared to the deterministic model solution (black circle). In contrast, 10% more suitable aquatic habitat area was available in low budget cluster. The high budget cluster mediod increased suitable floodplain habitat area whereas the low budget mediod decreased floodplain habitat. While both medoids show some improvements and decreases over the deterministic model solution, numerous other Monte Carlo runs in both clusters simultaneously improve all three aquatic, floodplain, and wetland habitat areas over the mediod and deterministic solutions (areas in Figure 3.7 up, to the right, and with darker blue color than the mediods). Similarly, many runs simultaneously decrease all three habitat areas compared to the mediod run and deterministic solution.

Table 3.1 One-way ANOVA table for the three uncertain parameters in the input data uncertainty

Parameters	**Mean Square Error**	**F value**	**p-value**
Demand Requirements (Mm^3/yr)	281	3.814	0.062
Boundary Flows (Mm^3/yr)	22658	0.289	0.592
Budget ($)	5,211,186,505	605.182	0.001

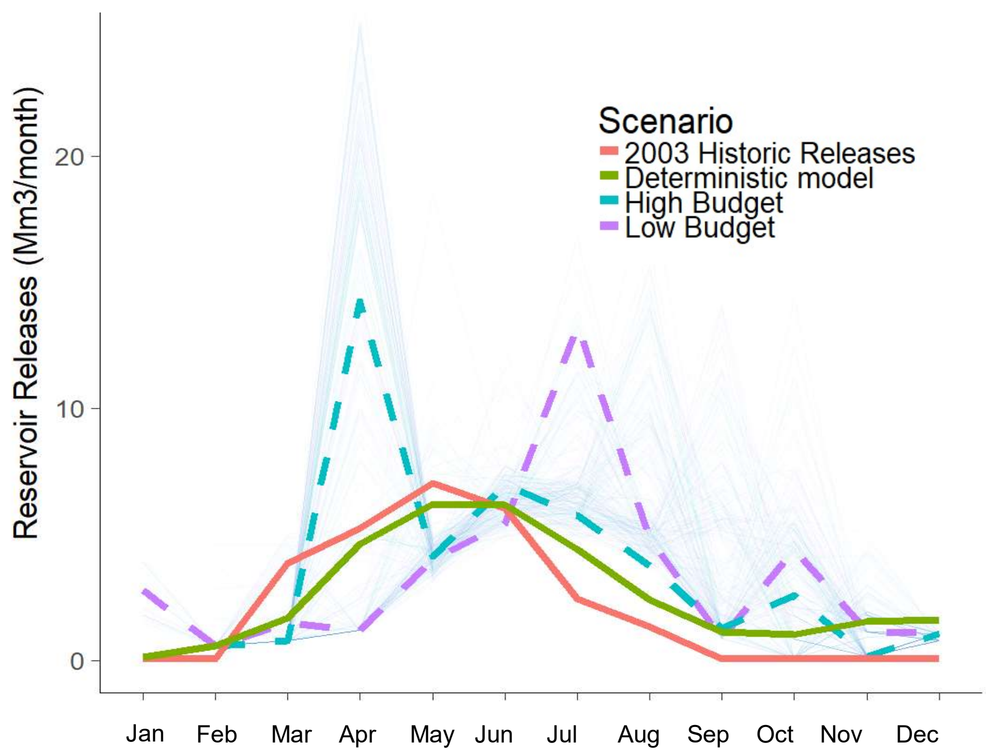

Figure 3.6 Monthly reservoir releases for Hyrum Reservoir for 2003 for the two clusters, deterministic model, and historical releases. Dashed lines are the medoids and background lines are Monte Carlo runs for each cluster

Table 3.2 List of uncertain parameters in WASH model and their probability distribution

Parameter	Model Symbol	Habitat Type	Unit	Value in Deterministic Model	Probability Ranges	Distribution	Sources/ References
Management Objective 1: Improve habitat under uncertain human system parameters							
Boundary flows	reachGain	All habitats	Mm^3/mo	Bear River head flow on January: 21*	75%, 150%, 180% of base value	Discrete	(USGS, 2012; UWRL, 2009)
Budget	b	All habitats	$	650,000	min = 500,000 max = 750,000	Uniform	JUB (2013)
Demand requirements	dReq	All habitats	Mm^3/mo	Bear River Canal Company on May: 42*	min = 70% max = 120%	Uniform	Adams et al. (1992)
Management Objective 2: Improve habitat under ecological uncertainty							
Floodplain area	Cmax	Floodplain	Mm^2	Site just below Cutler Reservoir on the Bear: 0.7*	min = 80% max =120%	Uniform	USDA (2014)
Impounded wetlands area	aw	Wetland	Mm^2	156	min= 90% max = 110%	Uniform	Alminagorta et al. (2016) UDWR (2004)
Suitable depth ranges for adult BCT	rsi	Aquatic	m	Adult Bonneville cutthroat trout: 0.1 – 0.45	Adult brown trout: 0.3 – 0.75	Discrete	Gosse (1981), (Braithwaite, 2011)
Suitable flood recurrence to inundate cottonwood	fci	Floodplain	-	Fremont cottonwood: 2-year flood recurrence at Stateline*: centroid= 252.3 slope= 15.31	Pacific willow: 5-year flood recurrence at Stateline*: centroid= 140.17, slope= 14.75	Discrete	Derived analytically from Kauffman et al. (1997), Dettenmaier and Howe (2015), Richter and Richter (2000)
Aquatic suitability relationship parameters	rsi_par	Aquatic	-	Adult BCT: centroid =0.29 slope= 0.02	Cutthroat trout: centroid= [0.15 – 0.4] slope = [0.01 – 0.06] Brown trout: centroid= [0.35 – 0.70] slope = [0.01 – 0.06]	Discrete pairs of centroid and slope	Sampled from Hickman and Raleigh (1982) SI relationship ranges
Wetland suitability relationship parameters	wsi_par	Wetland	-	January*: intercept=0.33	January (μ, σ): intercept= (0.56, .014)	Normal	Constructed relationships from Alminagorta et al. (2016) data

* A sample data for one reach at one-time step. Full time-series of stochastic data for all rivers are available on GitHub (Alafifi, 2017).

To examine the input parameters for all these runs, we plotted the deterministic model solution (black line), the two medoids (dashed lines), the better- (thick lines), and the worse- (thin lines) performing runs on a parallel coordinate plot (Figure 3.8). Each line crosses the parameter axis at the parameter value for the solution or simulation run. The medoids in the figure show that high budget allows for more floodplain area but slightly less aquatic and wetland areas. However, this increase in floodplain area was possible even with higher human demand requirements. The figure shows many other opportunities to improve overall habitat quality. For example, with a low budget of $538,000, reducing urban and agricultural demand in the basin by 5%, and having additional water from upstream rivers flowing into the system increase by 16% could increase aquatic, floodplain, and wetland habitat areas by 4%, 15%, and 1% respectively. The Pareto frontier for the both clusters (thick lines) show there are very few opportunities to improve overall habitat quality if human demand requirements increased or if boundary flows decreased with reference to deterministic model scenario.

3.6.2.2 Improve habitat quality under ecological uncertainty

We ran a second cluster analysis for 7 ecological parameters (Table 3.1) and four model outputs: the total habitat area objective function and three habitat areas. We used the Silhouette index to determine that two clusters are sufficient to describe the data. Exploring the two clusters using a one-way ANOVA test shows a statistically significant difference between the two cluster means. This difference was determined by indicator species and their habitat attributes defining habitat quality. Therefore, suitable water depth for trout and flood recurrence level for riparian trees were more prominent in defining the two

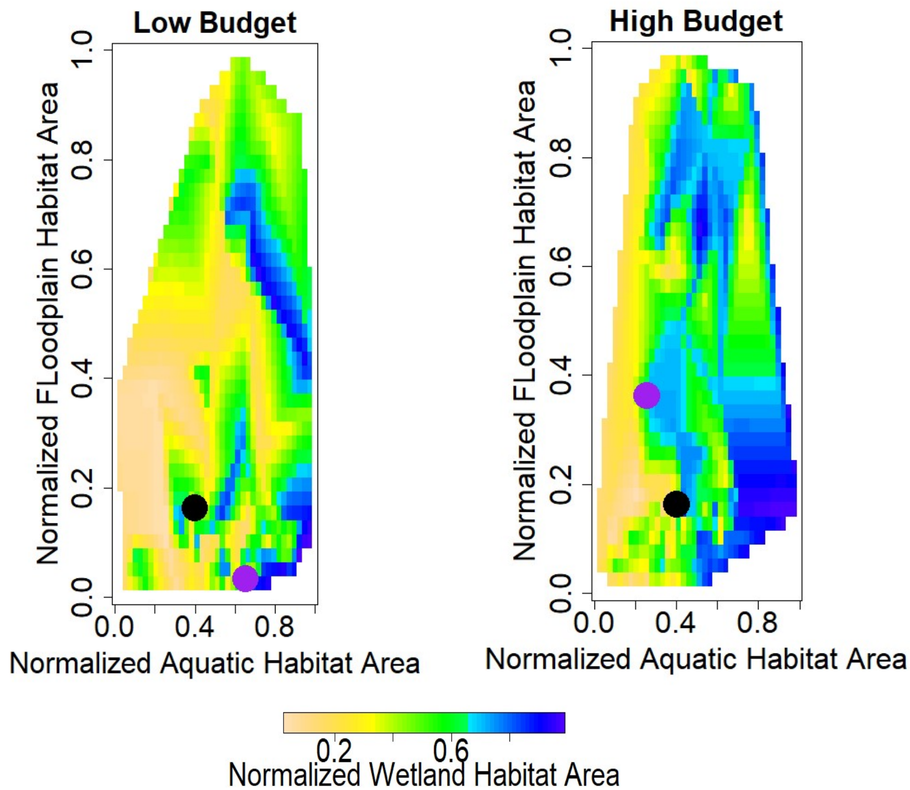

Figure 3.7 Tradeoff plots of normalized aquatic, floodplain and wetland habitats for all Monte Carlo runs. All values are normalized on the same scale [0-1]. Black circle is the deterministic model solution and purple circle is the medoid of each cluster

clusters. The clusters were insensitive to variations in wetland and floodplain areas, and habitat suitability curve parameters.

The 75 members (42% of feasible Monte Carlo runs) of the first cluster: *brown trout and Fremont cottonwood* have higher suitable water depth of 30-75 cm and lower flood recurrence value of 2 years. In contrast, the 105 members (58%) of the *cutthroat trout and Pacific willow* cluster have lower suitable water depth of 10-45 cm and higher flood recurrence of 5 years.

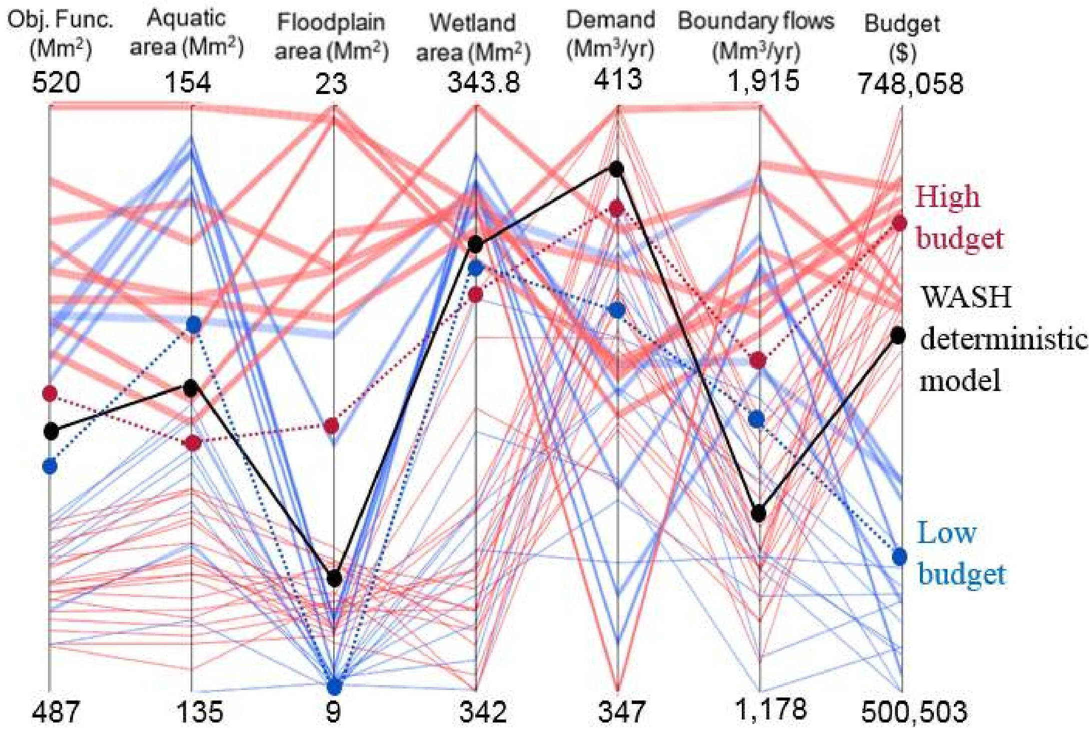

Figure 3.8 Parallel plot of the high budget cluster (red), low budget cluster (blue), and deterministic model (black). Dashed lines are the medoids of two clusters. Thick lines are the run that perform better than the medoid (Paretor-forntier) and thin lines are the worse performing runs for the two clusters respectively

Examining recommended reservoir releases for Hyrum Reservoir shows that both clusters, in general, have larger summer releases but different operations to improve habitat for the indicator species (Figure 3.9). For brown trout and cottonwood cluster, the model recommends releasing more water in late spring which primarily helps improve lateral connectivity with cottonwood trees that live adjacent to streams. In the cutthroat trout and willows cluster, the model recommends releasing more water in late summer and winter months which could provide more water for cutthroat trout spawning season.

Examining the tradeoffs between the two clusters in Figure 3.10 shows that, in the cutthroat and willow scenario, the suitable aquatic habitat area (purple circle for medoid) increased by 19% compared to the deterministic model solution (black circle) while the floodplain area decreased by 10%. In contrast, 9% more floodplain area and 17% less aquatic area was available in the brown trout and cottonwood scenario. This tradeoff and the input conditions for each cluster is better illustrated in the parallel coordinate plot (Figure 3.11) for all the parameters used in cluster analysis. Similar to Figure 3.8, the plot shows all better and worse performing Monte Carlo runs with reference to the two medoids.

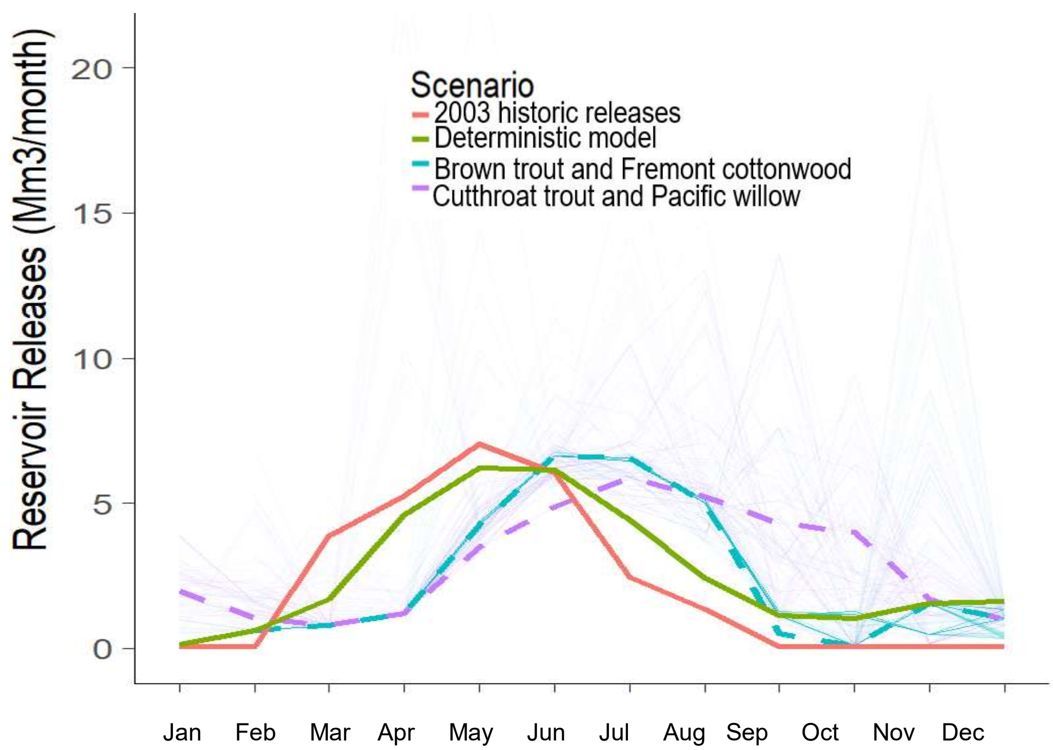

Figure 3.9 Monthly reservoir releases for Hyrum Reservoir for 2003 for two clusters derived from ecological parameters, the deterministic model, and historical releases. Background lines are Monte Carlo runs

Figure 3.11 shows that the cutthroat trout and Pacific willow cluster medoid increased aquatic habitat area over floodplain area because of the low water depth suitable range of cutthroat trout. Conversely, brown trout and Fremont cottonwood increased floodplain area because cottonwood trees live adjacent to the river banks and have low flood frequency suitable range. However, the two clusters had only two Monte Carlo runs that performed worse than the medoid for all three habitats. This means that the medoids here might not be good representatives of their clusters. Other runs that increased all three habitats show better management alternatives. For example, while managing for brown trout and cottonwood trees, increasing available floodplain area to plant riparian trees in the basin by 8% could help increase floodplain suitable habitat area by 30%.

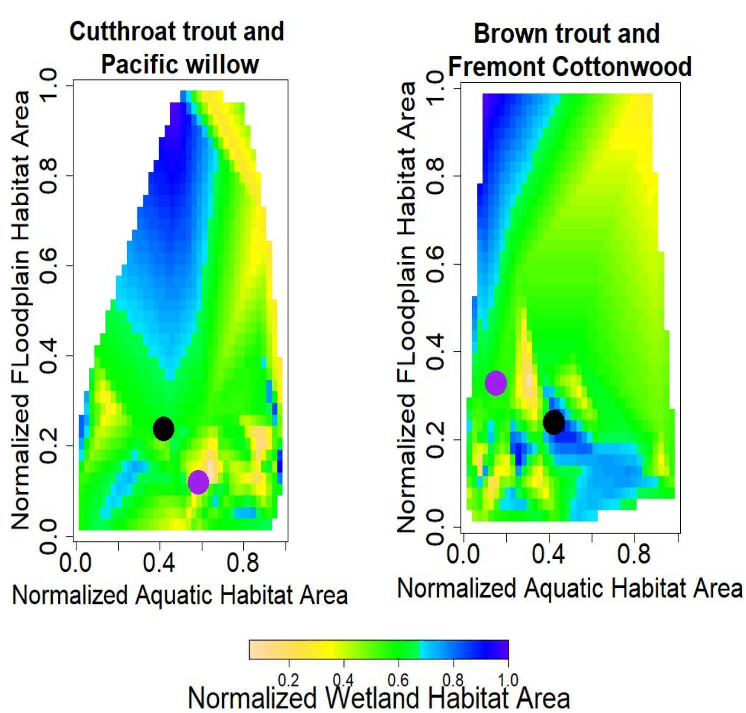

Figure 3.10 Tradeoff plots of the aquatic, floodplain and wetland habitats for all observations. All values are normalized on the same scale [0-1]. Purple circle is the medoid of each cluster and black circle is the deterministic model solution

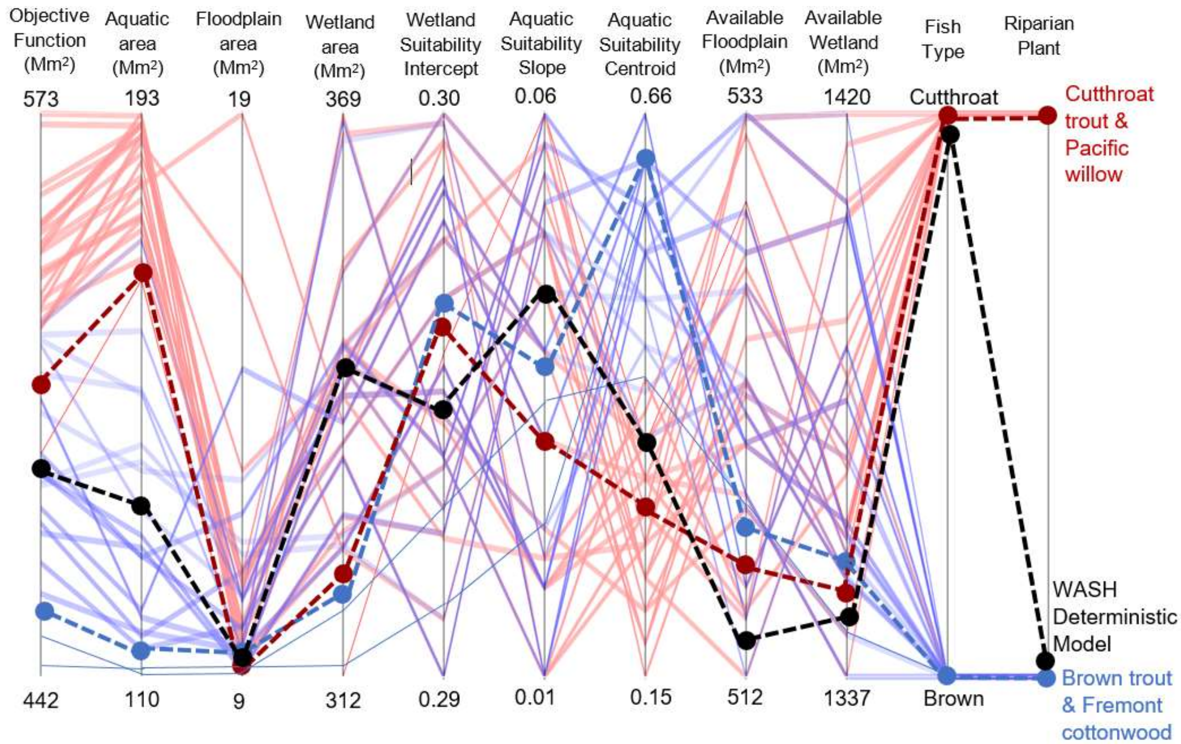

Figure 3.11 Parallel plot of the two clusters in red for cutthroat and willow, blue for brown trout and cottonwood, and black for the deterministic model. Dashed lines are the medoids of two clusters. Thick lines are the better performing runs and thin lines are the worse performing runs for the two clusters respectively

3.7 Discussion

Incorporating uncertainty into a deterministic habitat management model emphasized the importance of understanding the sources, ranges, and impacts of uncertainties in water management decisions. Many uncertainty analysis studies use visuals such as scatter and parallel coordinates plots to assess the credibility of the sensitivity analysis approach and identify trends in model results. However, for large problems with lots of uncertain input parameters, these visuals might not be useful to evaluate model robustness and cannot identify spatial or temporal trends or implications for management (Pianosi et al., 2016b). In the case of the Watershed Area of Suitable Habitat model for the lower Bear River, our approach used semi-supervised cluster analysis to improve understanding of uncertain model behavior, reduce the uncertain space, and assess the credibility of sensitivity assumptions.

Further, our approach showed that performing a local search for clusters helped discover clusters that would be otherwise overlooked. For example, we tested a case of unsupervised clustering where we considered all WASH parameters in a clustering algorithm. The results of this test case were very similar to the results of the first group of parameters where only hydrologic and management inputs (i.e. inflow, demand, and budget) were considered. This similarity indicated that although selection of indicator species and their habitat quality attributes are significant factors in water management decisions, these ecological parameters were overshadowed by more dominant parameters such as budget and boundary flows.

Examining the variability within clusters is also important to recommend management decisions. While other water resources cluster analysis studies have used the centroids or medoids as representatives of their clusters, our analysis showed that the variability within each cluster can reveal many alternatives that may be more desirable to managers such as opportunities to simultaneously improve all three aquatic, floodplain, and wetland habitat areas beyond the medoids and the deterministic model solution. These opportunities were more evident for the second group of uncertain ecological parameters where only two runs performed worse than the medoids for both clusters. For habitat models with many uncertain parameters distributed over different scales, our results indicate that cluster means or mediods may overshadow more desirable alternatives within clusters.

Figures on reservoir releases (Figures 3.6 and 3.9) and tradeoff analyses (Figures 3.8 and 3.11) show opportunities to improve habitat quality under different sources of uncertainty. For example, if managers have a budget to plant cottonwood trees in riparian areas, they can release more water in spring and early summer to increase instream flow and allow lateral connectivity to coincide with seed germination for successful recruitment. This could increase available and suitable floodplain area to plant riparian trees which could help improve habitat quality, return lands to floodplain functions, and restore lateral connectivity with the river. However, for a low budget scenario, managers can release more water to maintain water depth in late summer and early fall spawning seasons to improve aquatic habitat quality. Further, ecological uncertainty and assumptions of indicator species' response to changes in flow regimes translate into different reservoir operational schemes. For example, releasing more water in late spring primarily helps achieve lateral connectivity with cottonwood trees that live adjacent to streams over brown trout. Similarly, releasing more water in late summer and winter months could improve habitat quality of cutthroat trout over willows. This means that selection of indicator species is important and has the potential to fundamentally change results, quantity and timing of reservoir releases and available habitat for different priority species. Therefore, reservoir operators can benefit from our analysis that considers management and ecological parameters to select an operating scheme that meets human needs and improves habitat quality.

While the WASH stochastic model represented the budget to plant riparian trees as an uncertain parameter, restoration projects are more likely to have an incremental budget that is conditioned on completing project phases. This practice could reduce uncertainty in meeting restoration project expected outcomes. The WASH model used an expected budget for future restoration projects and therefore we assumed a range of possible available budget. This assumption could be further improved if river managers have a set budget or a clear target for restoration projects.

Our analysis considered a large number of uncertainties in habitat models' data and parameters. However, uncertainties in model formulation and structure were not considered. One change in model structure could include using arithmetic or geometric means to aggregate multiple indices where multiple species are managed in the same habitat (Ahmadi-Nedushan et al., 2006). Another change in structure would be to use different weights to reflect management preferences for species, times, and locations.

Using Monte Carlo simulation to randomly sample from probability distributions of many uncertain parameters required that we generate a sufficient number of runs to span the uncertain space. We compared model results for a single run using BARON global and CONOPT local solvers and found that the objective function value of the local solution is only 3% lower than the value for the global solver and took 2 minutes compared to 2 hours and 15 min. Performing runs with a global solver will likely produce slightly higher habitat areas but will not affect our reservoir release and tradeoff findings.

Other sampling approaches such as Latin Hypercube, which stratifies the probability distributions of uncertain parameters into equal intervals and takes a random sample from each interval (Helton and Davis, 2003), could also improve our methods. This sampling approach is promising because it could significantly reduce the number of runs required for sensitivity analysis and could potentially allow use of a global optimum solver. However, Latin Hypercube sampling assumes all uncertain parameters with different probability distributions are independent and therefore ignores correlated parameters (Vořechovský and Novák, 2009) that often occur in habitat models. Another promising approach is conditional sampling, such as Gibbs (Casella and George, 1992), which could be used to condition sample the combinations of parameters that only produce feasible alternatives, thus eliminating the need to generate a large number of observations and filtering infeasible alternatives before clustering.

While our analysis showed a promising application of cluster analysis to water and habitat management, there are some limitations to this approach. First, the clustering algorithm will always produce clusters regardless of parameter values or data structure. Second, there is no consensus on the best clustering algorithm or distance method to use for different numeric and nominal data sets. Therefore, selecting the number of clusters, cluster approach, and interpreting management scenarios is specific to the data and management objectives of the clustering exercise. Third, the grouping of uncertain input parameters could dictate the outcomes. Therefore, the modeler should test and select a method (e.g. variance to the objective function) to filter uncertain parameters and objectively select inputs to the cluster analysis algorithm.

The approach of this paper can be applied to other uncertain water and habitat models. While many habitat model uncertainty analyses narrowly focus on a few stochastic parameters and produce ranges of possible model results, our approach can help mangers better explore the large space of possible alternatives, define key uncertain parameters, and identify few promising management actions to improve habitat quality. Applying this approach to other habitat models requires identifying uncertain parameters and sampling from their probability distributions to generate model runs. Then, managers need to define groups to subset parameters based on their management priorities or preferences. Using semi-supervised cluster analysis can reduce hundreds of model runs into a few plausible future scenarios which facilitates communicating uncertainty to water and habitat managers.

Communicating uncertainty in habitat models can be improved by identifying a few management scenarios within the large and multivariate space of possible alternatives. Narrowing to a few scenarios helps focus management efforts on the important parameters to measure and monitor more carefully. Characterizing clusters and exploring variability within clusters also allows manager to infer tradeoffs between alternatives and recommend management options that improve overall habitat quality.

3.8 Conclusions

Managing rivers to improve habitat quality should consider a large number of hydrologic, ecologic, and management uncertainties. Identifying and quantifying multiple uncertainty sources and how they propagate through the model results makes it challenging to find and communicate useful insights to manage complex ecological systems . Here, we presented an application of semi-supervised cluster analysis as a data-mining tool to reduce a large dimensional uncertainty problem and focus management efforts on important parameters to measure and monitor more carefully. Applying cluster analysis to water and habitat management problems allow managers to identify few scenarios to allocate resources to improve habitat quality.

We applied this approach to a case study of a large nonlinear habitat optimization model for the Lower Bear River, Utah. The model recommends water and money allocations to improve habitat quality and area for selected aquatic, floodplain, and wetland species. We characterized and quantified uncertainty in the model and applied cluster analysis to two groups of parameters, one group with only uncertain parameters describing human systems and a second group with only uncertain ecological parameters. Results identified four possible management scenarios where budget to plant riparian trees in the floodplains in addition to the attributes defining habitat quality for indicator species were the main factors that guided management decisions. Our analysis also recommended four reservoir operations alternatives that improve habitat quality under different uncertainty schemes. Reservoir operations can coordinate spring and summer releases with both planting efforts for successful plant recruitment and fish restoration efforts to maintain water depth for fish spawning and maturing. Our approach allowed for examining the tradeoffs between different habitats and finding the conditions that can improve all three habitats together for selected species in the watershed.

3.9 References

Adams, T.D., Cole, D.B., Miller, C.W., Stauffer, N.E., 1992. GENRES A Computer Program System for Reservoir Operation with Hydropower, In: Resources, U.D.o.W. (Ed.).

Ahmadi-Nedushan, B., St-Hilaire, A., Berube, M., Robichaud, E., Thiemonge, N., Bobee, B., 2006. A review of statistical methods for the evaluation of aquatic habitat suitability for instream flow assessment. River Research and Applications 22(5) 503-523.

Alafifi, A., 2017. ayman510/WASH: First release of WASH code. doi:10.5281/zenodo.801509. URL: https://github.com/ayman510/WASH

Alafifi, A., Rosenberg, D.E., In Review. Systems Modeling to Improve River, Floodplain, and Wetland Habitat Quality and Aea. Environmental Modeling & Software.

Alminagorta, O., Rosenberg, D.E., Kettenring, K.M., 2016. Systems modeling to improve the hydro-ecological performance of diked wetlands. Water Resources Research 52(9) 7070-7085.

Ayllon, D., Almodovar, A., Nicola, G.G., Elvira, B., 2012. THE INFLUENCE OF VARIABLE HABITAT SUITABILITY CRITERIA ON PHABSIM HABITAT INDEX RESULTS. River Research and Applications 28(8) 1179-1188.

Bair, E., 2013. Semi-supervised clustering methods. Wiley Interdisciplinary Reviews: Computational Statistics 5(5) 349-361.

Basu, S., Banerjee, A., Mooney, R., 2002. Semi-supervised clustering by seeding, In Proceedings of 19th International Conference on Machine Learning (ICML-2002. Citeseer.

Bear River CAP, 2008. The Bear River, A conservation priority. The Nature Conservnacy: Utah.

Bender, L.C., Roloff, G.J., Haufler, J.B., 1996. Evaluating confidence intervals for habitat suitability models. Wildlife Society Bulletin 24(2) 347-352.

Bostock, M., Chang, K., Russell, K., 2016. parcoords: htmlwidget for d3.js parallel coordinates chart, p. R package version 0.4.0.

Braithwaite, N.R., 2011. The Effect of Stream Restoration on Preferred Cutthroat Trout Habitat in the Strawberry River, Utah, Watershed Sciences. Utah State Univeristy: Logan, UT, p. 950.

Burgman, M.A., Breininger, D.R., Duncan, B.W., Ferson, S., 2001. Setting Reliability Bounds on Habitat Suitability Indices. Ecological Applications 11(1) 70-78.

Candelieri, A., Archetti, F., 2014. Identifying Typical Urban Water Demand Patterns for a Reliable Short-term Forecasting – The Icewater Project Approach. Procedia Engineering 89 1004-1012.

Cao, Z., Carling, P.A., 2002. Mathematical modelling of alluvial rivers: reality and myth. Part 2: Special issues, Proceedings of the ICE - Water and Maritime Engineering, pp. 297-307.

Casella, G., George, E.I., 1992. Explaining the Gibbs Sampler. The American Statistician 46(3) 167-174.

Chen, D., Leon, A.S., Hosseini, P., Gibson, N.L., Fuentes, C., 2017. Application of Cluster Analysis for Finding Operational Patterns of Multireservoir System during Transition Period. Journal of Water Resources Planning and Management 143(8) 04017028.

Clifford, N.J., Acreman, M.C., Booker, D.J., 2008. Hydrological and Hydraulic Aspects of River Restoration Uncertainty for Ecological Purposes, In: Darby, S., Sear, D. (Eds.), Managing the

Uncertainity in Restoring Physical Habitat. John Wiley & Sons, Ltd: England.

Cressie, N., Calder, C.A., Clark, J.S., Hoef, J.M.V., Wikle, C.K., 2009. Accounting for uncertainty in ecological analysis: the strengths and limitations of hierarchical statistical modeling. Ecological Applications 19(3) 553-570.

Dettenmaier, M., Howe, F.P., 2015. Taking Care of Streams and Rivers in Cache Valley, USU Extension. Utah State University: Logan, Utah.

Di Baldassarre, G., Montanari, A., 2009. Uncertainty in river discharge observations: a quantitative analysis. Hydrology and Earth System Sciences 13(6) 913.

Douglas, S.J., Newton, A.C., 2014. Evaluation of Bayesian networks for modelling habitat suitability and management of a protected area. Journal for Nature Conservation 22(3) 235-246.

Downard, R., Endter-Wada, J., 2013. Keeping wetlands wet in the western United States: Adaptations to drought in agriculture-dominated human-natural systems. Journal of Environmental Management 131(0) 394-406.

Drud, A.S., 1996. A System for Large Scale Nonlinear Optimization, Reference Manual for CONOPT Subroutine Library. ARKI Consulting and Development A/S: Bagsvaerd, Denmark p. 69.

Fox, G.A., Muñoz-Carpena, R., Sabbagh, G.J., 2010. Influence of flow concentration on parameter importance and prediction uncertainty of pesticide trapping by vegetative filter strips. Journal of Hydrology 384(1) 164-173.

Gosse, J.C., 1981. Brown trout (Salmo trutta) responses to stream channel alterations, their microhabitat requirements, and a method for determining microhabitat in lotic systems. Utah State University: Logan, UT, p. 138 pp.

Gower, J.C., Ross, G.J.S., 1969. Minimum Spanning Trees and Single Linkage Cluster Analysis. Journal of the Royal Statistical Society. Series C (Applied Statistics) 18(1) 54-64.

Groves, D.G., Lempert, R.J., 2007. A new analytic method for finding policy-relevant scenarios. Global Environmental Change 17(1) 73-85.

Hamel, P., Bryant, B.P., 2017. Uncertainty assessment in ecosystem services analyses: Seven challenges and practical responses. Ecosystem Services 24 1-15.

Harper, E.B., Stella, J.C., Fremier, A.K., 2011. Global sensitivity analysis for complex ecological models: a case study of riparian cottonwood population dynamics. Ecological Applications 21(4) 1225-1240.

Helton, J.C., Davis, F.J., 2003. Latin hypercube sampling and the propagation of uncertainty in analyses of complex systems. Reliability Engineering & System Safety 81(1) 23-69.

Hickman, T., Raleigh, R., 1982. Habitat Suitability Index Models: Cutthroat Trout, Biological Services Program. Fish and Wildlife Service.

Hozlar, E., 1990. Gams - General Algebraic Modeling System for Mathematical-Modeling. Ekonomicko-Matematicky Obzor 26(1) 96-99.

Hughes, F.M.R., Colston, A., Mountford, J.O., 2005. Restoring riparian ecosystems: The challenge of accommodating variability and designing restoration trajectories. Ecology and Society 10(1).

Janssen, J.A.E.B., Krol, M.S., Schielen, R.M.J., Hoekstra, A.Y., de Kok, J.L., 2010. Assessment of uncertainties in expert knowledge, illustrated in fuzzy rule-based models. Ecological Modelling 221(9) 1245-1251.

JUB, 2013. Cache County Water Master Plan. Cache County, UT, p. 375 pp.

Katz, R.W., 2002. Techniques for estimating uncertainty in climate change scenarios and impact studies. Climate Research 20(2) 167-185.

Kauffman, J.B., Beschta, R.L., Otting, N., Lytjen, D., 1997. An ecological perspective of riparian and stream restoration in the western United States. Fisheries 22(5) 12-24.

Lek, S., 2007. Uncertainty in Ecological Models. Ecological Modelling 207 1-2.

Lempert, R.J., Popper, S.W., Bankes, S.C., 2010. Robust decision making: coping with uncertainty. The Futurist 44(1) 47.

Li, H., Wu, J., 2006a. Chapter 2: Perspectives and Methods of Scaling, In: Wu, J., Jones, K.B., Li, H., Loucks, O.L. (Eds.), Scaling and Uncertainty Analysis in Ecology: Methods and Applications. Springer: The Netherlands.

Li, H., Wu, J., 2006b. Chapter 3: Uncertainty Analysis in Ecological Studies: An Overview, In: Wu, J., Jones, K.B., Li, H., Loucks, O.L. (Eds.), Scaling and Uncertainty Analysis in Ecology: Methods and Applications. Springer: The Netherlands.

Loucks, D.P., Van Beek, E., Stedinger, J.R., Dijkman, J.P.M., Villars, M.T., 2005. Water Resources Systems Planning and Management: An Introduction to Methods, Models and Applications. Unesco.

Maechler, M., Rousseeuw, P., Struyf, A., Hubert, M., Hornik, K., 2016. cluster: Cluster Analysis Basics and Extensions, p. R package version 2.0.4.

Mahoney, J., Rood, S., 1998. Streamflow requirements for cottonwood seedling recruitment—An integrative model. Wetlands 18(4) 634-645.

Mooney, C.Z., 1997. Monte carlo simulation. Sage Publications.

Noiva, K., Fernández, J.E., Wescoat, J.L., 2016. Cluster analysis of urban water supply and demand: Toward large-scale comparative sustainability planning. Sustainable Cities and Society 27 484-496.

Null, S.E., Lund, J.R., 2012. FISH HABITAT OPTIMIZATION TO PRIORITIZE RIVER

RESTORATION DECISIONS. River Research and Applications 28(9) 1378-1393.

O'Hagan, A., 2012. Probabilistic uncertainty specification: Overview, elaboration techniques and their application to a mechanistic model of carbon flux. Environmental Modelling & Software 36 35-48.

Pappenberger, F., Beven, K.J., 2006. Ignorance is bliss: Or seven reasons not to use uncertainty analysis. Water Resources Research 42(5) n/a-n/a.

Parsons, L., Haque, E., Liu, H., 2004. Subspace clustering for high dimensional data: a review. Acm Sigkdd Explorations Newsletter 6(1) 90-105.

Pianosi, F., Beven, K., Freer, J., Hall, J.W., Rougier, J., Stephenson, D.B., Wagener, T., 2016a. Sensitivity analysis of environmental models: A systematic review with practical workflow. Environmental Modelling & Software 79 214-232.

Pianosi, F., Beven, K., Freer, J., Hall, J.W., Rougier, J., Stephenson, D.B., Wagener, T., 2016b. Sensitivity analysis of environmental models: A systematic review with practical workflow. Environmental Modelling & Software 79(Supplement C) 214-232.

Pinto, R., Patricio, J., Baeta, A., Fath, B.D., Neto, J.M., Marques, J.C., 2009. Review and evaluation of estuarine biotic indices to assess benthic condition. Ecological Indicators 9(1) 1-25.

Poudyal, M., Rothley, K., Knowler, D., 2009. Ecological and economic analysis of poaching of the greater one-horned rhinoceros (Rhinoceros unicornis) in Nepal. Ecological Applications 19(7) 1693-1707.

R Core Team, 2016. R: A language and environment for statistical computing, R Foundation for Statistical Computing: Vienna, Austria.

Richter, B.D., Richter, H.E., 2000. Prescribing Flood Regimes to Sustain Riparian Ecosystems along Meandering Rivers
Prescripción de Regímenes de Inundación para Mantener Ecosistemas Riparios a lo Largo de Ríos Sinuosos. Conservation Biology 14(5) 1467-1478.

Rivaes, R., Rodríguez-González, P.M., Albuquerque, A., Pinheiro, A.N., Egger, G., Ferreira, M.T., 2013. Riparian vegetation responses to altered flow regimes driven by climate change in Mediterranean rivers. Ecohydrology 6(3) 413-424.

Romesburg, C., 2004. Cluster Analysis for Researchers. Lulu.com.

Rood, S.B., Braatne, J.H., Hughes, F.M.R., 2003. Ecophysiology of riparian cottonwoods: stream flow dependency, water relations and restoration†. Tree Physiology 23(16) 1113-1124.

Rousseeuw, P.J., 1987. Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. Journal of Computational and Applied Mathematics 20 53-65.

Sahinidis, N.V., 1996. BARON: A general purpose global optimization software package. Journal of Global Optimization 8 201-205.

Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., Saisana, M., Tarantola, S., 2008. Global Sensitivity Analysis: The Primer. Wiley.

Sarstedt, M., Mooi, E., 2014. Chapter 9: Cluster Analysis. Springer Berlin Heidelberg.

Schwartz, P., 2012. The Art of the Long View: Planning for the Future in an Uncertain World. Crown Publishing Group.

Shiau, J.T., Wu, F.C., 2013. Optimizing environmental flows for multiple reaches affected by a multipurpose reservoir system in Taiwan: Restoring natural flow regimes at multiple temporal scales. Water Resources Research 49(1) 565-584.

Sobol, I.M., 1993. Sensitivity estimates for nonlinear mathematical models. Mathematical Modelling and Computational Experiments 1(4) 407-414.

UDWR, 2004. Utah Division of Water Resources, Bear River Basin, Planning for the Future: Utah.

UDWRe, 2000. Bear River Development, Utah Divion of Water Resources: Salt Lake City, UT.

USDA, 2014. USA NAIP Imagery: NDVI, Esri Living Atlas of the World.

USGS, 2012. USA NHDPlusV2, Esri Living Atlas of the World.

UWRL, 2009. Little Bear River WATERS Test Bed. Utah Water Research Laboratory, Utah State University: Logan, UT.

Van der Lee, G.E.M., Van der Molen, D.T., Van den Boogaard, H.F.P., Van der Klis, H., 2006. Uncertainty analysis of a spatial habitat suitability model and implications for ecological management of water bodies. Landscape Ecology 21(7) 1019-1032.

Veerender, G., 2007. Forecasting the water demand using regression and cluster analysis for Salt Lake City, Civil and Environmental Engineering. Utah State Univeristy: Logan, UT, p. 84.

Vořechovský, M., Novák, D., 2009. Correlation control in small-sample Monte Carlo type simulations I: A simulated annealing approach. Probabilistic Engineering Mechanics 24(3) 452-462.

Vucetic, D., Simonović, S.P., 2011. Water Resources Decision Making Under Uncertainty, Water Resources Research Report. Department of Civil and Environmental Engineering, The University of Western Ontario: London, ON CANADA

Wilhere, G.F., 2012. Using Bayesian networks to incorporate uncertainty in habitat suitability index models. Journal of Wildlife Management 76(6) 1298-1309.

Williams, J.G., 1996. Lost in space: Minimum confidence intervals for idealized PHABSIM studies. Transactions of the American Fisheries Society 125 458-465.

Zajac, Z., Stith, B., Bowling, A.C., Langtimm, C.A., Swain, E.D., 2015. Evaluation of habitat suitability index models by global sensitivity and uncertainty analyses: a case study for submerged aquatic vegetation. Ecology and Evolution 5(13) 2503-2517.

CHAPTER 4

INTERACTIVE WEB GIS APPLICATIONS TO VISUALIZE WATER RESOURCES MODEL OUTPUTS[3]

Abstract

Interactive interfaces can help researchers and managers communicate water resources model outputs with policy makers, the public, and solicit feedback on model development and results. Web GIS applications offer platforms that provide spatial representation of water resources system components and help make spatially-informed decisions. Current web GIS platforms display spatial data in GIS-accepted file formats. While the outputs of some hydrologic models are described in GIS formats, many river and reservoir water allocation models use node and link concepts to represent the spatial network of rivers and on- and off-stream infrastructure such as reservoirs, demand sites, and diversion canals. Constructing a node-link network for a web map requires considerable time, technical web, and GIS experience. Here, we present an open-access tool that simplifies the creation of nodes and links networks on web maps. The tool allows water resources modelers to create web GIS layers and use a web GIS platform as an interactive interface for model outputs. The interfaces require only a web browser to access and can display, disseminate, and communicate water resources model outputs in user-friendly web maps We demonstrate the tool for a Watershed Area of Suitable Habitat (WASH) optimization model for the lower Bear River, Utah and a Water Evaluation and Planning (WEAP) simulation model of the tri-state Bear River Basin of Utah, Idaho, and

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[3] Co-authored by David E. Rosenberg

Wyoming.. The two apps facilitated the collaborative development of water resources models and helped communicate water allocation and habitat improvement decisions to river managers. The apps also provided venues for collaboration between model developers and policy makers, and made model outputs accessible to the public. Interactive web maps can be easily constructed to visualize results for many types of node-link water resources models.

4.1 Introduction

Water resources models are computer-aided mathematical tools that inform decisions to help plan and manage water resources systems. Models can include components such as water sources, water uses, reservoirs, conveyance, and operation of these and other natural and engineering infrastructure for a variety of purposes such as water supply, hydropower generation, habitat improvement, and/or flood damage reduction (Loucks et al., 2005). These models are often spatially distributed across cities, watersheds, and regions. They also vary over time (Barbour et al., 2016). Water managers work with complicated systems and must effectively present, share, and communicate their work with policy makers and the public in user-friendly interface (Verma et al., 2012). Successfully engaging policy makers and the public will also allow managers to solicit feedback on model development and results to improve models.

Many existing water resources decision support systems have three architecture components: data, a computational algorithm, and a user interface (Figure 4.1). Water resources model data are the inputs to and outputs from the mathematical algorithm and are often defined spatially on a grid or on a network of nodes and links. Computational algorithms process input data and generate outputs that are displayed by the user interface. These interfaces often use Geographic Information Systems (GIS) to spatially represent hydrologic and hydraulic systems (Martin et al., 2005). Therefore, many hydrologic models have integrated GIS interfaces and geoprocessing capabilities to perform spatial analyses to generate model inputs such as surface runoff, flood zoning, and drainage areas. Example models include the Soil and Water Assessment Tool (SWAT; Gassman et al., 2007) and the Water Erosion Prediction Project (WEPP; Flanagan and Nearing, 1995).

Other models, such as water allocation models, use a network of nodes and links as a schematic representation of the spatial distribution of river basin features (Meeks and Rosenberg, 2017). These models are based on water volume-balance and are used to simulate the storage, flow, and water supply in a system of reservoirs and river reaches (Porse and Lund, 2016; Wurbs, 2005). Wurbs (2005) reviewed 15 of the most common node-link river and reservoir models including the river basin management decision support system MODSIM (Labadie, 2005), Water Evaluation And Planning (WEAP; Kirshen et al., 1995), RiverWare (Zagona et al., 2005), and the U.S. Army Corps of Engineers Hydrologic Engineering Center Reservoir System Simulation (HEC-ResSim; Klipsch and Hurst, 2007). All 15 software products integrate model outputs within the software interface. This integration poses a challenge to interpret and disseminate model outputs without the modeling software. Users and stakeholders need to use, often proprietary, software to view and interact with model results. It is also difficult to compare results generated using different modeling software systems. While many software products allow modelers to export tabular outputs as text files, communicating these

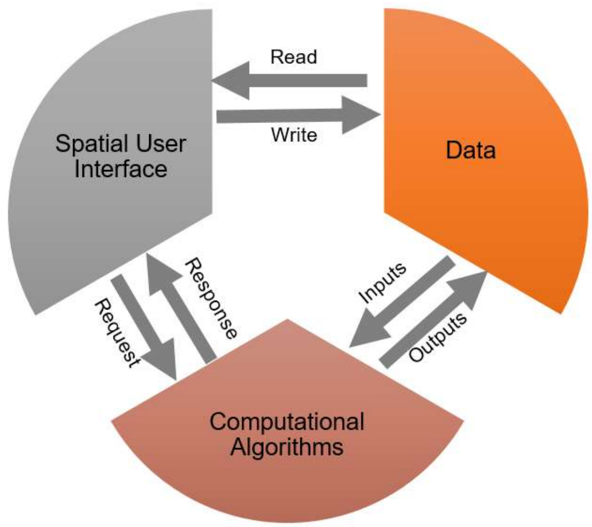

Figure 4. 1 General architecture of water resources models

outputs to decision makers and the public can be improved by using model-agnostic, web-accessible, and interactive mapping platforms.

Web GIS platforms can offer a model-agnostic alternative to using software-specific user interfaces (McKinney and Cai, 2002). Web GIS applications (or apps) are web-accessible interfaces that provide an online hosted GIS platform without the need for GIS desktop software (Choi et al., 2005). These apps can facilitate and complement node-link water resources model development and communication of results by providing a mapping interface to display, query, analyze, and interact with spatially- and temporally-distributed data (Delipetrev et al., 2014; Sui and Maggio, 1999; Swain et al., 2015). Web-accessible GIS apps can disseminate water resources model data, solicit a focused participation in the modeling process, and communicate specific and targeted results to non-technical users (Rathore et al., 2010; Verma et al., 2012). For example, Castrogiovanni et al. (2005) developed an interactive web GIS interface to display the results of a hydrologic model for flood discharge and risk assessment in Sicily, Italy. Similarly, Rathore et al. (2010) created an app to display drought conditions and reservoir operations for water availability scenarios in India. Developing these web apps, however, requires considerable technical experience to synthesize a multitude of services including database servers to store spatial data, geoprocessing servers with mapping libraries to perform analysis, and web development languages to customize and configure user interfaces (Chang and Park, 2006; Delipetrev et al., 2014; Zhao et al., 2012).

Some commercial and open-source software have been developed to provide coding-free platforms to interactively design, publish, and host web GIS apps. For example, Esri's Web AppBuilder is part of the ArcGIS Online platform (www.arcgis.com) that allows novice users to create, deploy, and customize web mapping apps without coding. Web AppBuilder uses JavaScript custom-made templates to build web apps with no need for an on-premises GIS server (Fu, 2016). Since its inception in 2009, ArcGIS Online has been a popular platform for many users and has been used to assist water and natural resources management (Scopel, 2015). Esri, a proprietary software vendor, has documented the geospatial web services used in ArcGIS Online, allowing developers to build, customize, and deploy applications on their own machines (Esri, 2010). Another web app platform is HydroShare (https://www.hydroshare.org) which was developed for sharing water and hydrologic models and data. HydroShare provides an applications programming interface (API) and mechanism for web apps developed in any environment to be launched from and interact with data in HydroShare. These include a suite of web applications for acting on and visualization of hydrologic data, some of which were developed using the Tethys Python-powered platform and are hosted at http://apps.hydroshare.org (Tarboton et al., 2013). One example is the HydroShare GIS app that facilitates interactive display and sharing of spatial data (Crawley et al., 2017). Another app platform is Google Earth Pro, developed using Google Earth Engine's JavaScript and Python libraries. Google Earth Pro allows its users to utilize Google's large set of spatial data and web services to build web applications and perform spatial analysis (Gorelick et al., 2017). Carto Builder (https://www.carto.com) is another platform that allows users to create and customize web applications to share and visualize spatial data. Carto Builder allows users to perform spatial analysis, query, and filter their data using PostrgreSQL geodatabase.

Despite their many advantages, these web GIS platforms are underutilized. One main challenge for water resources modelers to use these platforms is that the platforms require geo-referenced data. None of the reviewed web GIS platforms allow water resources modelers to create these layers. Creating web GIS layers on desktop GIS software requires considerable time and GIS experience to describe all river nodes and links in GIS data structure and format (McKinney and Cai, 2002; Sui and Maggio, 1999).

Describing nodes and links model data in GIS map format is challenging because, whereas GIS seeks to accurately represent the world's geography, node and link networks seek to simplify the actual system. Similarly, GIS wants to accurately locate point, line, polygon and other features in space. In contrast, Node-Link networks are only concerned about connectivity between nodes. For example, GIS maps display natural rivers and lakes based on geography (Cai et al., 2006). However, nodes and links conceptually represent the spatial distribution of rivers including on- and off-stream infrastructure such as reservoirs, demand sites, water supply sources, and diversion canals within the basin (Loucks et al., 2005). Water resources modelers will need to create GIS layers of nodes and links in order to publish their model outputs to a GIS map. This requires creating new or editing existing GIS layers of rivers to capture the modeler specific design. For example, a shapefile layer in a GIS map could have a single line to represent a river (e.g. Logan River in Figure 4.2a). The modeler's specific network could have multiple connected links to describe the same river (e.g. 5 links for the Logan River in Figure 4.2b). In addition, the network could have nodes that aggregate and represent other features such as demand sites and reservoirs. Building this network of nodes and links in a GIS map (Figure 4.2c) requires considerable time, access to and good knowledge of GIS software (Taher and Labadie, 1996).

Here, we present an open-access web tool to help water resources modelers interactively build web GIS layers of river nodes and links with no coding. Modelers can use the GIS layer in a web GIS app to share spatially and temporally distributed model outputs.

Section 2 presents the new tool to build web GIS layers for river networks. Section 3 overviews how to use these web layers to build an interactive web GIS app as an interface for water resources model outputs. Section 4 presents two use cases for water resources web apps that were developed using the new tool to provide interfaces to an optimization and a simulation water resources models. Section 5 discusses the benefits of web apps to facilitate collaborative decision making to manage scarce water.

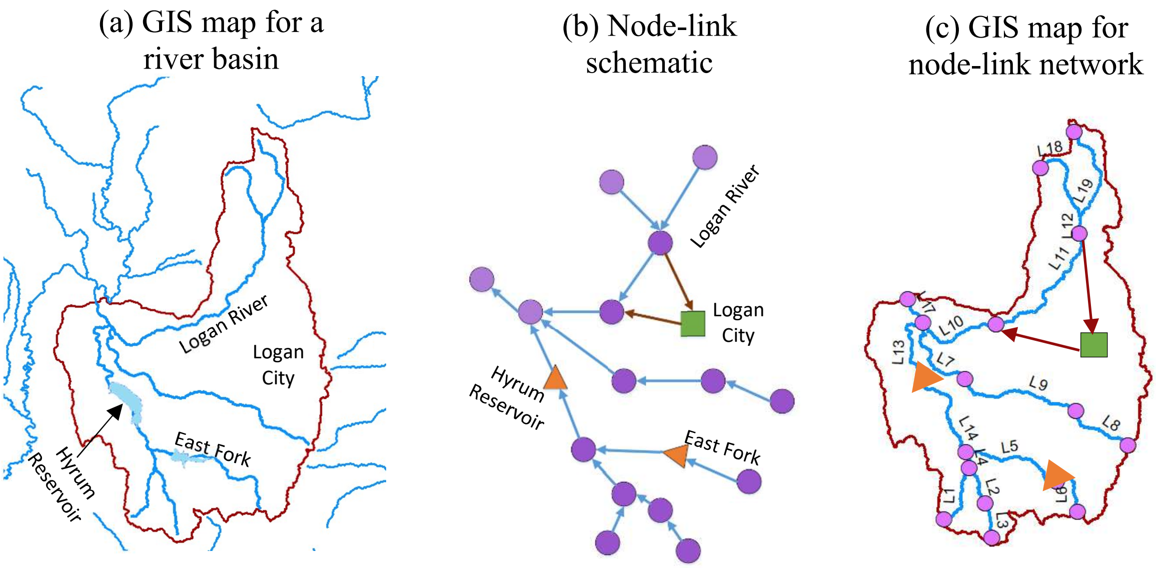

Figure 4.2: Examples of a GIS map and a node-link schematic for the Little Bear Basin, Utah

4.2 Create River Network web tool

To create nodes and links directly on a web map, we developed and published a geoprocessing tool named ‘Create River Network’. The geoprocessing tool was first developed and tested on Esri ArcMap, published to a GIS web server, and then hosted on an ArcGIS Online web application using the web server-provided Representational State Transfer (REST) URL. The tool is accessible at: http://WebMapBuilder.usu.edu. The tool Python script, REST URL, and detailed instructions are available on a GitHub repository (Alafifi, 2017). The tool geoprocessing workflow is described in more details in Figure C.1 in appendix C. The tool significantly reduces the time and effort required to construct and customize web GIS layers of river nodes and links as evident by the workflow of the tool in comparison to traditional desktop GIS methods in Figure 4.3.

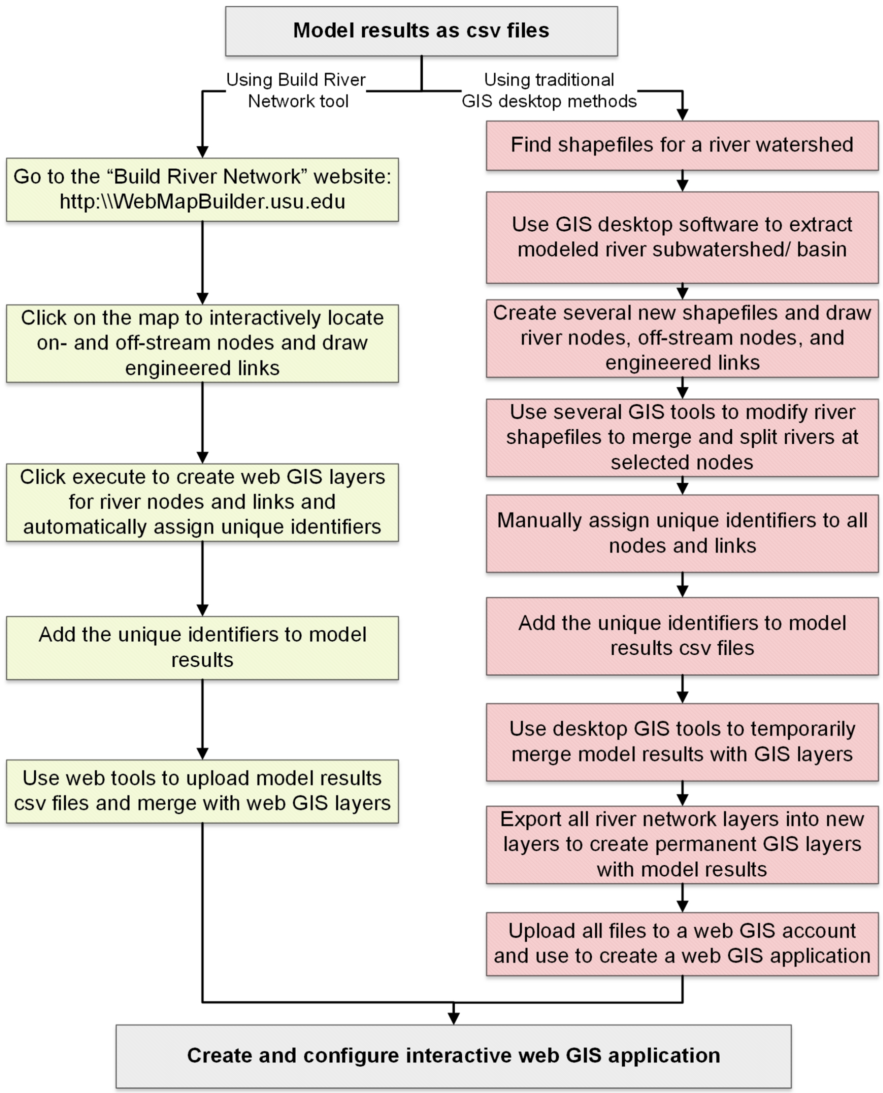

Figure 4.3: Workflow of the Create River Network web tool verses tradition methods to create web GIS layers for river network

The tool website comes preloaded with the United States Rivers layer (NOAA, 1998), but users can load their own river basins as a shapefile using the add icon. We selected the NOAA rivers because they only show common natural rivers, while other databases such as the National Hydrography Dataset (NHDPlus V2, 2016) displays additional artificial pathways and canals.

The user then selects the following inputs (Figure 4.4a):

- Watershed boundaries: select or manually draw the basin boundary area directly on the map
- River nodes: click on the map to add nodes, using the ‘ctrl’ button to snap nodes to rivers
- Demand sites and reservoirs: Similarly, click on the map to locate demand sites and reservoirs
- Engineered links: draw lines on the map to denote diversions and return flow. The lines snap to existing nodes and river features.

Click ‘Execute’ creates 5 web GIS layers for river nodes, demand sites, reservoirs, river links, and engineered links (Figure 4.4b). The tool creates river links by first dissolving all river lines together and then splitting river lines at user-selected on-river nodes where river links are created between nodes. Each web GIS layer will have a field for unique identifiers for every feature, for example “N1” and “L1” for every on-river node and river link. Once the tool is executed, new layers will appear on the tool web map and the user will be able to download or save them directly on their Esri ArcGIS Online account.

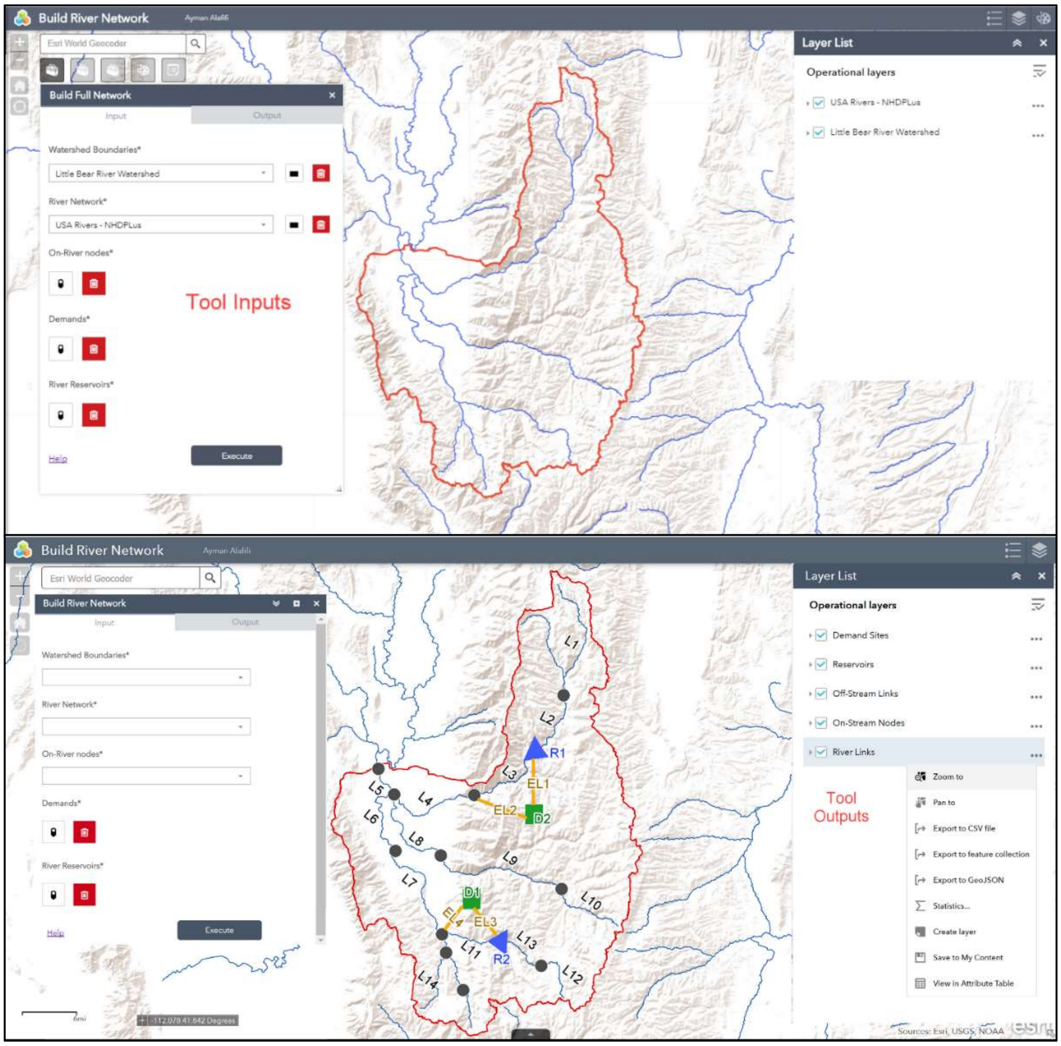

Figure 4.4 Screenshots of the Create River Network geoprocessing tool. Top: tool inputs selected from a list or drawn directly on the map. Bottom: outputs of river network layers

4.3 Using the tool to develop water resources web GIS apps

The Create River Network tool could be used as a first step to create web GIS layers for river network (Figure 4.5). To create a web GIS application, water resources modeler will need to (1) upload their model data to a web map, and (2) configure the user interface, and (3) share settings. Here we demonstrate this approach using Esri's ArcGIS Online platform because the platform allows joining tabular data (model outputs) with web layers. Completing these steps requires an Esri ArcGIS Online publisher account:

4.3.1 Load model outputs and layers into a new web map

The user here creates a new web map on ArcGIS Online and follows these steps to add model outputs:

1. Export water resource model outputs to a text file, such as comma separated values (csv). Assign the same identifiers that were generated by the Create Network tool to all node and link entities in text file.
2. Create a new web map on ArcGIS Online. Upload to the web map all model output files and the web GIS layers created by the Create Network tool.
3. Use the 'join layers' option in ArcGIS Online to merge web GIS layers with their respective model output files.

4.3.2 Configure interactive interface

Next, customize the user experience:

1. Add basemaps and additional layers that provide geographical context.
2. Add interactive tools and widgets such as informational popups that appear when a user clicks on a feature in the map, time-animated slider to visualize temporal data and patterns, chart-builder to compare two or more features, query data, and editing tools to allow users to add to the map or comment on data.
3. Add meta data to describe the web app, data, and results

The Create River Network tool, coupled with ArcGIS Online interactive functionalities, enables water resources modelers to build user-friendly interfaces that only require a web browser and internet connection to access. In the next section, we provide 2 use cases as examples of the interface functionalities that were accessible in ArcGIS online using our tool.

4.4 Use Cases for the Water Resources Web Apps

We present two use cases for two apps that were developed as a web interfaces for a Watershed Area of Suitable Habitat (WASH) optimization model for the lower Bear River, Utah and a Water Evaluation and Planning (WEAP) simulation model of the tri-state Bear River Basin of Utah, Idaho, and Wyoming. Both apps were developed on the web using the Create River Network tool and ArcGIS Online and were used to support water resources decision making. The two models are developed at different spatial and temporal scales and have different networks. We developed web apps to complement these two models and communicate targeted information to river managers to better formulate strategies to manage scarce water.

4.4.1 Study Area: The Bear River Watershed

The Bear River is a 491-mile long river that runs through Wyoming, Idaho, and Utah and covers an area of about 7,600 square miles. The river and its tributaries provide water to numerous cities and counties across the three states. It also provides water to five run-of-river hydroelectric plants and over 450 irrigation companies delivering water to over 400,000 acres of agricultural land (UDNR, 2017). The river is central to the growth and development planning debate for several counties within the basin such as Cache and Box Elder Counties, Utah, in addition to the off-basin Wasatch Front metropolitan region (UDWR, 2004; UDWRe, 2000). The river is also vital to maintain critical wildlife habitat

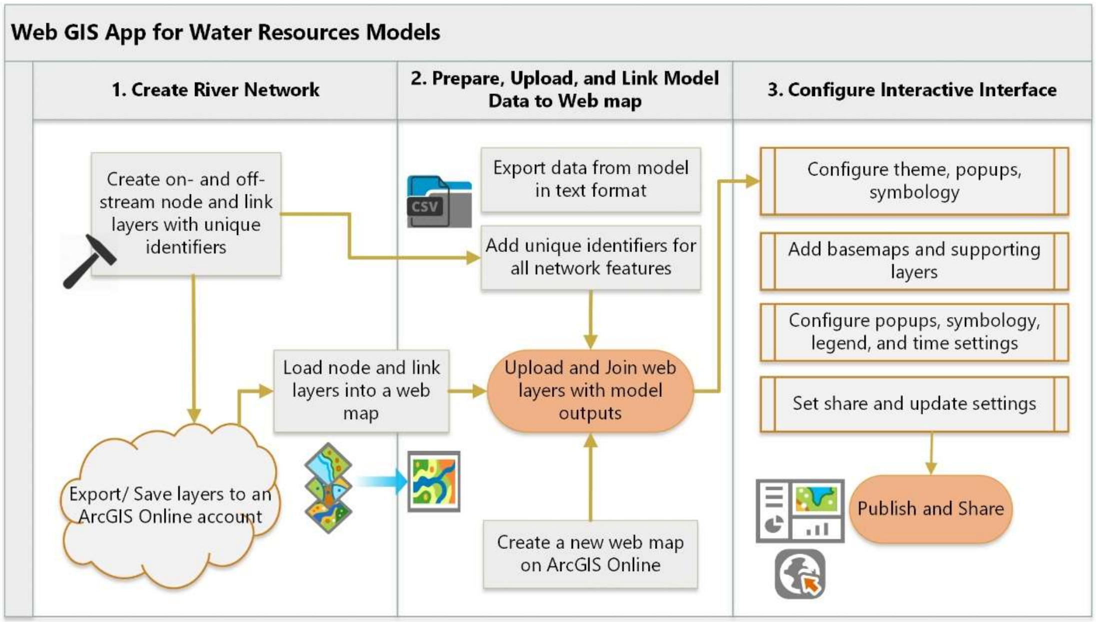

Figure 4.5 Workflow to build a water resources model web app using the Create River Network web tool

for many native and threatened river and floodplain species (Bio-West, 2015). It also serves as the largest water source flowing into the Great Salt Lake and the 30,000 acre-Bear River Migratory Bear Refuge. The Refuge is home to over 250 migrating bird species that use the Refuge for feeding, resting, nesting, and breeding every year (Alminagorta et al., 2016).

Sustainable management and future development of the Bear River needs to consider multiple competing demands and objectives to ensure that ecosystem health and human beneficial uses for irrigation and water development are maintained into the future. Interactive and user-friendly web maps can help facilitate collaborative modeling to manage scarce water in the Bear River and communicate model outputs with regional water managers.

4.4.2 Use Case 1: Water Management to Improve Habitat

The Lower Bear River is the downstream sub-basin of the Bear River from the Utah-Idaho state line to the river terminus at the Great Salt Lake. Threats of land development and intensive agricultural and grazing activities along the Lower Bear River triggered habitat conservation efforts to identify important areas for restoration, prioritize species, and allocate water between human and environmental users in the watershed (Bio-West, 2015). The efforts led by The Nature Conservancy in collaboration with several state agencies, counties, private businesses, and landowners resulted in developing the Bear River Conservation Action Plan (CAP). One of the primary objectives of CAP is to determine the amount, timing, and location of water needed to sustain key riparian, aquatic, and wetland species (Bear River CAP, 2008).

A mathematical systems model determined the allocation of water to maximize aquatic, floodplain, and wetland habitat quality while meeting or exceeding municipal and agricultural water needs. Alafifi and Rosenberg (In Review) developed the Watershed Area of Suitable Habitat (WASH) systems optimization model using the General Algebraic Modeling System software (GAMS; Hozlar, 1990) for the Lower Bear basin. WASH measures habitat quality and area for every reach in the basin using stakeholder-verified habitat suitability indices for cutthroat trout (*Oncorhynchus clarki utah*), brown trout (*Salmo trytta*), cottonwood (*Populus fremontii)*, black-necked stilt (*Himantopus mexicanus*), American avocet (*Recurvirostra Americana)*, and tundra swan (*Cygnus columbianus*). Each suitability index is a function of a measureable habitat attribute that influences priority species' survival and abundance, such as water depth, flood recurrence, and Phragmites *(Phragmites australis)* invasive plant cover. Indices take values between 0 at poor habitat conditions to 1 at excellent conditions. Some of the key results of WASH include recommending monthly reservoir releases and diversion volumes that improve habitat quality for priority species over observed conditions. In addition, WASH reports the suitability index values for every reach, month, and habitat type based on recommended instream flow. These indices help identify which species is in need for restoration, where in the watershed, and at what seasons.

The WASH web app (Figure 4.6; http://WASHmap.usu.edu) was developed following the steps in Table 4.1. GAMS, the optimization engine of WASH model, generates these key results as tabular data defined on 46 nodes and 51 links over 12 months in 2003 (Figure 4.7). We used the Create River Network tool to create web layers of on- and off-stream features with unique identifiers. Then, we added these identifiers to the model outputs files. We created a new web map on ArcGIS Online, loaded river network layers, and uploaded WASH output files. Then, we joined the data with the web layers for all features and configured interactive settings (Table 4.1).

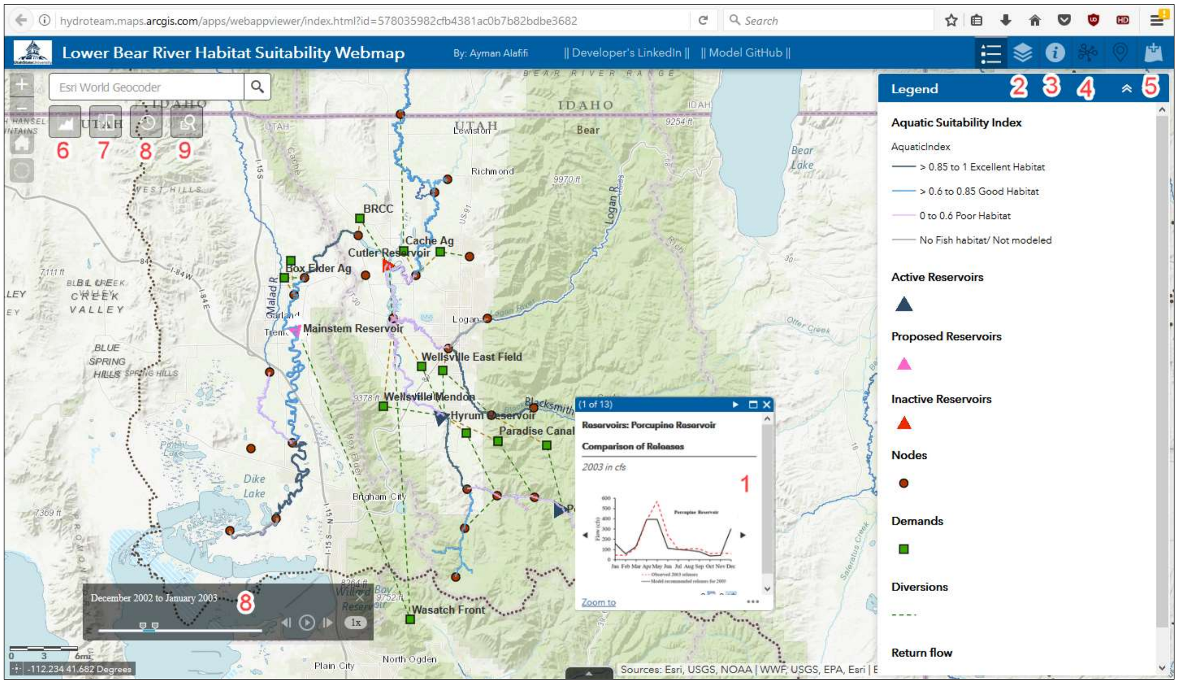

Figure 4.6 Lower Bear River watershed area of suitable habitat model web app, available at: http://WASHmap.usu.edu

4.4.3 Use Case 2: Urban and Agricultural Water Supply and Demand Management

Managing and planning water resources are often a challenge in urban and rural communities. In semi-arid climates like Utah and Southern Idaho, the challenge is even greater as an inadequate supply might result in conflicts over land and water use in addition to economic losses for farmers (BRAG, 2015). The Bear River is one of the few rivers in Utah that has water development potential (UDWRe, 2000). To meet future water demand requirements for multiple urban and agricultural users, managers need tools to help them quantify and understand the reliability of current water supply system in the basin.

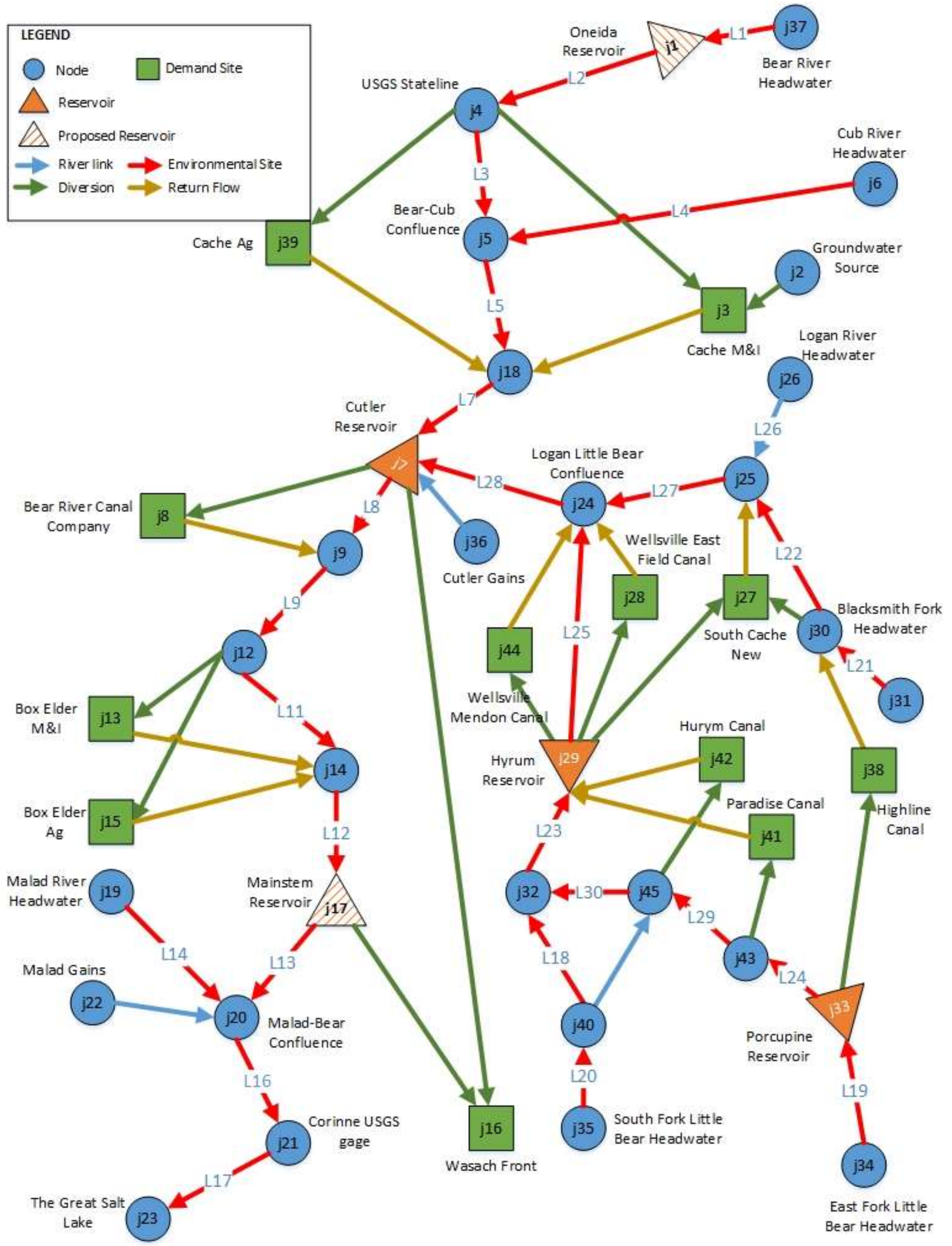

Figure 4.7 Lower Bear River Network of Nodes and Links. j and L denotes nodes and links

Table 4.1 Steps to build a web GIS app for the Lower Bear River habitat management case

1. Build River Network on a Web Map	**2. Prepare and Upload Model Results**	**3. Configure Interactive Features**
Go to http://webmapbuilder.usu.edu to access the 'Create River Network' tool: - Draw basin area on the map - Click on the map to draw on-river nodes, demand sites, off-stream links, and reservoirs - Click 'execute'	- Use the same unique identifiers created in Step 1 to assign identifiers for WASH nodes and links input data	Some of the main features of the WASH app are labeled on Figure 4.7 and include: - Categorized and symbolized reaches into excellent, good, and poor habitat based on the suitability index values for every habitat type at every month
	Run the optimization model and export the following outputs as csv files: - Demand sites: monthly demand requirements (Mm^3/month) - Reservoirs: monthly releases and storage (Mm^3/month) - River links: monthly flows, habitat suitability index values (0-1; unitless) - Engineered links: diversion and return flow monthly volumes (Mm^3/month)	- Popups (label 1) to display model-recommended vs historic volumes of reservoir releases, storage, river flow
		- List of layers (label 2), model background (3), node-link network (4), and ability to add own data to the map (5)
		- Chart widget (label 6) to plot monthly releases for multiple reservoirs -
The following layers are created and unique identifier are given to each feature: - A layer for 29 on-river nodes - A layer for 27 river links - A layer for 5 reservoirs - A layer for 12 municipal and agricultural demand sites - A layer with 24 off-stream links for diversions and return flow canals	- In ArcGIS Online: Create a new web map	- Vertical swipe widget (label 7) to compare multiple habitat layers.
	- Load created layers from Step 1 to the new web map	- Time-slider (label 8) to visualize monthly variations in habitat suitability for every habitat type.
	- Upload WASH outputs as csv files to the map	Query widget (label 9) to select reaches that meet user-specific criteria, such as reaches with poor aquatic habitat stability in February 2003.
- Save all created layers to ArcGIS publisher account - Download layers attribute tables as csv including unique identifiers for all features	- Join each output layer with its respected map layer by matching the identifier field in both layers	

The Water Evaluation And Planning (WEAP) software was used to simulate water supply, demands, and allocations across the Bear River basin. WEAP is a software package that operates on the principles of water mass balance to allocate water based on available water supply and priorities for demand sites (Stockholm Environmental Institute, 2016). A WEAP model for the Bear River was developed to plan and manage available water resources. The model simulates 40 years (1966 – 2006) of monthly historical water supply from the Bear River and its tributaries and allocates water for 34 urban and agricultural demand sites in Wyoming, Idaho, and Utah (Figure 4.8). Results of the WEAP model include time series of monthly unmet demand (or shortage) for each demand site. These results can help managers identify shortages in the basin and measure reliability of water supply system.

While a software package like WEAP provides a user interface to display model schematic of nodes and links overlaid on GIS layers, WEAP users need a software license in addition to training to access, find, and interpret the Bear River model results within the WEAP interface. They also need a local copy of the WEAP area with model results. Therefore, to disseminate and communicate WEAP results to policy makers across the basin, we created a web app to display WEAP model outputs. First, we exported unmet demand results from WEAP as csv files. Second, we assessed and described water supply performance for each demand site by measuring the reliability (%), which is the likelihood of a supply system to meet delivery targets, resilience (%), which describes how quickly the system recovers once a shortage occurs, and vulnerability (acre-ft), which measures the magnitude of shortage (Hashimoto et al., 1982). We also measured the longest period of shortages in months. The WEAP web app was developed following the steps in Table 4.2 and is available at: http://BearRiverWEAP.usu.edu. In this use case, we assigned the unique identifiers from the Create River Network tool to WEAP outputs after exporting the results to a csv file.

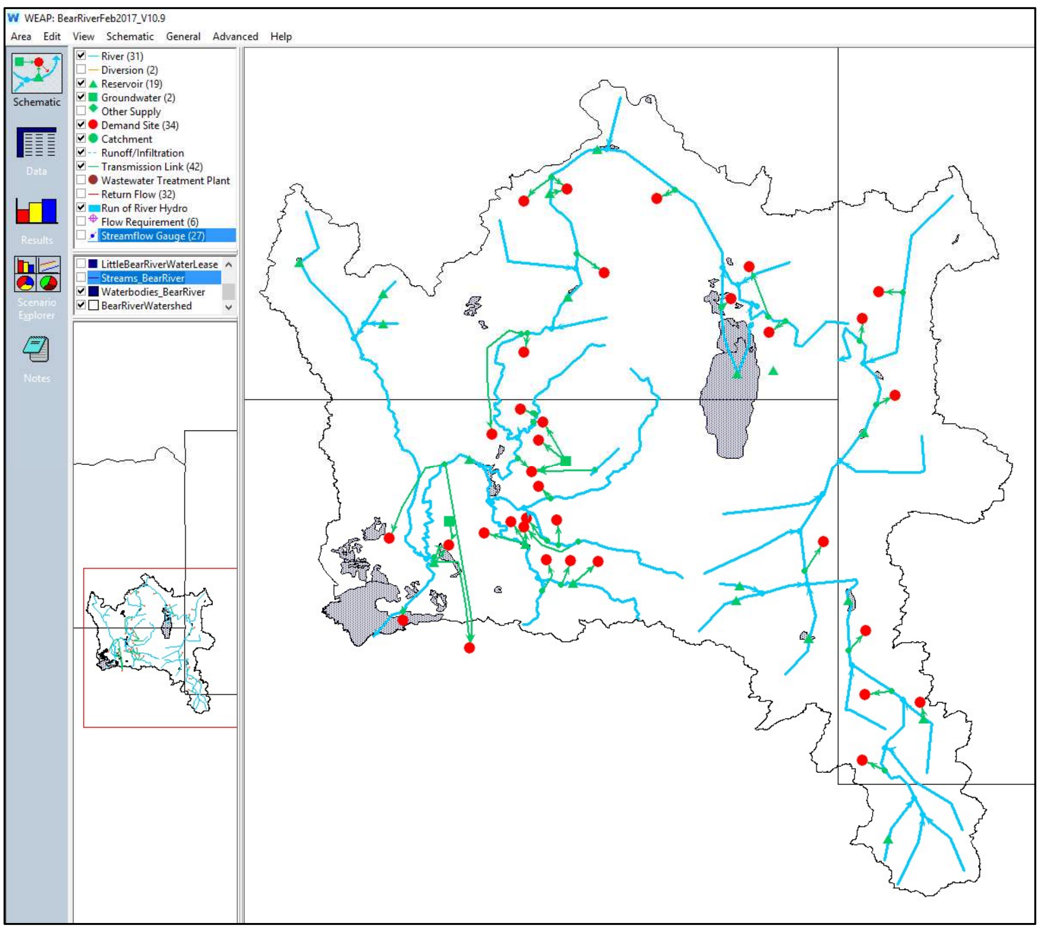

Figure 4.8 WEAP interface and schematic of the Bear River network model

Table 4.2 Steps to build a web GIS app for the Bear River water demand management case

<table>
<tr><th>1. Build River Network on a Web Map</th><th>2. Prepare and Upload Model Results</th><th>3. Configure Interactive Features</th></tr>
<tr><td rowspan="2">Go to http://webmapbuilder.usu.edu to access the ‘Create River Network’ tool:
- Select Bear River watershed as the basin for study area
- Click on the map to draw on-river nodes and demand sites
- Click ‘execute’</td><td>Run WEAP model and export these outputs for demand sites as csv files:
- Monthly demand requirements (acre-ft)
- Unmet demand (acre-ft)</td><td rowspan="2">Some of the main features of the WEAP water demand app are labeled on Figure 4.8 and include:
- Categorized and symbolized reaches by shortage as (%) of annual demand</td></tr>
<tr><td>Measure additional indicators for water supply system performance for each demand site:
- Shortage as (%) of annual demand
- Reliability (%)
- Resilience (%)
- Vulnerability (acre-ft)
- Longest period of shortage (months)
- Number of months in shortage</td></tr>
<tr><td rowspan="5">The following layers are created and unique identifiers are given to each feature:
- A layer for 22 on-river nodes
- A layer for 31 river links
- A layer for 34 municipal and agricultural demand sites</td><td>- Update all model output csv files and add an identifier field to match the names created using the tool in Step 1</td><td>- Popups (label 1) to display information about each demand site including supply performance and monthly delivery targets</td></tr>
<tr><td>- In ArcGIS Online: Create a new web map</td><td rowspan="2">- List of layers and legend (label 2)</td></tr>
<tr><td>- Load created layers from Step 1 to the new web map</td></tr>
<tr><td>- Upload WEAP outputs as csv files to the map</td><td rowspan="3">- Time-slider (label 3) to visualize monthly variations of shortage</td></tr>
<tr><td rowspan="2">- Join Demand Sites output layer with its respected map layer by matching the identifier field in both layers</td></tr>
<tr><td>- Save all created layers to ArcGIS publisher account
- Download layers attribute tables as csv including unique identifiers for all features</td></tr>
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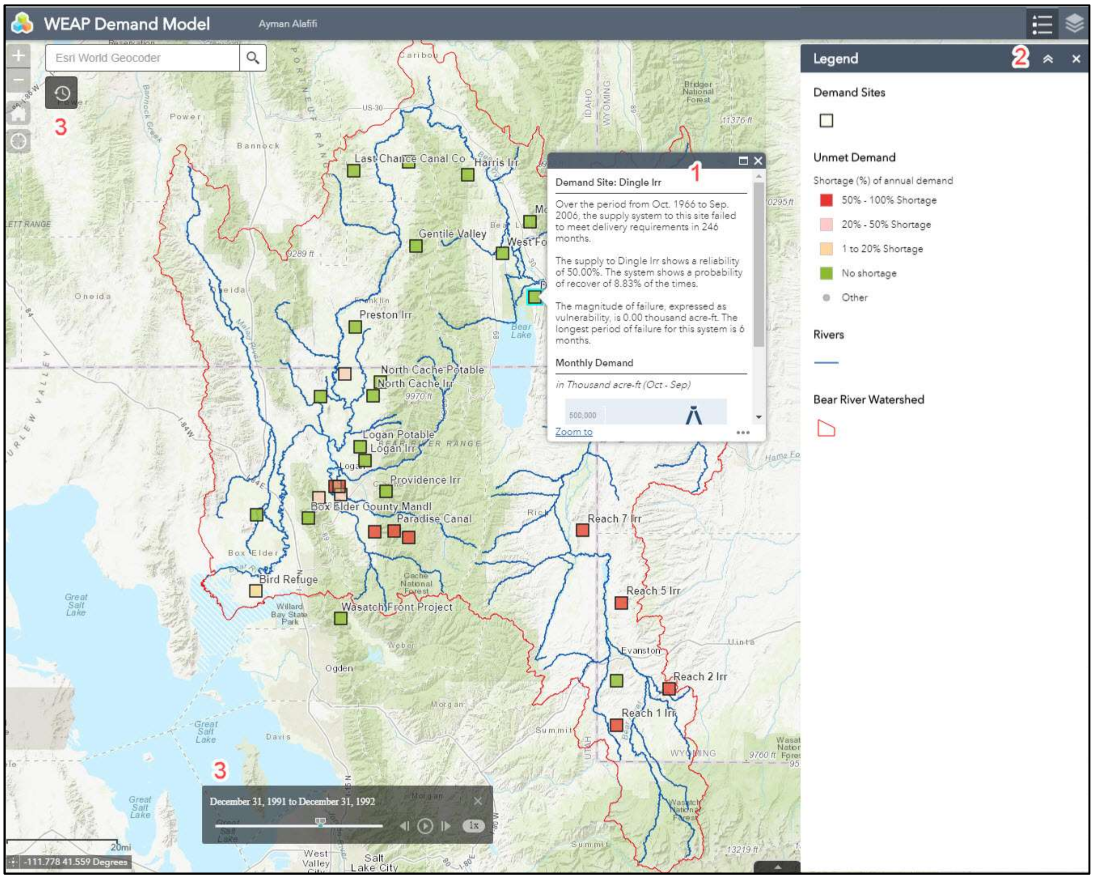

Figure 4.9 A screenshot of the Bear River Urban and Agricultural Water Management web app, available at: http://BearRiverWEAP.usu.edu

4.5 Discussion

The WASH web app was first presented to CAP stakeholders on December 2, 2015 as part of the model development process, where we solicited feedback on the spatial distribution of the node-link network and used the app to define sites for priority species. Next, we added the optimization model results to the app which included recommended and historical reservoir releases and instream flows. We presented these model results to CAP stakeholders during a workshop session on July 21, 2016. We encouraged participants to use the available tools to spatially and temporally compare habitats using the swipe and time-slider widgets. They were asked to report on what they thought are promising results to improve habitat quality and flag data, model components, or results that they saw as missing or problematic. For example, participants liked comparing recommended and historic releases and highlighting months of reservoir spills. They also liked the ability to visually compare water allocation and restoration needs for different locations, times, and species. However, they pointed out the need to further disaggregate agricultural demand sites served by the Little Bear River into smaller water users. They also provided feedback on the spatial distribution of cutthroat trout, brown trout, and bluehead suckers which assisted selecting indicator species for every reach in the model. We updated the web app to incorporate these improvements on the model network and the results. Between September and December, 2016, the app was also presented to various other groups within the study area and at national conferences (Alafifi, 2016b, a; Alafifi and Rosenberg, 2016). Over the course of 10 months from July 2016 to May 2017, the app received 331 views, or an average of over 1 view per day (Figure 4.10).

The WEAP web app supports ongoing research to formulate strategies to manage water in the face of drought events in the Bear River basin. The current version of the WEAP model simulates 40 years (1966-2006) of system operations using historic flows and current demand to provide insights into the reliability of the water supply system. This web app complements the WEAP model and allows for a better dissemination of results among water managers across the three states. Further work on the Bear River WEAP model will include scenarios of extreme drought events that are estimated from 4 centuries (1605-2006 CE) of reconstructed monthly natural flows generated using tree rings (Allen et al., 2013; DeRose et al., 2015). New scenarios will also include changes in water demand projected until 2050. Following our approach, these scenarios can be added to the web app in future iterations to provide managers with an interactive tool to visually compare system response to multiple drought events.

The approach we presented in this paper can be used to build similar web GIS apps. First, use the Create River Network tool that we published at http://webmapbuilder.usu.edu to interactively draw on the map to create their network. Clicking execute will create web GIS layers of their network with unique identifiers. They can then create a new map in ArcGIS Online, upload these web layers along with their model outputs and use the identifiers to join both layers. Detailed instructions and examples are provided in the tool GitHub repository (Alafifi, 2017). This framework allows to relatively quickly build and design a targeted web GIS app to communicate water resources models.

Developing an interactive web GIS app encompasses a planned workflow that starts with knowing the target audience for the app, selecting the information to be shown on the

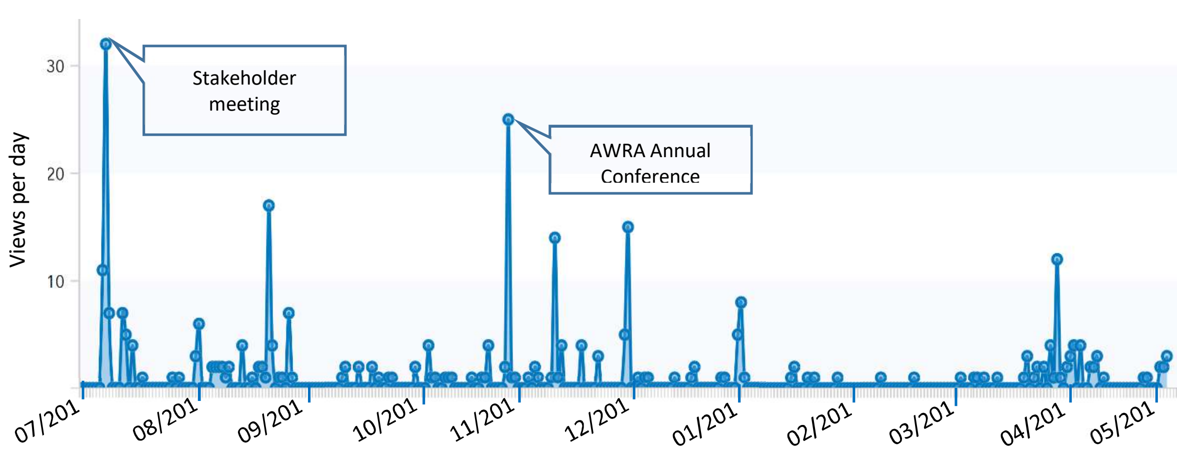

Figure 4.10 Lower Bear River web app usage activity

map, and designing user experience and customizing interactivity based on the audience. The recommended approach of building apps using ArcGIS Online allows for the separation of web maps and web apps. For example, a single web map was developed for the WASH optimization model to host several layers of the model spatial and temporal data. However, multiple apps were built and configured to communicate different parts of the model to different users, such as single reservoir operators, or water managers from a sub-basin in the watershed. It is also important for web app developers to consider that users need to use the app and access its data with minimal instructions. Therefore, in building the two use cases web apps, we followed best practices in web design and development such as colors, fonts, symbols, and authorship. For example, we provided users with a welcome window screen that appears before users start to interact with the app. The screen provides information about the app purpose and authors and instructions to use. Also, we also made the symbols and labels legible and dynamic with map extent.

The tool we presented in this paper facilitates displaying and interacting with model outputs in web app environments. Interactivity can be further improved beyond viewing outputs to connecting the web interface to the water resources model computational algorithm (Figure 1). This will allow users to ask “what if” questions on model inputs and see new outputs on the web map. This integration could be achieved by running a water resources model on a web server and enabling the web GIS app to manipulate model inputs, perform web-based simulations, and display new outputs (Byrne et al., 2010).

While ArcGIS Online provides many functionalities and options to develop web apps, users might need to supplement their apps with their own tools to perform analyses that are not supported by ArcGIS Online platform. For example, users can author a geoprocessing tool that measures the inundated area for user-predicted flood level on ArcMap and share it on a web app. Users will need to host their geoprocessing tools on a web server to share it on a web app. In addition, users can produce and add their own charts to the popups as images which could be more informative and useful to communicate model results than existing chart-building tools. Another important consideration for ArcGIS Online is the costs associated with developing a web app. ArcGIS Online is freely available for noncommercial use with a public account that allows users to publish data and create apps with limited functionalities. A free public account allows uploading node data, but does not allow merging layers with user data. ArcGIS Online full capabilities are available with premium plans that are based on annual subscription to use Esri's online servers in addition to number of credits in exchange of some spatial analysis tools.

While ArcGIS Online offers many features that are not available in other platforms, some water resources modelers might hesitate to sign up for a paid account. Therefore, we see a great value in developing and incorporating our approach in other free and open-source platforms such as HydroShare. For example, allowing users to create river networks directly on a web map in addition to the ability to join features can further advance the use of HydroShare GIS to display, collaborate on, and share water resources data. This will also further encourage researchers to develop and share tools that will improve the ability to run models and update results directly from a web app.

Web apps provide interactive user interfaces that only require a web browser to access which facilitates discussions between model developers and river managers. The two web apps developed for the Bear River use cases are examples of the power of using web interfaces to facilitate sharing and communicating model outputs with decision makers.

4.6 Conclusions

This paper addressed the problems to represent node-link networks of water allocation models as GIS layers and allow users to interact with model results and the network in an interactive web mapping app. Building web GIS apps for water resources models makes spatial and temporal information convenient and readily-accessible and independent of modeling software. Web GIS apps are useful tools to provide a venue for collaboration between model developers and policy makers, facilitate communication of model outputs, and make outputs accessible to the public. Current web GIS platforms can only display spatial data in GIS-accepted formats. While the outputs of some hydrologic and water resources models are described in GIS formats, many water allocation models use node and link network schema. Constructing a node-link network on web maps requires technical experience that can be a challenge for many water resources modelers. Here, we presented an open-access tool to build a node-link network and use it to create a web GIS app without coding or GIS desktop software. Our new tool allows users to click on a map to place on- and off-stream nodes and links and returns layers of river network with unique identifiers. Users can then use available tools in ArcGIS Online to upload and join their model outputs with network layers on the web map.

We demonstrated two use cases of web apps that were developed to complement the collaborative approach of two water resources models to allocate water in the Bear

River basin. One case study showed that model development process was supported by a web app to define node-link network, priority sites, and species. The web app was then used to facilitate communicating model results of recommended reservoir releases and instream flow with project stakeholders and guided locating habitat restoration needs.

Both web apps allowed presenting model outputs in a focused and directed format and enabled decision makers to prioritize restoration sites and assess vulnerability of the watershed supply system. The Create River Network tool leverages advances in web technology to support general trends in water resources models towards making model data and results available and accessible to users, which opens up new opportunities to collaborate on water research and to better communicate with non-technical users.

4.7 References

Alafifi, A., 2016a. Systems Modeling to Measure Performance and Evaluate Management Alternatives to Improve River and Riparian Habitat Quality, Utah Section. American Water Resources Assocaition: Salt Lake City, UT.

Alafifi, A., 2016b. Systems Modeling to Measure Performance and Evaluate Management Alternatives to Improve River and Riparian Habitat Quality, Annal Conference. American Water Resources Assocaition: Orlando, FL.

Alafifi, A., 2017. GitHub Respositry for the Build River Network Tool. URL: https://github.com/ayman510/BuildRiverNetwork.

Alafifi, A., Rosenberg, D.E., 2016. Systems Modeling to Improve River, Riparian, and Wetland Habitat Quality and Area, American Geophysical Union, Fall General Assembly 2016: San Francesco, CA.

Alafifi, A., Rosenberg, D.E., In Review. Systems Modeling to Improve River, Floodplain, and Wetland Habitat Quality and Aea. Environmental Modeling & Software.

Allen, E.B., Rittenour, T.M., DeRose, R.J., Bekker, M.F., Kjelgren, R., Buckley, B.M., 2013. A tree-ring based reconstruction of Logan River streamflow, northern Utah. Water Resources Research 49(12) 8579-8588.

Alminagorta, O., Rosenberg, D.E., Kettenring, K.M., 2016. Systems modeling to improve the hydro-ecological performance of diked wetlands. Water Resources Research 52(9) 7070-7085.

Barbour, E.J., Holz, L., Kuczera, G., Pollino, C.A., Jakeman, A.J., Loucks, D.P., 2016. Optimisation as a process for understanding and managing river ecosystems. Environmental Modelling & Software 83 167-178.

Bear River CAP, 2008. The Bear River, A conservation priority. The Nature Conservnacy: Utah.

Bio-West, 2015. Little Bear and Blacksmith Fork Rivers Environmental Flows: Background Report. Bio-West Inc.: Logan, UT.

BRAG, 2015. Pre-Disaster Mitigation Plan, Bear River Region, Utah, In: Bear River Association of Govenments (Ed.).

Byrne, J., Heavey, C., Byrne, P.J., 2010. A review of Web-based simulation and supporting tools. Simulation modelling practice and theory 18(3) 253-276.

Cai, X., Ringler, C., Rosegrant, M.W., 2006. Modeling Water Resources Management at the Basin Level: Methodology and Application to the Maipo River Basin. International Food Policy Research Institute.

Castrogiovanni, E., La Loggia, G., Noto, L., 2005. Design storm prediction and hydrologic modeling using a web-GIS approach on a free-software platform. Atmospheric Research 77(1) 367-377.

Chang, Y.S., Park, H.D., 2006. XML Web Service-based development model for Internet GIS applications. International Journal of Geographical Information Science 20(4) 371-399.

Choi, J.-Y., Engel, B.A., Farnsworth, R.L., 2005. Web-based GIS and spatial decision support system for watershed management. Journal of Hydroinformatics 7(3) 165.

Crawley, S., Ames, D., Li, Z., Tarboton, D., 2017. HydroShare GIS: Visualizing Spatial Data in the Cloud. Open Water Journal 4(1) 2.

Delipetrev, B., Jonoski, A., Solomatine, D.P., 2014. Development of a web application for water resources based on open source software. Computers & Geosciences 62 35-42.

DeRose, R.J., Bekker, M.F., Wang, S.Y., Buckley, B.M., Kjelgren, R.K., Bardsley, T., Rittenour, T.M., Allen, E.B., 2015. A millennium-length reconstruction of Bear River stream flow, Utah. Journal of Hydrology 529(Part 2) 524-534.

Esri, 2010. Esri Releases the Open GeoServices REST Specification: Redlands, CA.

Flanagan, D., Nearing, M., 1995. USDA-Water Erosion Prediction Project: Hillslope profile and watershed model documentation. NSERL report.

Fu, P., 2016. Getting to know web GIS. Esri Press.

Gassman, P.W., Reyes, M.R., Green, C.H., Arnold, J.G., 2007. The soil and water assessment tool: historical development, applications, and future research directions. Transactions of the ASABE 50(4) 1211-1250.

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., Moore, R., 2017. Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sensing of Environment.

Hashimoto, T., Stedinger, J.R., Loucks, D.P., 1982. Reliability, resiliency, and vulnerability criteria for water resource system performance evaluation. Water Resources Research 18(1) 14-20.

Hozlar, E., 1990. Gams - General Algebraic Modeling System for Mathematical-Modeling. Ekonomicko-Matematicky Obzor 26(1) 96-99.

Kirshen, P., Raskin, P., Hansen, E., 1995. WEAP: A Tool for Sustainable Water Resources Planning in the Border Region,, Proceedings of the 22nd Annual Water Resources Planning and Management Division Conference, ASCE. Integrated Water Resources Planning for the 21st Century, : Cambridge, MA, USA.

Klipsch, J.D., Hurst, M.B., 2007. HEC-ResSim reservoir system simulation user's manual version 3.0. USACE, Davis, CA 512.

Labadie, J., 2005. MODSIM: River basin management decision support system. Watershed Models. CRC Press, Boca Raton, Florida.

Loucks, D.P., Van Beek, E., Stedinger, J.R., Dijkman, J.P.M., Villars, M.T., 2005. Water Resources Systems Planning and Management: An Introduction to Methods, Models and Applications. Unesco.

Martin, P.H., LeBoeuf, E.J., Dobbins, J.P., Daniel, E.B., Abkowitz, M.D., 2005. INTERFACING GIS WITH WATER RESOURCE MODELS: A STATE-OF-THE-ART REVIEW1. JAWRA Journal of the American Water Resources Association 41(6) 1471-1487.

McKinney, D.C., Cai, X., 2002. Linking GIS and water resources management models: an object-oriented method. Environmental Modelling & Software 17(5) 413-425.

Meeks, L., Rosenberg, D.E., 2017. High Influence: Identifying and Ranking Stability, Topological Significance, and Redundancies in Water Resource Networks. Journal of Water Resources Planning and Management 143(6) 04017012.

NHDPlus V2, 2016. NHD Plus V2 Attribute Extensions, In: Systems, H. (Ed.), Great Basin (Vector Processing Unit 16). Esri.

NOAA, 1998. Rivers of the U.S., In: National Oceanic and Atmospheric Administration (Ed.). National Operational Hydrologic Remote Sensing Center (NOHRSC),: Silver Spring, MD.

Porse, E., Lund, J., 2016. Network Analysis and Visualizations of Water Resources Infrastructure in California: Linking Connectivity and Resilience. Journal of Water Resources Planning and Management 142(1) 04015041.

Rathore, D.S., Chalisgaonkar, D., Pandey, R., Ahmad, T., Singh, Y., 2010. A Web GIS Application for Dams and Drought in India. Journal of the Indian Society of Remote Sensing 38(4) 670-673.

Scopel, C., 2015. Water Resources Layers on ArcGIS Online. Esri: Redlands, CA.

Stockholm Environmental Institute, 2016. WEAP Water Evaluation and Planning System, 2016.01 ed.

Sui, D.Z., Maggio, R.C., 1999. Integrating GIS with hydrological modeling: practices, problems, and prospects. Computers, Environment and Urban Systems 23(1) 33-51.

Swain, N.R., Latu, K., Christensen, S.D., Jones, N.L., Nelson, E.J., Ames, D.P., Williams, G.P., 2015. A review of open source software solutions for developing water resources web applications. Environmental Modelling & Software 67 108-117.

Taher, S.A., Labadie, J.W., 1996. Optimal design of water-distribution networks with GIS. Journal of Water Resources Planning and Management-Asce 122(4) 301-311.

Tarboton, D.G., Idaszak, R., Horsburgh, J., Ames, D., Goodall, J., Band, L., Merwade, V., Couch, A., Arrigo, J., Hooper, R., 2013. HydroShare: an online, collaborative environment for the sharing of hydrologic data and models, AGU Fall Meeting Abstracts, p. 1510.

UDNR, 2017. Draft Bear River Comprehensive Management Plan, In: Utah Division of Forestry Fire and State Lands (Ed.). SWCA, Hansen, Allen and Luce Inc., ERM, CRSA: Salt Lake City, Utah.

UDWR, 2004. Utah Division of Water Resources, Bear River Basin, Planning for the Future: Utah.

UDWRe, 2000. Bear River Development, Utah Divion of Water Resources: Salt Lake City, UT.

Verma, S., Verma, R.K., Singh, A., Naik, N.S., 2012. Web-Based GIS and Desktop Open Source GIS Software: An Emerging Innovative Approach for Water Resources Management, In: Wyld, D.C., Zizka, J., Nagamalai, D. (Eds.), Advances in Computer Science, Engineering & Applications: Proceedings of the Second International Conference on Computer Science, Engineering & Applications (ICCSEA 2012), May 25-27, 2012, New Delhi, India. Volume 2. Springer Berlin Heidelberg: Berlin, Heidelberg, pp. 1061-1074.

Wurbs, R.A., 2005. Comparative evaluation of generalized river/reservoir system models. Texas Water Resources Institute.

Zagona, E., T. Magee, D. Frevert, T. Fulp, Goranflo, M., Cotter, J., 2005. RiverWare. Taylor & Francis/CRC Press, Boca Raton, FL.

Zhao, P., Foerster, T., Yue, P., 2012. The Geoprocessing Web. Computers & Geosciences 47 3-12.

CHAPTER 5

SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

5.1 Summary and Conclusions

Managing regulated rivers to improve habitat can be improved by tools that determine when, where, and how to allocate water between competing users in the basin. These tools need to capture the inevitable uncertainty in habitat models and provide ways to communicate model outputs to policy makers and the public. This dissertation presented three tools to: (1) recommend times, locations, and magnitudes of water and budget allocation to improve aquatic, floodplain, and wetland habitat quality, (2) quantify and communicate uncertainty in habitat models by inferring few management scenarios from large multivariate space of alternatives, and (3) build web maps that allow water resources modelers to share and display model outputs in user-friendly, accessible, and interactive platforms. These tools and their applications to improve water and habitat management and decision making were presented in three studies for the Bear River Basin.

Chapter 2 addressed the problems of determining when, where, and how to allocate water between competing users in the basin. While prior system models to manage stream flow have included species' water needs as constraints on flow or as a penalty to minimize deviations from natural flow regimes, this chapter presented a novel systems optimization model that formulates and maximizes an ecological objective as the suitable aquatic, floodplain, and wetland habitat area. This measurable and observable habitat area objective allows for comparison of locations, times, and species to identify opportunities in the basin to most improve overall habitat quality. The new systems model was applied to the Lower

Bear River, Utah, using stakeholder-verified species- and site-specific habitat suitability curves. The model recommended reservoir releases, river flows, and planting efforts to maximize habitat area subject to physical, infrastructure, and management constraints.

Chapter 3 addressed the problems of communicating a large number of alternatives from habitat models that consider hydrologic, ecologic, and management uncertainties. Prior work on uncertainty analysis in habitat models have recommended large ranges of possible management alternatives. Chapter 3 presented a semi-supervised cluster analysis approach to reduce a large dimensional uncertainty problem and focus management efforts on important parameters to measure and monitor more carefully. This approach was applied to the deterministic systems model of chapter 2 using the Lower Bear River, Utah, as a case study. This approach helped characterize and quantify the effects of uncertainty on model results. It also facilitated including management preferences in the search for clusters and identifying few possible reservoir release patterns that most improve habitat quality.

Chapter 4 addressed the problems to represent node-link networks of water allocation models as GIS layers and allow users to interact with model results and the network in an interactive web mapping app. Prior tools required GIS and web technical experience to share model outputs on web maps. Chapter 4 presented an open-access web tool that allows modelers to create water resources model nodes and links on web maps. The tool returns web layers of river network with unique identifiers which allows creating web applications for water allocation models. The chapter presents an approach that uses this tool to develop user-friendly and interactive interfaces to communicate spatially and temporally-distributed water resources model outputs with policy makers and the public. Chapter 4 demonstrated this tool with two use cases. First, a web application was developed to display some results from Chapter 2 optimization model application to the Lower Bear River. This web app supported the model development process and was used to communicate model results with project stakeholders to guide locating habitat restoration needs. A second web app was developed to display results of ongoing simulation modeling efforts to manage water for future supply and demand scenarios for the entire Bear River Basin. The second web app helps formulate strategies to manage water in the face of drought events in the Bear River basin.

All the modeling tools presented in this dissertation offer novel approaches to improve water and habitat management decisions. These tools provide managers with an integrated approach to identify opportunities to effectively allocate resources to most improve habitat quality and area. Together, these tools provide managers with a better understanding of the tradeoffs in river habitat decisions and facilitate communicating these decisions with policy makers and the public. All the tools presented in this dissertation were developed in collaboration with stakeholders and decision makers in the Bear River basin. Several state and county regulators, environmental groups, river and wetland manager, and landowners provided data and significant feedback on the tools development process and applications. The participatory modeling approach helped tailor the applications of the presented tools to management objectives and priorities and facilitated the adoption of these tools in habitat management decision-making process.

5.2 Management Recommendations

Recommendations from applying the tools of this dissertation to the Lower Bear River basin include:

- Release more water from Porcupine and Hyrum reservoirs in winter months and reduce late spring spills. Comparing recommended releases of these two reservoirs to historic releases in Chapter 2 showed that these changes in releases patterns will improve brown trout spawning in late fall and maintain the eggs in gravel redds until they hatch in spring.
- Restoration efforts on the Lower Bear River basin should focus on the Little Bear River and the Blacksmith Fork rivers. Shadow value results in Chapter 2 showed that the greatest returns for each unit of water flow in the system occurred on both the East Fork of the Little Bear River for most months of the year and on the Blacksmith Fork from April to October. Efficient water management of these two rivers can most improve habitat quality.
- River managers should set up agreements and conservation easements with riparian landowners, particularly along the Bear River main stem, to protect floodplains and encourage seed germination for native riparian trees. Model results in Chapter 2 showed that floodplain area along the river is restricted by private agricultural fields and grazing lands. Results in Chapter 3 showed that an increase in available floodplain area to plant riparian trees could help improve habitat quality, return lands to floodplain functions, and restore lateral connectivity with the river.

- Wetlands managers at the Bear River Migratory Bird Refuge should actively communicate with upstream users to protect the Refuge's summer water rights. Comparing wetland habitat suitability index and recommended flows at the Refuge against historic conditions in Chapter 2 showed that the Refuge currently does not receive its allocated water rights during summer months. The model flow recommendations can improve the Refuge habitat conditions but the Refuge managers should acquire upstream water storage rights.
- River managers should work collaboratively with local, federal, and nonprofit organizations to accurately forecast supply and demand and plan for high flow year and for droughts. The 5-year analysis in Chapter 2 showed that the ecosystem quality responded to variations in available water. Therefore, managers should be directly involved in ongoing discussions of future water developments in the Bear River basin and carefully consider water availability to the Refuge and to the Great Salt Lake.
- Managers should also work with stakeholders to recognize and protect environmental flows in the water permitting and planning process. Although Utah water law does not currently allow new appropriations of water for instream flow, more restrictive temporary or permanent transfers of existing rights to environmental users are possible. Transfer mechanisms may include donation, lease, or purchase but must go to either the Utah

Division of Wildlife Resources, the Division of Parks and Recreation, or a nonprofit fishing group such as Trout Unlimited.

- Managers should consider tradeoffs between habitats and plan timely-reservoir releases to improve habitat quality when species need water. For example, recommended reservoir releases in Chapters 2 and 3 showed that spring and early summer releases that coincide with seed germination improves cottonwood recruitment. Late summer and early fall releases support spawning seasons for brown trout.

5.3 Future Work

This dissertation presented novel decision-support tools that improve water and habitat management. There are several opportunities to further improve these tools and extend their applicability to other river systems. Future work includes:

- Extend the WASH model of Chapter 2 to explicitly include water quality parameters such as dissolved oxygen or turbidity. The model currently only includes water depth and flood frequency as the flow-related attributes defining habitat quality. Including water quality parameters can provide insights on other attributes that are critical for the survival of priority species. Including other attributes requires describing relationships between these attributes and model decision variables (i.e. reservoir releases, diversions, and planting area).
- Extend the WASH model to include additional species, habitat attributes, or habitat types such as natural, oxbow, seasonal, or other wetlands in the

watershed that were not included in the Lower Bear River study. This will be useful to demonstrate the applicability of the systems model to new or additional parameters. It could also reveal more sources of uncertainty that were not included in Chapter 3.

- Apply the WASH model on a finer (e.g. reach-level) scale and include the dynamics of stream habitat ecology. This will help test the model assumptions of riparian trees proximity to river banks and could help include other important biotic and abiotic factors for seedling survival, such as groundwater level, soil salinity, and other plants' competition for water.
- Couple the WASH systems model with a hydrologic model that more accurately accounts for water availability in the basin and considers variability in snowpack, losses in instream flow, and return flow. This could improve the model assumptions of water availability in the system and help plan for possible future water development or draught conditions.
- Extend the sources of uncertainties considered in Chapter 3 to include model formulation and structure uncertainty. This includes WASH aggregation method for habitat suitability indices for multiple species within a habitat. This also includes how WASH aggregates multiple habitat areas and the use of weights to reflect management preferences for species, times, and locations. These additional sources of uncertainty could test the robustness of the cluster analysis approach by adding more nominal and ordinal dimensions to the clustering algorithm.

- Extend the sampling approach of Chapter 3 by using other sampling methods such as Latin Hypercube and Gibbs conditional sampling. This could reduce the number of runs required for sensitivity analysis and could allow for using a global optimum solver.
- Extend the approach of Chapter 4 beyond viewing water resources model outputs to connecting the web interface to the models themselves. This will allow users to ask "what if" questions on model inputs and see new outputs on the web map. This integration could be achieved by running a water resources model on a web server and enabling the web GIS app to manipulate model inputs, perform web-based simulations, and display new outputs.

Managing river flow involves making decisions on the allocation of water between different users across the basin. Managers look for tools to help them make holistic decisions on the amounts, times, and locations to apply scarce resources. This dissertation presented a set of management tools that aim to improve water and habitat management decision making. These tools were developed in collaboration with river managers and stakeholders and were applied to real-case problems. The applications of these tools provid river managers with recommendations and insights to make informed decisions to improve river habitat quality.

APPENDICES

Appendix A: Lower Bear River Network

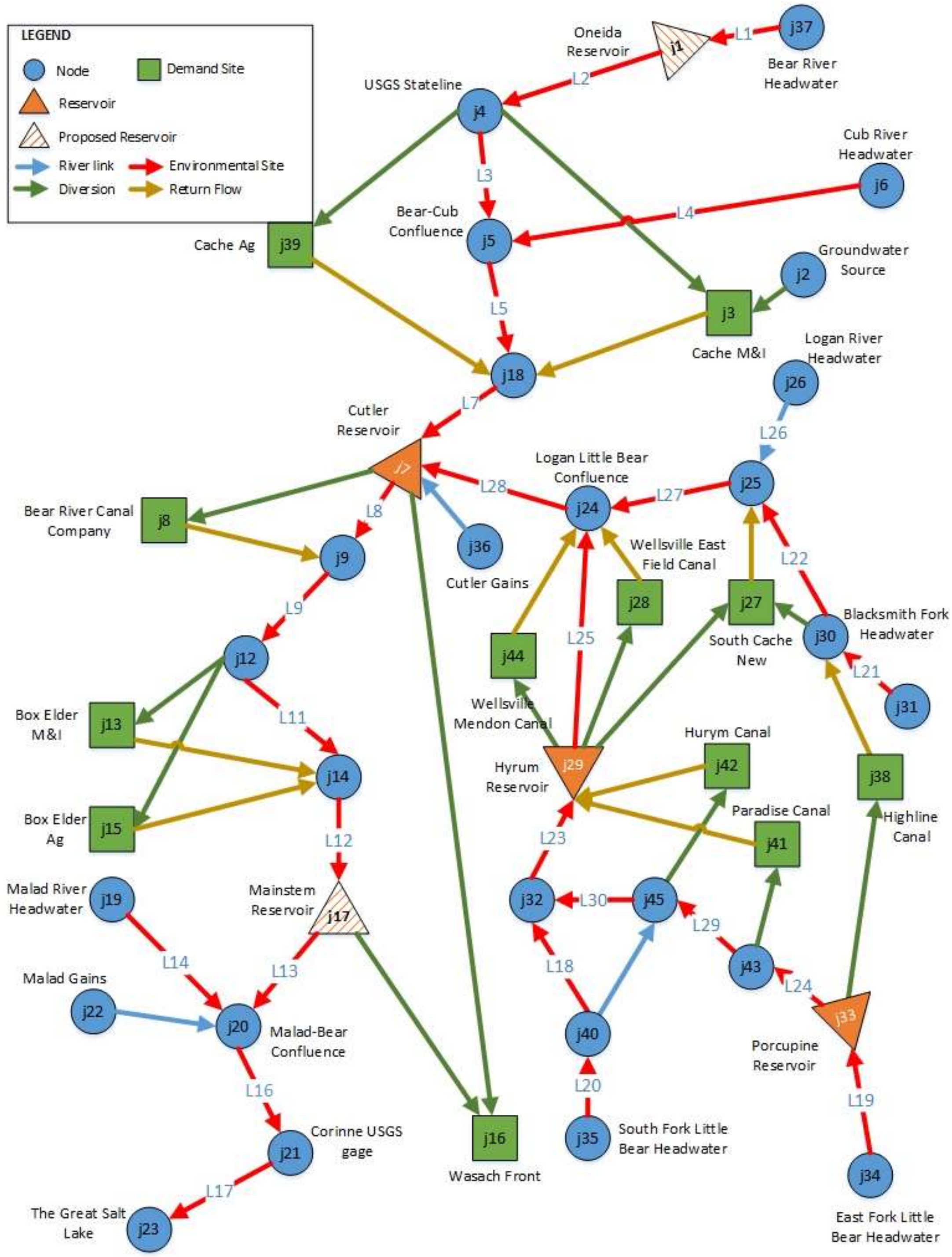

Figure A.1 Lower Bear River network represented as a group of nodes and links

Appendix B: Model Formulation for the Watershed Area of Suitable Habitat

This appendix provides the model formulation for the Watershed Area of Suitable Habitat (WASH) including the decision variables that managers control, the objective function to maximize, and the physical, infrastructure, and management constraints.

Decision Variables

Decision variables include reservoir releases $RR_{v,t}$ [million cubic meters per month, Mm^3] at reservoir *v* in month *t*, diversions volumes $Q_{j,dem,t}$ [Mm^3/month] from the river at node *j* to demand sites *dem* in month *t* to satisfy urban and agricultural demand, floodplain planting area $RV_{j,k,t,n}$ [Mm^2] by seeding or planting species *n*. These variables control a group of state variables that include reservoir storage volume $STOR_{v,t}$ [Mm^3], reservoir surface area $RA_{v,t}$ [Mm^2], river flow $Q_{j,k,t}$ [Mm^3/month] from node *j* to node *k* in month *t*, river water depth $D_{j,k,t}$ [m/month], channel surface area $A_{j,k,t,}$ [Mm^2], channel width $WD_{j,k,t}$ [m], and floodplain plant cover $C_{j,k,t,n}$ [Mm^2].

Objective Function

The WASH objective function maximizes the weighted sum of the suitable areas of aquatic [$IND_{aquatic,j,k,t}$], floodplain [$IND_{floodplain,j,k,t}$], and wetland [$IND_{wetland,j,k,t}$] habitats [Mm^2] in reach *j* to *k* in month *t* where $wght_{s,j,k,t}$ are the stakeholders-decided weights for habitat indictor *s* in reach *j* to *k* at month *t.* Weights take values from 0 (not important) to 1 (important).

$$Max\ \ WASH = \sum_{s,j,k,t} wght_{s,j,k,t} \cdot\ IND_{s,j,k,t} \qquad \text{-- [1]}$$

The value of each habitat indicator is the product of a suitability index and an affected area. Suitability indices (*SIs*) are functions of the habitat attribute(s) that influence priority species survival and abundance. Values of SIs approach 1 (excellent conditions) when priority species exist (or their density exceeds a certain threshold). In contrast, *SIs* tend towards 0 (poor conditions) when priority species do not live or their density is below a threshold (Roloff and Kernohan, 1999). SIs are constructed using empirical data, or absent data, they are assigned based on expert opinion.

Aquatic Habitat

The aquatic habitat indicator is calculated by multiplying the Aquatic Suitability Index (rsi; unitless) and channel surface area (Eq. 2). With multiple fish species (*y*), we multiply suitability indices together to emphasize the concurrent need for suitable water depths for all species at the same time and location.

$$IND_{aquatic,j,k,t} = \prod_y rsi_{j,k,t,y}(D_{j,k,t}) \cdot A_{j,k,t}\,, \qquad \forall\, j,k,t \qquad \text{---- [2]}$$

Floodplain Habitat

The floodplain connectivity indicator is calculated by multiplying a floodplain connectivity index (fci) by the area of plant cover (*C*) for each month *t* and then summing the values for each plant species *n* [eq. 3]. fci is a function of streamflow and takes the value of 1 [excellent lateral connectivity] if the instream flow $Q_{j,k,t}$ equals or exceeds the 2-year recurrence flow. fci takes the value of 0 [poor connectivity] when flow is at or below the 1-year recurrence value.

$$IND_{floodplains,j,k,t} = \sum_n fci_{j,k,t,n}(Q_{j,k,t}) \cdot C_{j,k,t,n} \qquad \forall\, j,k,t \qquad \text{----[3]}$$

Impounded Wetlands

The Wetland Suitability Index (wsi) of WASH represents the suitability of impounded wetlands to improve water depth and native plant cover for priority bird species. In Eq. [4], we use *WSI* to define an aggregate index that describes the suitability of water depth and native plant cover for multiple wetland bird species. The impounded wetland indicator is calculated by multiplying a *wsi* index by the total wetland surface area aw [Mm^2].

$$IND_{wetlands,j,k,t} = WSI_{j,k,t}\left(Q_{j,k,t}\right) \cdot aw_{j,k,t}, \qquad \forall\, j,k,t \qquad \text{----- [4]}$$

Constraints

a. **Reservoir storage balance**: reservoir storage for each reservoir *v* at the beginning of each time step *t+1* equal storage at the beginning of prior time step *t* plus net flows of links leading to the reservoir minus reservoir releases and minus evaporation losses [eq. 5]. Reservoir releases are flows along all links that leave reservoir *v* in month *t* [eq. 6]. Evaporation losses are estimated by multiplying a monthly evaporative rate $evap_{v,t}$ [m/month] by the reservoir surface area. $RA_{v,t}$ is a function of reservoir storage. The term $lss_{j,v,t}$ [%] is the net loss rate on links connecting to reservoir *v* and is expressed as a fraction of link flow.

$$STOR_{v,t+1} = STOR_{v,t} + \sum_j\left[Q_{j,v,t} \cdot (1 - lss_{j,v,t})\right] - RR_{v,t} - \left[evap_{v,t} \cdot RA_{v,t}(STOR_{v,t})\right] \forall v,t \quad \text{-- [5]}$$

$$RR_{v,t} = \sum_j Q_{v,j,t} \qquad \forall v,t \qquad \text{----- [6]}$$

b. **Mass balance at junctions**. Flows entering each non-reservoir node *j* must equal or exceed evaporative losses plus flows leaving the node [eq. 7]. $localInflow_{j,t}$ [Mm^3/month] are reach gains, groundwater inflows, or other flows that accumulate at node *j* in time *t*. At the most upstream nodes in a network, *localInflow* is the head flow and represents the boundary condition and cumulative contribution of climate, runoff, and other hydrologic processes. *linkEvap* [m/month] describes the evaporative loss rate on links; link evaporation [m^3/month] is the product of the evaporative loss rate and channel surface area.

$$localInflow_{j,t} + \sum_k Q_{k,j,t} \cdot (1 - lss_{k,j,t}) - \sum_k A_{k,j,t} \cdot linkEvap_{k,j,t} \geq \sum_k [Q_{j,k,t}] \; \forall j,t \quad \text{---[7]}$$

c. **Mass balance at each demand site**. Total flow to each demand site *dem* in time *t* must equal or exceed the return flow back to the river [eq. 8]. Total flow is reduced by the depleted flow amounts that include diversion losses $lss_{k,dem,t}$ and urban or agricultural consumptive use fraction $Cons_{k,dem,t}$ [both % of inflow received].

$$\sum_k Q_{k,dem,t} \cdot (1 - lss_{k,dem,t}) \cdot Cons_{dem,t} \geq \sum_k Q_{dem,k,t} \qquad \forall dem, t \qquad \text{---- [8]}$$

d. **Plant cover**. Plant cover $C_{j,k,t,n}$ [Mm^2] for each species *n* in each link *j* to *k* at time step *t* equals cover at prior time step *t-1* plus planted areas $RV_{j,k,n}$ [Mm^2] and natural growth or death $g_{j,k,n}$ [Mm^2; eq. 9]. Plant cover $C_{j,k,t,n}$ cannot exceed the total floodplain area adjacent to each reach $cmax_{j,k}$ [eq. 10]. Planting $RV_{j,k,n}$ is also limited to growing season [eq. 11]

$$C_{j,k,t,n} = C_{j,k,t-1,n} + RV_{j,k,t,n} + g_{j,k,n} \qquad \forall\, j,k,t,n \qquad \text{---- [9]}$$

$$\sum_n C_{j,k,t,n} \leq cmax_{j,k} \qquad \forall\, j,k,t \qquad \text{---- [10]}$$

$$\sum_n RV_{j,k,t,n} \leq \begin{cases} cmax_{j,k}, & t \in growing\ season \\ 0, & otherwise \end{cases} \qquad \forall\, j,k,t \qquad \text{---- [11]}$$

e. **Channel topology relationships**. River flow, channel stage, width, and surface area are related on each link *j* to *k* in each time step *t* [eqs. 12-14]. These relationships are established based on measured data. We use linear relationship for stage-flow (sf) and (Leopold and Maddock (1953)) power function for width-flow (wf) relationships. $lng_{j,k}$ is the length of each river segment [m].

Stage-flow relationships: $D_{j,k,t} = sf_{1j,k} \cdot Q_{j,k,t} + sf_{2j,k} \quad \forall\, j,k,t$ ---- [12]

Width-flow relationships: $WD_{j,k,t} = wf_{1j,k} \cdot Q_{j,k,t} + wf_{2j,k} \quad \forall\, j,k,t$ ---- [13]

Channel surface area: $A_{j,k,t} = WD_{j,k} \cdot lng_{j,k} \quad \forall\, j,k,t$ ---- [14]

f. **Reservoir storage limits.** Storage in each reservoir *v* cannot go below a minimum storage volume $minstor_v$ [Mm^3] which is the reservoir dead pool; similarly reservoir storage cannot exceed the storage capacity $maxstor_v$ [Mm^3] at any time *t* or the top of the flood control pool, whichever is smaller [eq. 15].

$minstor_v \leq STOR_{v,t} \leq maxstor_v \quad \forall v,t$ ---- [15]

g. **Meet demand requirements**. Diversions to each demand site *dem* should meet requirements $dReq_{dem,t}$ [Mm^3/month] in each time *t* [eq. 16].

$\sum_k Q_{k,dem,t} \cdot (1 - lss_{k,dem,t}) \geq dReq_{dem,t} \quad \forall dem,t$ --- [16]

h. **Flow limits**. Minimum and maximum values $qmin_{j,k,t}$ and $qmax_{j,k,t}$ bound flow in each link *j* to *k* in time *t* [eq. 17]. Minimum levels may be minimum instream flow or diversion requirements. Maximum bounds can be channel, diversion, or other capacities.

$qmin_{j,k,t} \geq Q_{j,k,t} \geq qmax_{j,k,t} \quad \forall j,k,t$ ---- [17]

i. **Management budget**. The total cost to plant floodplain species [ct_n; \$/m^2], make reservoir releases, or adjust diversion gates [st_n; \$/m^3] should not exceed the financial budget *b* [\$; eq.18].

$\sum_j \sum_k \sum_n \sum_t (ct_n \cdot RV_{j,k,t,n}) + \sum_j \sum_j \sum_t (st_{j,k,t} \cdot Q_{j,k,t}) \leq b$ ------[18]

Appendix C: Build River Network Workflow

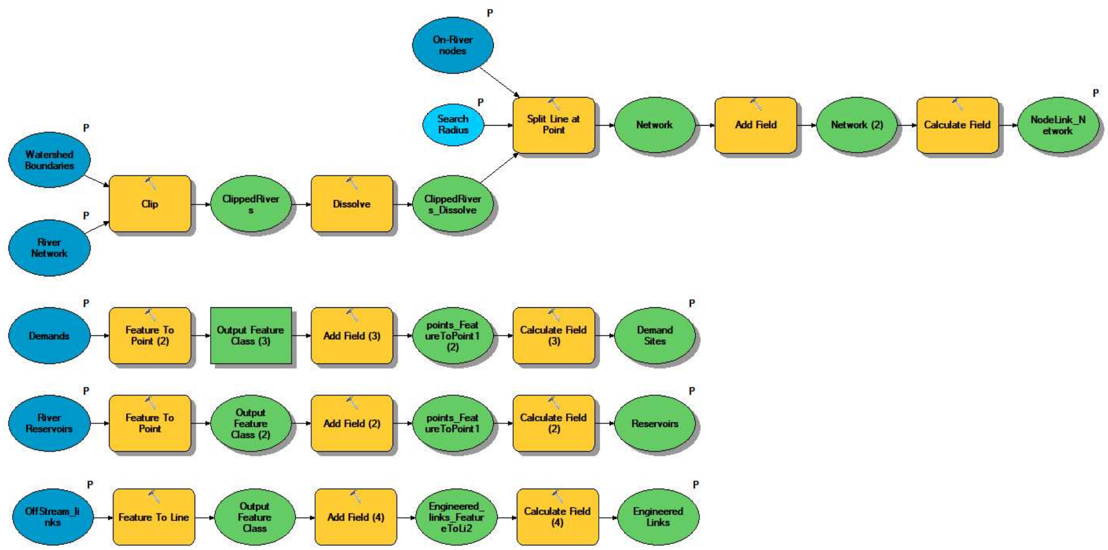

Figure C.1 Workflow of the Build River Network tool using ArcMap Model Builder

Appendix D: Permission to Reprint an Article

From: Ayman Alafifi aafifi@aggiemail.usu.edu
To: James Stagge james.stagge@usu.edu
On 12/14/2017

Hello Jim,

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Best regards,

James Stagg

Appendix E: Curriculum Vitae

Ayman Alafifi

Water Resources, Environment, and GIS Engineer
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HIGHLIGHTS

- 5+ years designing and modeling hydraulic and hydrologic systems, watershed models, and reservoir operations
- Proficient in developing systems models, watershed management plans, flood risk assessment, and GIS tools
- Experience in EPA regulations, water rights, TMDL, BMPs, NPDES, and NFIP
- Technical writing lead for 10 proposals ($2 million), 8 environmental studies, and 3 county-level assessments
- 40-hour Hazwoper OSHA certified and an IEMA certified environmental auditor
- Developed curriculum and delivered 50+ hours of GIS and hydraulic modeling training to city engineers
- Supervised 5 junior engineers and mentored and coached 20 undergraduate engineering students
- Nationally awarded for leading student design teams, student chapters, and writing research papers

EDUCATION

PhD Candidate, Water Resources Engineering, *Aug. 2017*
Utah State University, USA. GPA: 4.0/4.0. Dissertation: *Eco-Hydrologic Systems Models to Improve River, Riparian, and Wetlands Habitat Quality Under Uncertainty.* Advisor: Dr. David E. Rosenberg

- Developed an optimization model, web GIS interactive maps, and ArcGIS tools to allocate water to restore stream habitat quality for priority fish, tree, and bird species with 10+ local agencies and environmental groups
- Established monitoring sites to collect river flow, stage, cross section, temperature, and vegetation cover
- Trained and mentored 20 undergraduate research students and co-led the Bear River Fellowship program
- Led and advised 3 engineering clubs. Received 11 local and national honors and awards

MSc Environmental Strategy and Sustainable Development, *Sep. 2010*
University of Surrey, UK. *GPA: 4.0/4.0, Top 1%*. Thesis: *Water Footprint and Life Cycle Analysis of Hewlett Packard (HP) Personal Computers.* Advisor: Prof. Chris France. Received 2 awards. Developed several social and environmental responsibility and environmental risk assessment for oil, gas, and food industries

BSc Civil Engineering, *Jan. 2008*
The Islamic University of Gaza, Palestine. *GPA: 4.0/4.0, First-of-class and class valedictorian*. Senior Project: *Cost Estimation for Infrastructure Projects using Artificial Neural Networks.* Received 7 honors and awards

RELEVANT WORK EXPERIENCE

Watershed Coordinator Intern, Natural Resources Conservation Service (USDA-NRCS), *May– Aug 2016*

- Secured $650,000 for 5 water quality improvement projects through 5 grant proposals for the Utah Division of Water Quality and the U.S. EPA Non-Point Source Pollution programs
- Developed Watershed Implementation Plans for Mantua Dam and Maple Creek water quality projects which included a stream and BMP inventory, TMDL targets review, and a preliminary capital improvement plan
- Developed pre-project reference conditions through field work to collect soil, water quality, and macroinvertebrate samples with the Utah State Extension Program

Product Engineer Intern, Software Products, ESRI, *May– Aug. 2015*

- Developed 3 ecological habitat suitability web maps and web applications to contribute to the Living Atlas of the World online catalogue and the ArcGIS Online content
- Successfully recruited and retained a new large organization as a client for ESRI's ArcGIS Online Catalogue by showcasing customized web tools and geo-services

- Delivered a presentation and provided a day-long customer technical support during ESRI's annual User Conference in San Diego, CA.

Technical Reviewer Intern, U.S. Agency for International Development (USAID), *Dec. 2013 – Apr. 2014*

- Evaluated 45 technical proposals from 15 countries for the Water for Food Security grant. Proposals included advanced technologies in water and wastewater efficiency, collection, reuse, and desalination

Energy, Environment and Climate Policy Intern, Colorado State University, *Dec. 2013 – Sep. 2014*

- Researched and synthesized data for the *"Powering Forward: Presidential and Executive Actions to Drive Clean Energy in America"*. Assisted in technical writing for a panel of nationally-recognized experts

Environmental Engineer, Engineering and Management Consulting Center, Palestine, *Jun. 2007- Aug. 2012*

- Developed a water masterplan, 4 environmental management strategies and 8 environmental impact assessments for 20 local municipalities
- Assisted in the technical design of a large water carrier line, a booster pump station, an 8 MGD wastewater treatment plant, and 12 recovery wells
- Delivered 50 hours of training in WaterCAD, GIS, environmental reporting, and auditing to city engineers
- Prepared 10 project progress and final reports for several international funding agencies
- Assisted in the development, marketing and evaluation of 6 business and technology start-ups
- Secured over $0.5M and successfully negotiated 5 proposals for engineering services. Managed a team of 5

Environmental Engineer, Rai Consult Engineering, Palestine, *Jan. 2011 – Jul. 2012*

- Developed an environmental land use plan for the Gaza Industrial Estate Area
- Designed a municipal landfill and developed technical feasibility for a compost production facility
- Audited Hazard Analysis and Critical Control Point (HACCP) standards for 3 food-processing factories
- Carried out a post-conflict needs assessment for the water, wastewater, and energy sectors in Palestine

SELECTED AFFILIATIONS

- Tau Beta Pi Engineering Honor Society- Utah Gamma Chapter
- Engineering Graduate Senator at Utah State University
- OSHA 40-hour HAZWOPER certified
- President – Water Environment Association of Utah (WEAU) – Utah State University Chapter, 2 years
- Team leader, Water Environment Federation (WEF) Engineering Design Competition Team, 2 years
- Student Leader - the Young Professional networks of AWWA and WEF
- Design Lead – Engineers Without Borders (EWB) – Utah State University Chapter

SELECTED AWARDS

- 2016 1st place, American Water Resources Association (AWRA) – Utah Section Student Paper Competition
- 2015: 2nd place, American Water Works Association (AWWA) - Intermountain Section Paper Competition
- 2014 to 2016: 1st place, WEAU Wastewater Engineering Design Competitions
- 2014: 1st place, WEAU Graduate Scholarship Award
- 2014: 2nd place, WEF National Wastewater Engineering Design Competition (WEFTEC)
- 2014: Utah State University Graduate Enhancement Award for student leadership achievements
- 2014: USU International Student of the Year
- 2013: USU Sustainability Council award to implement daylight harvesting to conserve energy consumption
- 2013: AWWA Eva Nieminski Honorary Graduate Science and Engineering Scholarship
- 2003 to 2010: Full academic scholarships to the bachelor and master's degrees
- 2006 to 2008: Scholarships to 3 international exchange programs in Germany and South Africa
- 2008: Islamic University of Gaza President Honor List – Top Student at the College of Engineering

LANGUAGES

- English and Arabic (Fluent)

PUBLICATIONS

- Alafifi A. and Rosenberg D., (2017), Systems Models to Improve River, Riparian, and Wetland Habitat Quality and Area, Journal of Environmental Modelling and Software Society (iEMSs). In Review.
- Alafifi A., Stagge J., Null S., and Rosenberg D., (2017), Cluster Analysis to Improve River Habitat Quality Under Multiple Hydrologic, Ecologic, and Management Uncertainties. Journal of Environmental Modelling and Software Society (iEMSs). In Review.
- Alafifi A., (2016) Web GIS Mapping Applications to Visualize and Interact with Water and Habitat Management Model Data and Results, American Water Resources Association, Annual Conference, Orlando, FL.
- Rosenberg D., and Alafifi A. (2016), Near-optimal alternative generation using modified hit-and-run sampling for non-linear, non-convex problems, American Geophysical Union (AGU) Fall meeting 2016. San Francesco, CA
- Alafifi A. and Rosenberg D., (2014), Rethinking Riverine Habitat Quality: Integrated Systems Modeling to Improve Watershed Habitat Management and Decision Making. International Environmental Modelling and Software Society (iEMSs). 7th Intl. Congress on Env. Modelling and Software, San Diego, CA, USA, Daniel P. Ames, Nigel W.T. Quinn and Andrea E. Rizzoli (Eds.)
- Alafifi A., (2013) Mixed Integer linear programming to optimize future water requirements for Box Elder County, Utah http://goo.gl/DxvSaI
- Alafifi A., Mackley C., (2013), Municipal Use Model for Bear River Valley in Box Elder County, Utah http://goo.gl/dGRfKG