AN ABSTRACT OF THE DISSERTATION OF

Kevin N. McDonnell for the degree of Doctor of Philosophy in Fisheries Science presented on June 5, 2019.

Title: The Influence of Scale in a Structured Decision Making Framework for Chinook Salmon Management.

Abstract approved: ____
James T. Peterson

The goal of my dissertation was to explore how scale influences stream restoration prioritization strategies for an anadromous species and identify influential uncertainties that exist at different scales. My objectives were to (1) produce a comprehensive review of the Chinook salmon management challenges in California's Central Valley and identify the those related to scale of the management, (2) apply a structured decision making (SDM) to a large scale, spatially implicit stream restoration decision problem and derive an optimal stream restoration strategy, (3) apply a SDM to a small scale, spatially explicit stream restoration decision problem and use dynamic programming to derive an optimal stream restoration strategy, and (4) develop an approach to derive optimal policies for multi-scale stream restoration decision problem with multiple decision makers working in a hierarchy.

Issues of scale can create distinct problems in natural resource management. I used salmon management in the Central Valley of California an example where scale mismatches that have hindered conservation goals. Salmon stocks in California's Central Valley have been declining steadily over the last century, which has resulted the

congressional establishment of the Central Valley Plan Improvement Act (CVPIA) in 1992 to address the declines. Despite the oversight of the CVPIA, fisheries management in the basin has remained largely uncoordinated and unstructured with management actions often occurring simultaneously and at potentially conflicting scales. Having such large differences in spatial scales meant that any reduction of system uncertainties wasn't necessarily transferable to other populations of anadromous fish within the Central Valley. The hierarchical structure of the CVPIA and the entities that implement CVPIA related actions provide an opportunity to evaluate how scale may influence restoration decision making.

I developed a large scale, spatially implicit decision model to evaluate the effects of potential habitat restoration projects on populations of fall-run Chinook salmon in California's Central Valley. The extent of the model was the entire Central Valley and the grain was an individual watershed, 25 in total. Large scale natural resource management problems require special considerations relative to smaller scale problems due in part to the fact that uncertainties tend to increase as spatial scale increases. The model was primarily parameterized with expert judgement due to a lack of available empirical data at the watershed scale. This model and the decision alternatives were formatted as a Markov decision model (MDP) that I solved using dynamic programming and policy iteration. The results of the policy optimization suggest that focusing multiple restoration efforts on a small set of watersheds is the most effective habitat restoration strategy.

Most stream restoration efforts occur on a small spatial scales, often on reaches less than 1 km. I developed a fine scale, spatially explicit structured decision model to derive a state-specific stream restoration strategy for a population of Chinook salmon from a stream in lower American River. The decision problem was represented as Markov decision problem and I used dynamic programming to derive a state-specific, optimal policy for individual reaches within the study stream. The optimal policies depended on four pieces of observable information in a given reach: the amount of spawning habitat, the amount of juvenile rearing habitat, the average number of redds counted over a 5 year period, and the temperature suitability of the reach. Implementing the optimal policy during a 100 year simulation resulted in significant increases in natural production compared to a scenario where no actions were taken over the same time horizon.

Decision problems in natural resource management often involve several, interconnected decision makers, usually working at different temporal and spatial scales. Multitime-scale Markov decision processes (MMDPs) provide a framework to derive optimal decisions from hierarchically structured sequential decision making processes. The work in this study bridges the gap between large and small-scale decision models in natural resource management by applying a MMDP to a Chinook salmon management problem in CVPIA streams with two tiers of decision makers. The fundamental objective of each tier of decision makers was to maximize the production of natural origin Chinook salmon. The decision problem was structured with an upper tier decision maker (large scale) allocating funds to lower tier decision makers (fine scale) who actually implement on the ground restoration projects. The upper tier optimal policy identified optimal resource allocation strategies that favored providing funds to watersheds with high juvenile survival despite high costs.

The Influence of Scale in a Structured Decision Making Framework for Chinook Salmon Management

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APPROVED:

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Head of the Department of Fisheries and Wildlife

Dean of the Graduate School

I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

Kevin N. McDonnell, Author

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CONTRIBUTION OF AUTHORS

Dr. James T. Peterson served as a principal investigator, assisted in data acquisition and study design, and provided editorial comments for this dissertation. Dr. Chris Hammersmark also assisted in data acquisition and hydraulic modeling in the Lower American River.

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I would like to dedicate this dissertation to my parents Charles and Glenda McDonnell.
Thank you for instilling a sense of curiosity and wonder in me.

CHAPTER 1: GENERAL INTRODUCTION

The heart of natural resource management includes objectives, alternative management actions, and decision makers who choose the alternative that would best accomplish their objectives. Unfortunately, this process is subject to the uncertainty inherent in managed systems, which makes it difficult for the managers to decipher the best or optimal alternative management action (Conroy and Peterson 2013). This uncertainty is increased when objectives and management actions occur at different spatial and temporal scales (Peterson and Dunham 2010). There are two primary components to scale: extent and grain. Extent refers to the broadest spatial and temporal dimensions over which decisions are made (e.g., a management area or the time horizon) and grain refers to the finest spatial and temporal resolution that the decisions and observations (e.g., sample unit, time step) are conducted. For instance, broad natural resource management goals are often set at large or regional spatial extents and over extended time periods; however the specific or individual management actions usually take place on smaller, more local spatial scales and with greater frequency (Beechie and Bolton 1999, Beechie et al. 2008). Scale considerations coupled with stochastic variation in natural resources create problems in evaluating the efficacy of management actions, a requirement for effective adaptive resource management (Clemen 1996, Conroy and Peterson 2013). These scale related discrepancies between management goals and actions can make large, regional goals almost seemingly impossible to accomplish when management actions are implemented locally. Ideally, management actions and goals would be pursued at identical scales; however due to logistical constraints and uncertainties this is usually not an option. Monetary, spatial, and even political constraints can all prevent natural resource management actions and the evaluation of those actions from occurring at appropriate scales (Beechie and Bolton 1999, Hermoso et al. 2012).

Examples of how conflicting spatial scales can cause disconnect between management actions and management goals can be found in both terrestrial and aquatic systems. American Black Ducks (*Anas rupribes*) are migratory waterfowl that are found primarily in the Atlantic flyway of the United States and Canada. Since a noticeable decline in black duck populations in 1970's, managers in the region have been trying to increase population sizes for both conservation and recreational harvest purposes. However, the large region this species occupies, combined with the local (i.e., small scale) influence of many if not most management actions (e.g., increase breeding habitat) make it is difficult for managers to determine the efficacy of their actions (Conroy et al. 2002). Similar difficulties hinder the management of widespread freshwater aquatic invasive species (AIS; e.g. zebra mussels *Dreissena polymorpha* or rusty crawfish *Orconectes rusticus*). These species usually invade large areas of diverse habitats and complete eradication is not typically a feasible option (Vander Zanden and Olden 2008, Vander Zanden et al. 2010). Managers are forced to focus control efforts on individual lakes or sections of stream despite the regional extent of the invasion. Unfortunately, eradication or control efforts must be maintained almost indefinitely due to widespread distribution and high colonization rate of many AIS (Ricciardi and Rasmussen 1998). As a result, managers need to decide which sites to prioritize for control efforts to achieve a larger more regional objective of invasive species control. It's easy to imagine how the examples above can be further complicated when the temporal scales of management and ecological processes do not align. Both these examples demonstrate how a single problem can be dissected into different scales and how those scales can influence available management actions. The question of how local management actions can influence larger regional objectives can be difficult to decipher.

The causes for the decline of Pacific salmon and steelhead populations are well documented. With the arrival of Europeans came commercial fishing operations as well as mining, logging and large-scale agricultural industries. Starting at the turn of the 20th century, the ease that salmon and steelhead could be caught due to their predictable homing behavior and high densities attracted the interest of commercial fishing operations. The increase in fishing effort led to the stocks being over exploited with most fish being processed at canning facilities for export (Netboy 1974). Overexploitation was combined with practices that severely degraded salmon habitat, such as dredge mining, logging, water development for agricultural irrigation, and impoundment (Busch 2000, Montgomery 2003). In fact, salmon in the Pacific Northwest of the United States only occur in 40% of their historical range and approximately one half of those remaining are at risk of extinction in the next 100 years (Nehlsen et al. 1991, Levin and Schiewe 2001). However, salmon runs have increased in the last 50 years with the help of several conservation efforts. Habitat restoration, fishing quotas and hatcheries have all contributed to help slow and in some cases, reverse the decline many salmon stocks. Unfortunately, these efforts have failed to restore salmon and steelhead to their historic distribution and densities (Lichatowich 1999, Ruckelshaus et al. 2002).

Attempts to increase Pacific salmon and steelhead populations vary in scope and scale but most include some or all of the following: habitat restoration/remediation, harvest reduction, and use of hatcheries (Roni et al. 2002, Ruckelshaus et al. 2002). Most habitat restoration projects operate under the assumption that habitat is limiting at some point in the salmon or steelhead life cycle. These small scale (e.g. stream reach) projects usually involve adding spawning gravels, adult holding habitat, or engineering off-channel juvenile rearing habitat as an attempt to alleviate the hypothesized habitat bottleneck (Beechie et al. 1996, Beechie and Bolton 1999). On the other hand, a large scale management action that has been used to recover depressed populations is the reduction of both commercial ocean and recreational angler harvest (Ruckelshaus et al. 2002). Both these control measures attempt to ensure that salmon are not over exploited and have had some success at recovering populations. Lastly, and perhaps most controversial, is the use of hatcheries as a means to recover salmon populations. Hatcheries can be used as a means to rescue a population of fish that would otherwise go extinct without outside supplementation but more commonly, hatcheries are used to supplement harvest. In recent years it’s been shown that runs that require extensive hatchery supplementation tend to become dependent on supplementation and may lose their ability to self-sustain (Lackey 2003). Again, I would consider the use of hatcheries to be a large scale management action because hatcheries can influence the dynamics of the target population and potentially nearby populations as well.

There are several challenges that have hindered salmon and steelhead restoration in the North Pacific. The first has been the failure to identify explicit, achievable objectives (Lichatowich et al. 1995, Beechie et al. 2008). Too often multiple management actions are pursued simultaneously, often with conflicting or competing objectives. For instance, local (small scale) efforts to restore spawning habitat to increase natural production may occur in streams with hatchery supplementation whose aim is to provide angling opportunities. Previous studies demonstrated that when hatchery fish and wild fish interbreed, the net result is a decrease in fitness for their offspring and potentially an increase in straying rates (Nehlsen et al. 1991, Chilcote et al. 2011, Lister 2014). This illustrates how management actions, however well intentioned, can be counterproductive or less productive if appropriate objectives are not identified first. Salmon and steelhead also tend to have a highly variable life history, which creates difficulties in both monitoring and modeling populations (Groot and Margolis 1991, Gross 1991). This is especially evident in steelhead populations where within a single generation some offspring become resident rainbow trout and others become anadromous steelhead (Withler 1966, Thorpe 2007). Also, many salmon and steelhead populations have diverse life histories that allow young-of-year to migrate to the ocean as fry, parr, or smolts (Groot and Margolis 1991). These diverse life history strategies often exist in a single population and create substantial uncertainty of how specific management actions may influence population dynamics. Lastly, it is often not possible to assess an entire population of salmon or steelhead due to the large spatial area they inhabit. Intra-population differences in adult ocean residence time, which are typically between 2 and 6 years, add further complexity to population or management action assessments. Instead, population size and status often has to be extrapolated from a handful of observations and the grain of the monitoring efforts often do not match the scale of the overall management objectives (Beechie et al. 2008, Beechie et al. 2009).

In general, the challenges outlined above all introduce substantial uncertainty into the decision making process when mangers are considering alternative management actions with the goal of recovering declining salmon populations. The uncertainty that exists in natural resource is often perceived as risk to decision makers. Risk is a well-defined concept that is represented as the possibility of an unintended, negative consequence for a given action (Walters 1997, Conroy and Peterson 2013). For salmon managers, this might be perceived as the possibility that salmon numbers or harvest rates decrease after an action that was meant to bolster the population or increase harvest rates. Management actions are typically not pursued if the perceived risk outweighs any expected potential benefits. The result is that managers tend to be risk adverse in their decision making, which can lead to inaction or actions that may not directly address their goal but are otherwise perceived as safe. Because management under significant or large uncertainty is generally perceived as more risky, an approach to management that acknowledges uncertainty and may be able to reduce key uncertainties in the decision making process is needed.

Structured decision making (SDM) and adaptive resource management may be useful tools for the management of Pacific salmon and steelhead. SDM approaches are valuable in natural resource problems because they directly connect quantifiable objectives and explicit alternative decisions with quantitative models to identify optimal management decisions (Clemen 1996, Conroy and Peterson 2013). As the name implies, a SDM approach structures and formulizes the decision making process, avoiding ad-hoc decision making. The first step in the SDM process is for decision makers and relevant stakeholders to identify and agree on objectives. This is perhaps the most critical step in

SDM because poorly worded or vague objectives can result in conflicts of interest or the implementation of ineffective decision alternatives. Secondly, the decision makers and stakeholders identify those decision alternatives that are available to meet the objectives. The next step in SDM process is to build quantitative models to connect decisions to objectives and estimate the outcomes of the various decision alternatives. Optimal decisions are then identified via a closed form mathematical equation or through heuristic optimization algorithms depending on the specific approach used. Although the details of the process are more involved than what I have outlined here, this is the basic framework of the SDM process.

Quantitative, structured approaches to fisheries management and decision making were first introduced over 30 years ago as adaptive resource management (ARM; (Holling 1978, Walters 1986). In fact, ARM is special case of SDM where decisions are revisited through time in an iterative process. In essence, ARM is just the SDM process repeated through time. The iterative process allows the effects of decisions to be fully realized through time (and /or space) and for the opportunity to learn about the system through continued monitoring, this process is sometimes known as information feedback. Part of what makes ARM so attractive for problems in natural resources is that it allows managers to make decisions while simultaneously reducing uncertainties about the system at hand. In fact, ARM allows for the explicit testing of competing hypotheses about system dynamics or processes through information feedback. This iterative process of observing the state of the system, implementing a decision alternative, and reevaluating the state of the system can be modeled as a Markov Decision Problem (Bather 2000, Ross 2014). MDP's require a class of optimization routines that allows managers to model sequential decisions that occur over time and also derive what the optimal sequence of decisions would be given a pre-specified utility function. MDP's are especially appealing for modeling natural resource management problems because they intuitively follow the decision making process (e.g. evaluate the system, make a decision, reevaluate the system and update current knowledge) and are able to incorporate environmental stochastic processes.

However since its development, ARM has yet to be widely applied. The primary impediments have kept this both ARM and SDM from being more widely adopted in natural resource management include: a lack of awareness from natural resource decision makers, inadequate funding, the lack of leadership to implement such plans, stakeholder dissention and high political risks (Walters 1997, McFadden et al. 2011). This kind of rigorous decision making framework has not been successfully applied to Pacific salmon and steelhead before, but given the numerous issues Pacific salmon and steelhead face, such an approach is needed.

The goal of my dissertation was to explore how scale influences stream restoration prioritization strategies for an anadromous species and to develop dynamic optimization approaches that acknowledge uncertainties that exist at different scales. My objectives were to (1) produce a comprehensive review to document the management challenges that are endemic to the salmon populations of California's Central Valley and identify the challenges that are related to scale of the management process, (2) apply a SDM approach to a large scale, spatially implicit stream restoration decision problem and use dynamic programming to derive an optimal stream restoration strategy, (3) apply a SDM approach to a small scale, spatially explicit stream restoration decision problem and use dynamic programming to derive an optimal stream restoration strategy, and (4) develop a approach to derive optimal policies for multi-scale stream restoration decision problem with multiple decision makers working in a hierarchy. Each objective of my dissertation attempted to examine how processes that operate at different scales can ultimately influence decision making process.

Each chapter of my dissertation was designed to address the objectives described above. In chapter 2, I examined how scalar discrepancies between management goals and actions can impede the successful management of natural resources. I used Chinook salmon management in California’s Central Valley as a case example to demonstrate the importance that scale can have on management outcomes. The primary objective of chapter 3 was to derive optimal habitat restoration decisions and policies for populations of fall-run Chinook salmon in California’s Central Valley using coarse resolution information at a sub-basin or watershed level. I used this model to examine which sources of uncertainty are influential in a large scale, spatially implicit decision model. For Chapter 4, my goal was to understand how a SDM approach could be applied to a fine-scale habitat restoration decision problem. I developed a decision model for fall-run Chinook salmon in the Lower American River, CA that operated an individual reach level and used that model to derive an optimal policy for habitat restoration. Lastly, in Chapter 5 I developed a hierarchical, a multi-agent stream habitat restoration decision model. This model was meant to act as a bridge between the large scale decision model (Chapter 3) and the small scale decision model (Chapter 4). I used this model to demonstrate how optimal habitat restoration policies can be derived in systems were decision makers operate at different spatial scales.

The research presented here presents an in-depth evaluation of how scale can influence the decision making process in natural resource management. Additionally, my research demonstrates how SDM can be implemented in the context of stream restoration decision problems. Each chapter shows the importance that the definition of scale can have on optimal decision making. Much is known about how scale can influence how we view ecological processes, conversely little is known on how scale influences decision making in natural resource management.

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CHAPTER 2: THE EFFECT OF SCALE ON THE MANAGEMENT OF CHINOOK SALMON IN CALIFORNIA'S CENTRAL VALLEY AND AN OVERVIEW OF THE CENTRAL VALLEY PLAN IMPROVEMENT

Abstract

Issues of scale can create distinct problems in natural resource management. I use salmon management in the Central Valley of California as an example where mismatches of scale have hindered conservation goals. Salmon stocks in California's Central Valley have been declining steadily over the last 100 years, which has resulted in many efforts to rehabilitate depressed populations. The Central Valley Plan Improvement Act (CVPIA) was passed by congress in 1992 to address the decline of several anadromous species in the Central Valley. Despite the oversight of the CVPIA, fisheries management in the basin has remained largely uncoordinated and unstructured with management actions often occurring simultaneously and at potentially conflicting scales. Having such large differences in spatial scales meant that any reduction of system uncertainties wasn't necessarily transferable to other populations of anadromous fish within the Central Valley. Structured decision making (SDM) and adaptive resource management may be useful tools for the management of Pacific salmon and steelhead. I believe that the salmon populations of California's Central Valley would benefit from a SDM approach to management that would allow for maximum transparency in the decision making process. The hierarchical structure of the CVPIA and the entities that implement CVPIA related actions, provide an opportunity to evaluate how scale may influence optimal decision making in an SDM/ARM framework.

Introduction

The heart of natural resource management includes objectives, alternative management actions, and decision makers who choose the alternative that would best accomplish their objectives. Unfortunately, this process is subject to the uncertainty inherit in managed systems, which makes it difficult for the managers to decipher the best or optimal alternative management action (Conroy and Peterson 2013). This uncertainty is increased when objectives and management actions occur at different spatial and temporal scales (Peterson and Dunham 2010). There are two primary components to scale: extent and grain. Extent refers to the broadest spatial and temporal dimensions over which decisions are made (e.g., a management area or the time horizon) and grain refers to the finest spatial and temporal resolution that the decisions and observations (e.g., monitoring) are conducted. For instance, broad natural resource management goals are often set at large or regional spatial extents and over extended time periods; however the specific or individual management actions usually take place on smaller, more local spatial scales and with greater frequency (Beechie and Bolton 1999, Beechie et al. 2008). Scale considerations coupled with stochastic variation in natural resources create problems in evaluating the efficacy of management actions, a requirement for effective adaptive resource management (Clemen 1996, Conroy and Peterson 2013). These scalar discrepancies between management goals and actions can make large, regional goals almost seemingly impossible to accomplish when management actions are implemented locally. Ideally, management actions and goals would be pursued at identical scales, however due to logistical constraints and uncertainties this is usually not an option. Monetary, spatial, and even political constraints can all prevent natural resource management actions and the evaluation of those actions from occurring at appropriate scales (Beechie and Bolton 1999, Hermoso et al. 2012).

Issues of scale can create distinct problems in natural resource management. For instance, vertebrate populations are often assessed or managed the over large regional extents (e.g., watersheds, basins, flyways), however management actions and associated monitoring, when present, are usually implemented on a much more local (smaller) scale (Bond and Lake 2003, Lake et al. 2007, Likens et al. 2009). Specifically, natural resource management objectives are often regional (e.g., increase recruitment in a specific population in a watershed), whereas management actions almost always occur on a very small scale relative to the objectives (e.g., rehabilitating 500m of stream habitat). It is difficult to use information that is collected at a small local spatial extent to make inferences on the state of the system over a large regional spatial extent without making large assumptions. Scale mismatches generally increase uncertainty and inhibit the flow of information (feedback) regarding the effectiveness of management actions making management across a large regional extent even more difficult. In addition, key ecosystem processes occur at different spatial and temporal extents, which can directly influence how any uncertainties about those processes are perceived (Peterson and Dunham 2010).

In this chapter, I hope to demonstrate that issues of scale that are not taken into consideration can adversely affect natural resource management restoration efforts. I will use salmon management efforts in the Central Valley of California as an example where mismatches of scale have hindered conservation goals. In fact, they can inhibit the implementation of effective adaptive resource management. Also, I will make a case for why a structured decision making may be an ideal approach to incorporate and resolve some of the uncertainties created by issues of scale.

Background of Pacific Salmon & California

Pacific salmon and steelhead (*Oncorhynchus sp.*) are an ideal example of animals whose management requires considerations of scale. Salmon stocks in the North Pacific have been declining steadily over the last 100 years, which has resulted in many efforts to rehabilitate depressed populations. The region-wide importance, both economically and culturally, of salmon and steelhead cannot be understated (Ruckelshaus et al. 2002). Historically, salmon and steelhead were essential for Native Americans that inhabited many areas of the Northern Pacific coast and currently salmon and steelhead remain an iconic species in areas where they still occur (Lichatowich 1999). In addition, the Pacific salmon fishery is the second largest commercial fishery in the United States with an estimated value of over 489 million dollars in 2012 (NOAA-Fisheries 2012). Recreational salmon fisheries are also one of the most important recreational fisheries in the Western U.S. (Nehlsen et al. 1991). As one would expect, there is substantial interest in preserving these stocks.

The causes for the decline of Pacific salmon and steelhead populations are well documented. With the arrival of Europeans came commercial fishing operations as well as mining, logging and large-scale agricultural industries. Starting at the turn of the 20th century, the ease that salmon and steelhead could be caught due to their predictable homing behavior and high densities attracted the interest of commercial fishing operations. The increase in fishing effort led to the stocks being over exploited with most fish being processed at canning facilities for export (Netboy 1974). Overexploitation was combined with practices that severely degraded salmon habitat, such as dredge mining, logging, and water impoundment for agricultural irrigation and flood control (Busch 2000, Montgomery 2003). In fact, salmon in the Pacific Northwest of the United States only occur in 40% of their historical range and approximately one half of those remaining are at risk of extinction in the next 100 years (Nehlsen et al. 1991, Levin and Schiewe 2001). However, salmon runs have increased in the last 50 years with the help of several conservation efforts. Habitat restoration, fishing quotas and conservation hatcheries have all contributed to help slow and in some cases, reverse the decline many salmon stocks. Unfortunately, these efforts have failed to restore salmon and steelhead to their historic distribution and densities (Lichatowich 1999, Ruckelshaus et al. 2002).

The story of the decline of California's Central Valley anadromous salmonids is similar to decline of Pacific anadromous salmonids in other areas of Pacific coast of North America. The Central Valley is a large region (approximately 22,500km^2) that drains the Sierra Mountains in the East and the Coastal Range in the west (Figure 2.1). The two primary tributaries in the Central Valley are the Sacramento drainage from the north and the San Joaquin drainage from the South. The tributaries that feed both Sacramento and San Joaquin are characterized by a very high gradient in their mountainous headwaters which tapers off as they enter the relatively flat historical floodplains of the Central Valley. The Sacramento and San Joaquin come together just east of San Francisco to form the Sacramento-San Joaquin River Delta, and eventually enter the sea at the San Francisco Bay. Historically, the Sacramento-San Joaquin Delta was a highly productive, complex estuary environment. This area and its streams and tributaries were historically one of the most productive areas for Pacific salmon.

Before the large scale decline of salmon and steelhead at the turn of last century, spawning salmon could be found in high densities throughout most of the Central Valley (Lichatowich 1999). In fact, before the arrival of European settlers more than one million Chinook Salmon (*Oncorhynchus tshawytscha*) were estimated to have returned to the Central Valley each year (Yoshiyama et al. 1998). However due to several unsustainable practices such as high intensity logging and mining as well as commercial fishing, by the early 20th century Pacific salmon in the Central Valley were severely reduced in their range and numbers. The main cause for the decline is attributed to actions associated with the Central Valley Project (CVP), which was enacted in 1933. The CVP was a joint venture between the state of California and the federal government to reengineer the hydrologic system of the Central Valley. The purpose of the CVP was to fund reclamation projects in the Valley to provide jobs in the area as well as to increase the availability of water for agricultural and municipal purposes. The need for water reclamation projects that would increase the amount of arable land intensified due to the dust bowl that was affecting the historical “bread basket” of the United States during this time. Additionally, these projects provided badly needed jobs due to high levels of unemployment that were prevalent during the Great Depression. The Central Valley Plan was an array of water reclamation projects aimed at providing flood control, irrigation, and hydroelectric power production projects throughout the Central Valley. The scope of the CVP meant these projects were located in most all of the large tributaries in the valley. Most these projects took the form of impoundments, aqueducts, or water diversions and very few provided any mitigation for the negative effects on native species dependent on those streams. The effects of the CVP along with other factors, such as continued overfishing in the ocean and poor logging and mining practices furthered the decline of salmon population numbers (Nehlsen et al. 1991, Cummins et al. 2008a). By the 1980's and into the 1990's, the population decline of salmon in the Central Valley caused the Federal government to get involved in restoration efforts (Figure 2.2).

Generally, CVP actions had negative effects on anadromous fish populations. In most cases, fish passage was not provided on impoundment projects nor were newly constructed irrigation diversions screened to prevent fish entrapment. From 1933 into the 1960s, almost every major tributary of the Sacramento and San Joaquin had a major impoundment preventing fish passage (Yoshiyama et al. 1998). It is estimated that after the construction of these dams that salmon were denied access to roughly one half of their traditional spawning and rearing grounds. In some streams, dams and diversions blocked off up to 70-90% of historical spawning and rearing habitat (Cummins et al. 2008a). Additionally, the creation of these impoundments cut off the lower available reaches from their historical alluvial processes such as natural flow regimes, floodplain inundation, and gravel recruitment. It should be kept in mind that during this time that commercial salmon fishing was continuing with salmon being harvested at unsustainable levels. During the 1930's and 1940's, there was a substantial effort to provide supplemental hatcheries to mitigate the effect of lost spawning and rearing habitat. Hatcheries such as Coleman National Fish Hatchery on Battle Creek, Nimbus Fish Hatchery outside of Sacramento, and the Feather River Fish Hatchery, began raising and releasing salmon smolts in large numbers. These hatcheries also helped to sustain the commercial fishing industry that had developed around these once abundant fish. At the time, fisheries biologists were confident that the hatchery production would be able to compensate for the last productivity caused by the widespread habitat degradation. The main purpose of the hatcheries was to provide adult fish for the commercial fishery as well as to provide angling opportunities inland. In this light, the hatcheries could be viewed as a success. However, despite the success of the mitigation hatcheries, spawning and rearing success of the remaining wild populations continued to decline. The general result were fish populations that were heavily dependent on hatchery inputs, which is not a mark of self-sustainable populations.

By the 1980s, the state of California's Chinook salmon populations were stable thanks to the input of the mitigation hatcheries. However, there remained few places were wild salmon still had access to suitable spawning and rearing habitat. Beginning in the 1990s, ocean conditions began to shift due to several consecutive El Niño events. This caused higher ocean surface temperatures that has be related to decreases in ocean productivity and ultimately Pacific salmon ocean survival (Mantua 2015). The warmer weather associated with El Niño events also reduces snowpack inland, which ultimately causes increases in stream temperatures. This results in higher mortality rates for juvenile salmonids rearing in freshwater. By the early 1990's, salmon and steelhead numbers were at historic lows.

Central Valley Plan Improvement Act

This confluence of events set the stage for the passage of the Central Valley Improvement Act (CVPIA) by congress in 1992. The CVPIA is a large scale, multiagency restoration effort whose primary goal was to restore populations of anadromous species in the Central Valley. The species specifically identified by the CVPIA include: four runs of Chinook salmon, Steelhead (*O. mykiss*), delta smelt (*Hypomesus transpacificus*), Green sturgeon (*A. medirostris*), White Sturgeon (*A. transmontanus*) and nonnative Striped Bass (*Morone saxatilis*). As the name implies, the CVPIA aimed to rectify some of the adverse impacts of the original CVP. The passage of this legislation was timely, given the several salmon and steelhead stocks were on the brink of being federally listed as threatened or endangered under the Endangered Species Act. Also part of the legislation was the appropriation of moneys to fund reclamation and recovery projects to aid salmon. To date, the CVPIA is the largest federal salmon recovery program in the lower 48 states, with funding in excess of $25 million annually between 1993 and 2008 and over one billion dollars spent as of 2016 (Cummins et al. 2008b). Despite the high levels of funding, the CVPIA has yet to meet the goals it set more than 25 years ago.

One of the goals of the CVPIA was to bring together many of the agencies involved with salmon management in the Central Valley. Perhaps the largest problem with the CVPIA is the clear lack of structure that was provided by the legislation. Instead of a single entity implementing management actions, the CVPIA identifies multiple agencies, working groups and stakeholders. Officially, the Bureau of Reclamation (henceforth Reclamation) and the United States Fish and Wildlife Service (USFWS) act as co-program leads to implement the CVPIA. Reclamation’s responsibilities are primarily financial: distributing funds and creating program budgets. Any biological research, restoration planning, implementation or monitoring then fell to the USFWS. In addition to Reclamation and USFWS, the CVPIA also instructs those agencies to develop this restoration program “in consultation with other state and federal agencies, Indian tribes, and affected interests.” This created a situation where Reclamation and USFWS were required to coordinate with many other organizations, most of whom they do not have any direct authority over. As one can imagine, implementing such a large effort with so many interests proved to be challenging.

Within the CVPIA is an explicit list of goals, actions, tools and authorities available to Federal managers. Section 3406 of the legislation is perhaps the most important portion because it sets the stage for much of the structure of the implementation of the CVPIA. Section 3406(b) is especially important because it’s in this section we first see the “doubling goal” that the CVPIA is often associated with (CVPIA 1993; 3406(b)(1)). It also displays the most important aspects that would later become the CVPIA. Some of the section 3406(b) subsections are quite specific, even mentioning specific watersheds or projects, while others are quite vague in nature. This list would form the backbone and direction of the CVPIA. Although, it should be noted that some of these projects were already underway prior to the CVPIA.

The result of the subsections in 3406(b) was the proscription of several uncoordinated actions throughout the Central Valley. Usually, for each part of section 3406(b) a subcommittee was formed to enact that part of the legislation. Each of these subcommittees tended to act independently and with minimal coordination with the USFWS and Reclamation leadership.

Lack of Success & Issues of Scale

Ultimately, 2002 came and anadromous fish stocks had not recovered according to the “doubling goal” of the CVPIA. In fact, as of 2016 the doubling goal has yet to be reached. I believe this is in part due to how the CVPIA was structured and implemented, specifically the mismatch between management goals (e.g., basin wide doubling of all anadromous species) and management actions (e.g., small scale restoration activities). Below, I outline a few examples of how I believe issues of scale caused the initial implementation of the CVPIA to fail.

To date, fisheries management in the basin was largely uncoordinated and unstructured. This mostly was the result of multiple agencies (i.e., Fish and Wildlife Service, California Fish and Game, Bureau of Reclamation, Army Corps of Engineers) operating independently of one another despite all being part of the CVPIA (Cummins et al. 2008a). The way the CVPIA was structured in the past resulted in multiple agencies and working groups working independently sometimes at very different spatial and temporal scales. This situation typically arises when the various management agencies are responsible to serve different constituencies. For example, the Bureau of Reclamation is tasked with ensuring adequate access to fresh water for agriculture in the basin, whereas California Department of Fish and Wildlife (formerly California Fish and Game) are simultaneously tasked with providing sustainable angling opportunities to their residents. As this example demonstrates, natural resource management agencies can have competing and potentially conflicting management objectives within the basin. Perhaps the largest impediment to reaching the natural production doubling goal was the lack of structure and transparency in the decision making process within the CVPIA (Cummins et al. 2008a). In addition, I believe the decision making process has been hindered by the differences in spatial temporal scales that the decision makers and stakeholders operate at within the Central Valley.

Overall, the way the CVPIA has been structured has resulted in multiple uncoordinated management actions often occurring simultaneously and at potentially conflicting scales. The CVPIA lacks a single entity (i.e., decision maker) to enforce management decisions across the entire Central Valley. Rather, it is composed of multiple decision makers, all working at their own scales. This often created mismatches of scale between the working groups and the objectives of the CVPIA. Looking at section 3406(b) of the CVPIA, we can see several example of very specific actions. A great example of this was the creation of the gravel implementation team. This group was created specifically to satisfy section 3406(b)(13) of the legislation and they were tasked with improving spawning and rearing gravel throughout the Central Valley. The gravel team's efforts were effective at providing new spawning gravels to several Central Valley streams, however they have been generally uncoordinated with the larger CVPIA. This team's spatial grain for their projects were roughly 0.25 mile reaches on individual tributaries. Keep in mind that the overarching goal of the CVPIA is to double the number of anadromous fish in the Central Valley. Working at such a fine scale is necessary for implementing these kinds of projects. However, without any coordination with other programs within CVPIA these kinds of project may be successful locally but also may be misplaced on the larger scale of the Central Valley as a whole. Some decisions were being made at very local scales (e.g., river reaches) and other were being made at very large spatial scales (e.g., the entire Central Valley). This lack of coordination and overlapping spatial scales resulted in decisions being implemented that may or may not have been optimal given the doubling goal. In addition, because of the mismatch of scales across the all the actions in the Central Valley understanding and identifying the system uncertainties was often not possible.

On the other hand, there are aspects outlined by the CVPIA that focus on individual streams rather than specific actions. In section 3406(e)(6) several tributaries were identified as watersheds where future restoration activities should be considered to benefit salmon and steelhead population. These tributaries include: the Merced, Mokelumne, and Calaveras Rivers and Battle, Butte, Deer, Elder, Mill and Thomes Creeks. No specific actions are identified in this portion of the CVPIA, instead the restoration methods are left up to the implementing agencies. The CVPIA does not provide a guideline to prioritize actions among these watersheds or between different the target species. It’s also ambiguous as to how any actions implemented in these watersheds fit into the larger Central Valley wide doubling goal.

Having such large differences in spatial scales meant that any reduction of system uncertainties wasn’t necessarily transferable to other populations of anadromous fish within the Central Valley. For instance, there have been several efforts to develop a model for the Chinook salmon populations in the CVPIA (Bartholow et al. 1997, Consultants 2014, Hinkelman 2015). These models have typically been watershed-specific and unnecessarily complex that they are only useful in the single basin for which they were developed. The specificity of these models prevents the any derived restoration strategy from being applicable to other watersheds. Additionally, to date there is no coordinated effort to collect standardized monitoring data. Rather, each working group in the CVPIA is responsible for collecting and storing their own monitoring data.

This results in types of data that may be collected more than once or not at all. Additionally, this hinders transferability of knowledge in that information learned by one working group is not applicable to another working group. The result is that many of the uncertainties, systemic and parametric, that existed before the CVPIA still exist.

There are several challenges that have hindered salmon and steelhead restoration throughout the North Pacific and in California. The first has been the failure to identify explicit, achievable objectives (Lichatowich et al. 1995, Beechie et al. 2008). Too often multiple management actions are pursued simultaneously, often with conflicting or competing objectives. For instance, local (small scale) efforts to restore spawning habitat to increase natural production may occur in streams with hatchery supplementation whose aim is to provide angling opportunities. Previous studies demonstrated that when hatchery fish and wild fish interbreed, the net result is a decrease in fitness for their offspring and potentially an increase in straying rates (Nehlsen et al. 1991, Chilcote et al. 2011, Lister 2014). This illustrates how management actions, however well intentioned, can be counterproductive or less productive if appropriate objectives are not identified first. Salmon and steelhead also tend to have a highly variable life history, which creates difficulties in both monitoring and modeling populations (Groot and Margolis 1991, Gross 1991). This is especially evident in steelhead populations where within a single generation some offspring become resident rainbow trout and others become anadromous steelhead (Withler 1966, Thorpe 2007). Also, many salmon and steelhead populations have diverse life histories that allow young-of-year to migrate to the ocean as fry, parr, or smolts (Groot and Margolis 1991). These diverse life history strategies often exist in a single population and create substantial uncertainty of how specific management actions may influence population dynamics. Lastly, it is often not possible to assess an entire population of salmon or steelhead due to the large spatial area they inhabit. Intra-population differences in adult ocean residence time, which are typically between 2 and 6 years, add further complexity to population or management action assessments. Instead, population size and status often has to be extrapolated from a handful of observations and the grain of the monitoring efforts often do not match the scale of the overall management objectives (Beechie et al. 2008, Beechie et al. 2009).

Discussion

It has been recommended that the CVPIA adopt a more transparent, structured, and holistic approach to their management decision process (Cummins et al. 2008a). Specifically, there is a need to implement a structured decision making (SDM) process. This process would allow for more transparency in how decisions are made as well as allow decision makers to resolve important system uncertainties.

Structured decision making (SDM) and adaptive resource management may be useful tools for the management of Pacific salmon and steelhead. SDM can be valuable tool to address natural resource problems because they directly connect quantifiable objectives and explicit alternative decisions with quantitative models to identify optimal management decisions (Clemen 1996, Conroy and Peterson 2013). As the name implies, SDM structures and formulizes the decision making process, avoiding ad-hoc decision making. The first step in the SDM process is for decision makers and relevant stakeholders to identify and agree on objectives. This is perhaps the most critical step in SDM because poorly worded or vague objectives can result in conflicts of interest or the implementation of ineffective decision alternatives. Secondly, the decision makers and stakeholders identify those decision alternatives that are available to meet the objectives. The next step in SDM is to build quantitative models to connect decisions to objectives and estimate the outcomes of the various decision alternatives. Optimal decisions are then identified via a closed form mathematical equation or through heuristic optimization algorithms depending on the specific approach used. Although the details of the process are a bit more involved than what I have outlined here, this is the basic framework of SDM.

Quantitative, structured approaches to fisheries management and decision making were first introduced over 30 years ago as adaptive resource management (ARM; (Holling 1978, Walters 1986). In fact, ARM is special case of SDM where decisions are revisited through time in an iterative process. In essence, ARM is just the SDM process repeated through time. The iterative process allows the effects of decisions to be fully realized through time (and /or space) and for the opportunity to learn about the system through continued monitoring, this process is sometimes known as information feedback. Part of what makes ARM so attractive for problems in natural resources is that it allows managers to make decisions while simultaneously reducing uncertainties about the system at hand. In fact, ARM allows for the explicit testing of competing hypotheses about system dynamics or processes through information feedback. This iterative process of observing the state of the system, implementing a decision alternative, and reevaluating the state of the system can be modeled as a Markov Decision Problem (Bather 2000, Ross 2014). MDP’s require a class of optimization routines that allows managers to model sequential decisions that occur over time and also derive what the optimal sequence of decisions would be given a pre-specified utility function. MDP’s are especially appealing for modeling natural resource management problems because they intuitively follow the decision making process (e.g., evaluate the system, make a decision, reevaluate the system and update current knowledge) and are able to incorporate environmental stochastic processes.

However since its development, ARM has yet to be widely applied successfully. The primary impediments have kept this both ARM and SDM from being more widely adopted in natural resource management include: a lack of awareness from natural resource decision makers, inadequate funding, the lack of leadership to implement such plans, stakeholder dissention and high political risks (Walters 1997, McFadden et al. 2011). This kind of rigorous decision making framework has not been successfully applied to Pacific salmon and steelhead before, but given the numerous issues Pacific salmon and steelhead face, such an approach is needed.

I believe that the salmon populations of California’s Central Valley would benefit from a SDM approach to management. A SDM approach would allow for maximum transparency in the decision making process. This is critical especially when so many stakeholders are involved, as there have been in the prior efforts. Most importantly a SDM approach would require managers to identify fundamental and means objectives. The lack of clear objectives and how they relate to one another has been at the crux of the failure of the CVPIA’s efforts to date. In addition, I believe the SDM process would require managers to identify the scale that their management objectives are at and match them with complementary alternative management actions. Ultimately, this would allow for a greater and more efficient reduction of key uncertainties in these systems.

The hierarchical structure of the CVPIA and the entities that implement CVPIA related actions, provide an opportunity to evaluate how scale may influence optimal decision making in an SDM/ARM framework. The CVPIA has decision makers that work at very different spatial scales. For instance, the USACOE and Bureau of Reclamation tend to work at a coarse, valley-wide scale, whereas, local watershed managers work at a very fine scale. It's unknown how these differences in scale may influence how Chinook habitat restoration efforts are prioritized and implemented in CVPIA streams. The SDM/ARM approach allows me to directly, and transparently determine how differences in scale may lead to different optimal decision making rules or policies.

In this dissertation I modeled three different Chinook habitat restoration problems in CVPIA related streams. Each chapter considers a habitat restoration problem at a different spatial and temporal scale. In each chapter I developed a probabilistic decision model to evaluate the effect of different habitat restoration management actions. These models were then optimized using dynamic linear programming or a heuristic algorithm to derive optimal management actions. Each chapter provides insight on how spatial scale influences optimal decision making. In fact, for the last chapter I developed a hierarchical decision model with multiple decision makers, working a multiple temporal and spatial scales, to see how scale influences optimal decision making across different scales. It's my hope that these chapters will provide guidance to future managers and encourage them to consider the importance that scale can have on their decision making process.

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Figures

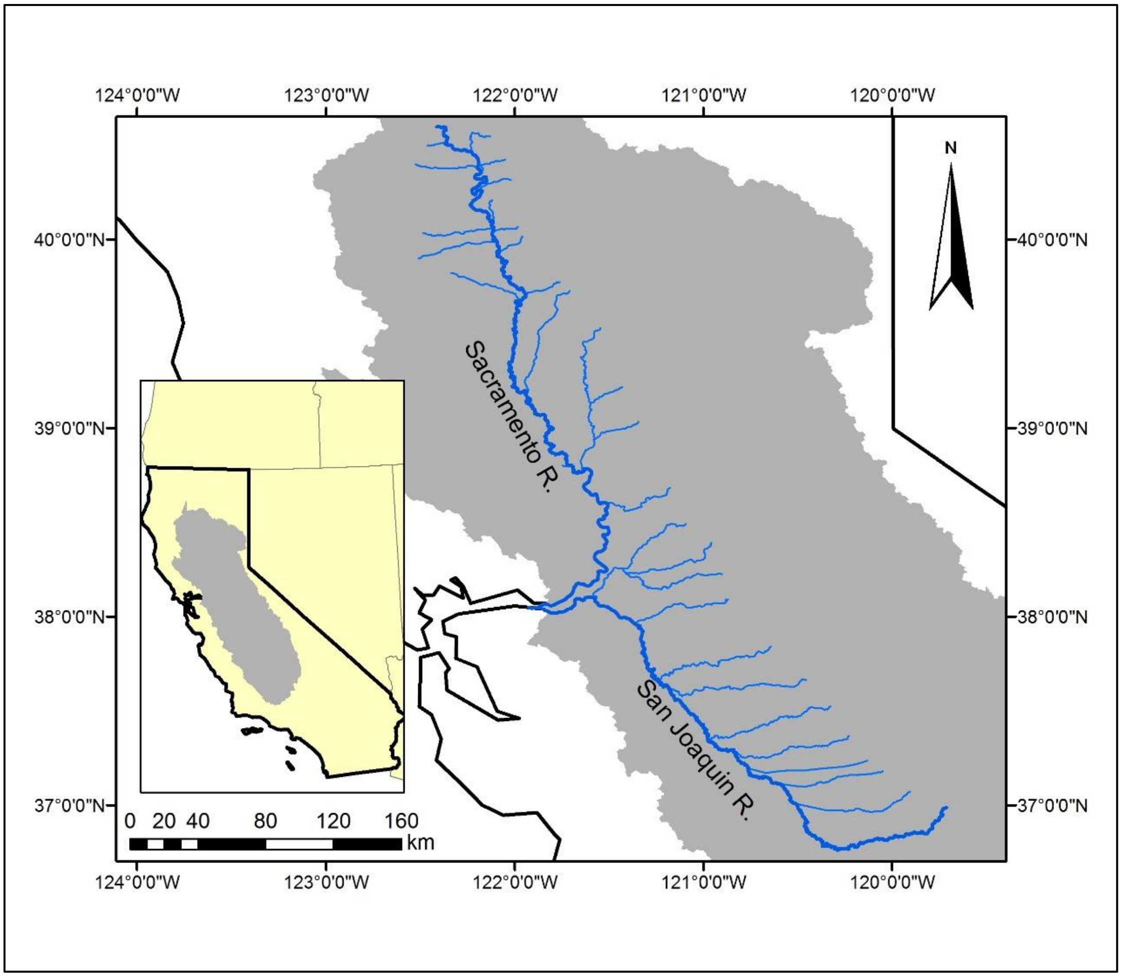

Figure 2.1 – A map of the California's Central Valley streams. The Central Valley is primarily made up of the Sacramento River to the North and the San Joaquin River to the South and their tributaries. Above depicts the waters where anadromous salmonids were once abundant and are also incorporated in the Central Valley Improvement Act.

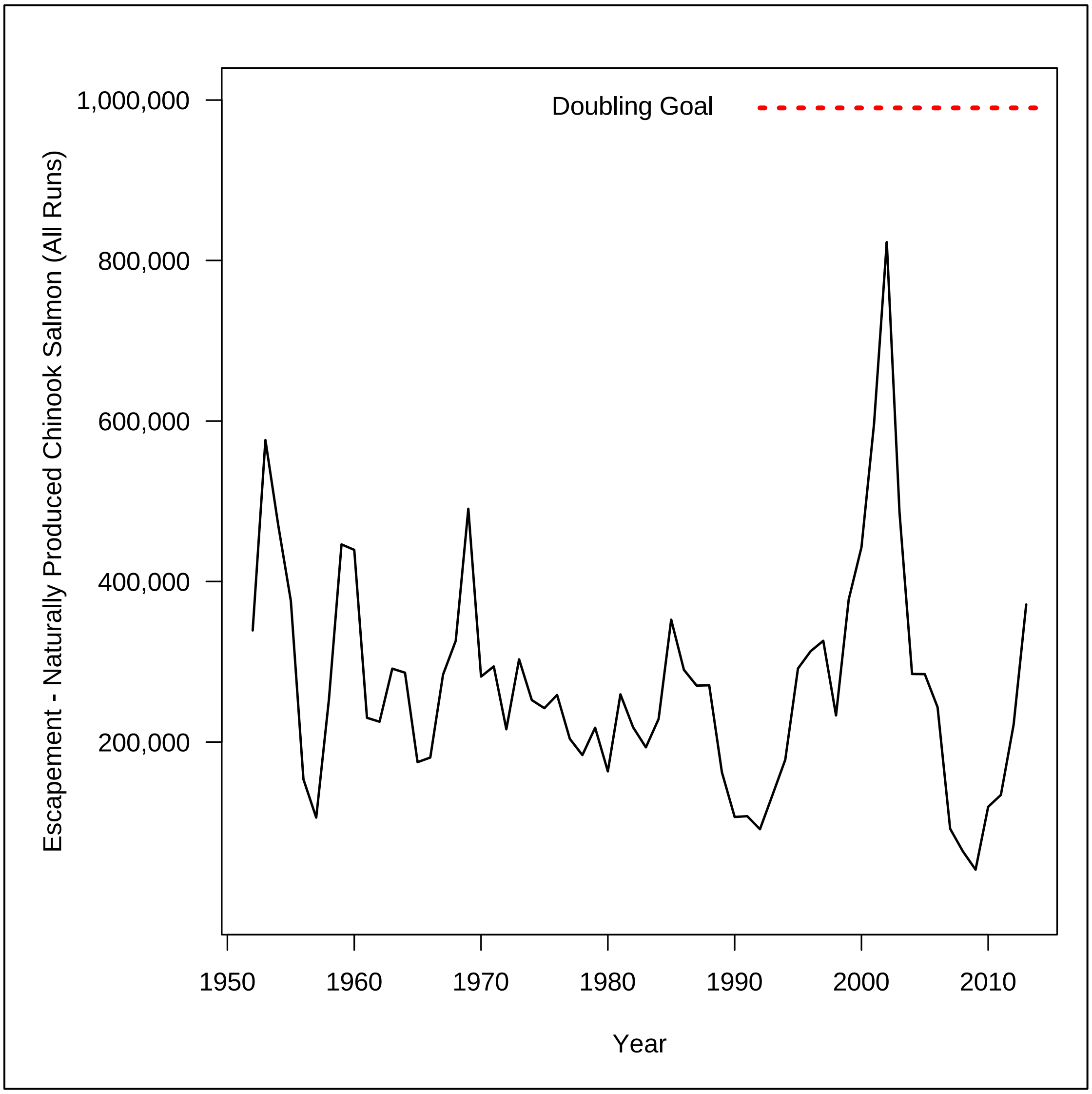

Figure 2.2 – Total number of naturally produced Chinook salmon (wild origin) in California's Central valley across all runs (fall, late-fall, winter, and spring) from 1950 to present and the natural production doubling goal (red dashed-line) identified in the Central Valley Plan Improvement Act of 1992.

CHAPTER 3: EVALUATING LARGE SCALE OPTIMAL HABITAT RESTORATION STRATEGIES FOR CENTRAL VALLEY CHINOOK SALMON USING QUANTITATIVE DECISION ANALYSIS

Abstract

Large scale natural resource management problems require special considerations relative to smaller scale problems due in part to the fact that environmental and structural uncertainties tend to increase as spatial scale increases. Despite this, decision makers are often required to make decisions through despite a lack of empirical information. Structured decision making (SDM) provides a framework to understand which factors drive the decision making process as well as a way to derive management strategies. I used populations of fall-run Chinook salmon in California’s Central Valley to demonstrate how a SDM approach can be used to derive a state-specific optimal strategy for large scale stream restoration prioritization. I developed a decision model that was able to simulate 25 populations of fall-run Chinook salmon as well as evaluate the effects of potential habitat restoration projects. The total extent of the model was the entire Central Valley and the grain was individual watersheds. The model was almost entirely parameterized with expert judgement due to a lack of available empirical data that exists as the scale that was identified. This model and the decision alternatives was used to parameterize a Markov decision model (MDP) that I solved using dynamic programming and policy iteration. The solution to the MDP provided a habitat state based optimal policy for each watershed. The results of the policy optimization suggest that focusing efforts on single watershed is an effective habitat restoration strategy. I also used the decision model to identify influential model components that could influence the decision making process. Model inputs such as fry outmigration survival and the amount

spawning habitat were both all highly influential to the decision making process. In this study I demonstrate that stream habitat restoration strategies can be derived using a dynamic programming approach at a large scale with limited empirical information.

Introduction

One of the most important considerations in decision making is the scale of the decision problem. Scale is a fundamental component of natural resource management and should be a consideration for any natural resource manager. Scale has two primary components, grain and extent (Peterson and Dunham 2010). Grain is the finest spatial and temporal resolution that decisions and observations are made and extent refers to the broadest spatial and temporal dimensions over which decisions are made. How scale is defined ultimately influences how data is collected as well as what types of decision alternatives that are available (Peterson and Dunham 2010, Falke et al. 2013). For instance, a fisheries manager would have to make different considerations when managing an individual stream reach versus an entire watershed due to how ecological processes operate at those different vastly different scales. Identifying the scale of natural resource management decision problem is a crucial component to the decision making process.

Large scale natural resource management problems require special considerations relative to smaller scale problems. In general, environmental and structural uncertainties tend to increase as spatial scale increases (Williams 2011, Getz et al. 2018). Environmental uncertainty is the naturally occurring variation in environmental processes and structural uncertainty refers to our lack of understanding regarding the relationships between those processes (Williams 2011). These sources of uncertainty can cause large scale management problems to appear too complex or variable for managers to resolve. Decision makers may choose less optimal actions or not to act at all if the total system uncertainty exceeds their risk thresholds (Thompson 2002, Cullen and Small 2004). Additionally, large scale decision problems often include large numbers of stakeholders and decision makers, each with their own objectives. Incorporating a diverse array of values and objectives into a decision problem is another challenge for decision makers that isn’t a common feature of small scale decision problems.

Structured decision making (SDM) is an approach to decision problems that incorporates environmental and structural uncertainties and provides a useful framework for natural resource managers. SDM is comprised of three basic components. The first is explicit, quantifiable objectives, the second is a set of explicit management alternatives, and the third is a model that is able to predict the effect of the management alternatives on the resource (Possingham et al. 2001, Martin et al. 2009, Conroy and Peterson 2013). The SDM process creates a transparent framework for identifying optimal decision alternatives as well as accounting for differing or competing objectives. One of the primary strengths in the SDM approach is the identification of influential parameters. An influential parameter is a parameter that may cause the optimal decision to change across its range of uncertainty (Nicholson and Possingham 2007, Martin et al. 2009). Identification of influential parameters can help prioritize future monitoring efforts to target key uncertainties (Conroy and Peterson 2013). The characteristics of SDM make it an intuitive option for large scale decision problems in natural resource management.

Decision problems in natural resource management require managers to make a series of decisions through time in the presence of environmental uncertainty. Solving dynamic, sequential decision problems requires optimization methods able to account and incorporate stochasticity. Often these problems are framed as Markov Decision Problems (MDPs; also known as stochastic decision processes). Most applications of MDPs frame a sequential decision problem as a set of discrete state transition matrices and reward vectors (Ross 2014). Dynamic programming is one of the most common approaches to solve MDPs. The system stochasticity is captured in the transition matrices where the state-specific transition rates influence the expected reward value for each discrete state. Dynamic programing results in state-specific optimal policies through a backwards inductive computation procedure (Bellman and Dreyfus 1962, Bather 2000, Puterman 2009). The ability of dynamic programing to capture large amount of uncertainty and deconstruct a decision problem down to its essential elements makes it a great approach for sequential, large scale natural resource decision problems. To date this approach has not been applied to the problem of prioritizing river habitat restoration across a large scale system.

Restoration of Chinook salmon populations in the California's Central Valley provides a great opportunity to evaluate decision alternatives in large scale decision problem. Chinook salmon occur in four distinct runs in the Central Valley which are identified by the time of year that spawners migrate into freshwater: Fall, Late-fall, Winter, and Spring (Vogel and Marine 1991, Fisher 1994). The fall-run is the largest run of Chinook salmon in the Central Valley and in turn it supports large commercial and recreation fisheries (Moyle 1994, Yoshiyama et al. 1998). Chinook salmon were once abundant throughout the Central Valley but since the turn of the last 20th century their numbers have been in decline (Yoshiyama et al. 2000). The decline of Chinook salmon populations in the Central Valley was primarily due to overharvest, habitat degradation and dams (Yoshiyama et al. 1998, Lichatowich 1999). In 1992 the Central Valley Improvement ACT (CVPIA) was passed by the U.S. Congress to restore anadromous fish populations to their historic population levels in the tributaries throughout the Central Valley, CA. The CVPIA became a necessary piece of legislation due to the serious decline of these Chinook salmon populations in the two decades leading up to its passage (Nehlsen et al. 1991, Cummins et al. 2008b). Species included in the CVPIA include striped bass (*Morone saxatillis*), sturgeon (*Acipenser medirostris* and *A. transmontanus*), and steelhead (*Oncorhynchus mykiss*), but the primary focus of the CVPIA has been on Chinook salmon (*O. tshawytscha*). One of the primary provisions of the CVPIA is to double the abundance of anadromous species in the Central Valley from their 1992 levels. Specifically, the doubling goal seeks to increase the number of naturally produced (non-hatchery origin) Chinook salmon in the watersheds it oversees. Spatially, the CVPIA considers 26 watersheds that make up the tributaries of the Sacramento and San Joaquin Rivers as well as the Sacramento-San Joaquin Delta. Although the CVPIA was passed in 1992, efforts are still on going to restore Chinook populations to the historic levels.

The large spatial scale and total number of watersheds that the CVPIA administers has hindered the effectiveness of past CVPIA activities. Despite hundreds of habitat restoration projects that have been implemented and over 1 billion dollars that have been spent, the CVPIA has yielded few significant results in terms of increasing fall

Chinook populations thus far. The CVPIA administers a huge area (> 70,000 km^2), and the vast majority of CVPIA funded activities occur at a small, reach level scale. This mismatch between restoration activities and the overall doubling objective can make it hard to evaluate the efficacy of said restoration activities. Careful consideration needs to be given to how scale is defined while implementing any approach for Chinook salmon management in the Central Valley. The CVPIA requires several agencies from different sectors to co-manage these populations of fish (e.g. Bureau of Reclamation, U.S. Fish and Wildlife Service, California Fish and Game, and non-governmental organizations; Cummins et al. 2008). The result has been lot of uncertainty or a complete lack of knowledge about both the physical (e.g. habitat availability, in-stream temperatures, measures of flow) and biological (e.g. juvenile survival, spawning success, and predation rates) characteristics of the watersheds the CVPIA oversees. It is especially difficult to prioritize management alternatives without an accurate picture of the current system state. Taken together, these factors have caused the CVPIA to remain rather ineffective in its efforts to reach the mandated doubling goal.

Previous attempts to model salmon population dynamics in the California's Central Valley have focused on understanding simple stock-recruit relationships or simulating the life history dynamics of Pacific salmon at a very fine scale (Bartholow et al. 1997, Williams 2006, Satterthwaite et al. 2010). Unfortunately, these models are typically very data intensive, require a huge number of parameters, and may not able to be able to directly evaluate the influence of potential management actions. A new, more parsimonious approach is needed that can incorporate all the necessary life history dynamics while simultaneously using the limited amount of information available in the

Central Valley. Specifically, an approach is required that is able to match the scale of the objectives, management alternatives and population dynamics model.

I developed a decision model that is able to replicate the large-scale system dynamics of fall-run Chinook salmon populations in the Central Valley with potential management actions identified by the CVPIA implementing agencies. To accurately model these dynamics, the model presented here incorporated available habitat and salmon escapement data, the effects of decision alternatives, as well as all the uncertainty that exists in the system. In addition, all the decision alternatives that are considered operate at the scale of an entire river basin and population. I believe this model will more accurately represent how decisions regarding Chinook salmon are made by CVPIA managers.

The primary objective of this chapter is to derive optimal decisions and policies for the fall-run Chinook salmon of the Central Valley using coarse resolution information at a sub-basin or watershed level. The secondary and tertiary objectives of this chapter are to evaluate how well the model performs and to identify key uncertainties that exist in the management of fall-run Chinook salmon in the Central Valley at this scale. Creation of a decision model at such a large scale will provides insight into what decisions are optimal for increasing natural production of fall-run Chinook salmon and how sensitive those optimal decisions are at this decision making scale. In this chapter I present a structured decision model that is able to derive optimal management actions as well as determine what environmental or structural uncertainties drive the decision making process and fall-run Chinook salmon production at the basin level spatial scale for the Central Valley.

Methods

Study Sites

California's Central Valley covers a huge area (>70,000 km^2) and is made up of two main tributaries (Figure 3.1). The Sacramento River is the longest river in California and begins in the Northern Sierra Nevada. From there it flows 719 kilometers south until it meets the confluence of the San Joaquin. The San Joaquin River begins in the southern Sierra Nevada and flows north. The confluence of these rivers creates the large and complex Sacramento-San Joaquin delta. The delta eventually empties into the Pacific through the San Francisco Bay. A total of 25 populations of fall-run Chinook salmon were included in the model (Table 3.1; Figure 3.1). Most the populations (19) are distributed throughout the Sacramento basin, with the remaining populations located in the San Joaquin basin. The watersheds vary in size from 18,000 – 3.5M ha (median 106,000 ha) with between 33 and 209 river kilometers open to anadromous species. These watersheds were chosen for this analysis because they are actively managed as part of the CVPIA fisheries program.

The Sacramento River was divided into two sections, the Upper-mid Sacramento and the Lower-mid Sacramento. The Upper-mid Sacramento included all of the main stem Sacramento above the Red Bluff Diversion Dam. The Lower-mid Sacramento Reach was defined as the section of the main stem Sacramento between the Red Bluff Diversion Dam and the confluence with the American River. The Upper-mid Sacramento was treated like all the other watersheds because it hosts its own spawning population of fall-run Chinook salmon. The lower-mid Sacramento River does not host its own spawning population of Chinook. Instead it acts as a migration corridor for outmigrating juveniles where they could potentially stop and rear during their migration. I assumed that all the juveniles in the Sacramento basin watersheds, except those from the American, Mokelumne and Consumnes Rivers, were routed through the lower-mid Sacramento. The San Joaquin did not need to be split into two distinct sections because unlike the Sacramento, there is no spawning population that uses the upper reaches of the San Joaquin. Instead the entire San Joaquin acted as the migration corridor and provided additional rearing habitat to outmigrating juveniles.

Each watershed was placed into evolutionary significant groups based, in part, by location and geological features: Basalt and porous lava, Northern Sierra Nevada, Northwestern California, and Southern Sierra Nevada (Figure 3.2; Lindley et al. 2007). They all currently have populations of fall-run Chinook salmon that were considered in the decision-making framework. Watersheds within these groups tend to have genetically similar populations of Chinook salmon and share similar stream characteristics. Most all these watersheds have experienced substantial habitat degradation due to mostly anthropogenic causes discussed in Chapter 1.

Decision Problem

Habitat restoration is the primary tool for rehabilitating Chinook salmon populations in Central Valley. Keeping that in mind, this decision problem was designed to prioritize habitat restoration projects in the Central Valley. This decision problem was framed from the point-of-view of the CVPIA implementing agencies: the U.S. Bureau of Reclamation and the U.S. Fish and Wildlife Service. These two agencies act jointly as the primary decision makers regarding habitat restoration activities in CVPIA streams. For this decision problem, I assumed there was a single decision maker acting on the behalf of the CVPIA implementing agencies. The decision maker is able to implement a single decision alternative in each annual time step. Decision alternatives are assumed to be implemented at the start of each time step so their effects can be realized within that same time step. The total extent of the decision problem was the entire Central Valley basin. The grain of problem was each individual watershed. This meant that decision alternatives were not implemented in any spatially explicit way but rather to the watershed as a whole.

Objectives

The decision maker's single fundamental objective was to maximize the total natural production of fall-run Chinook salmon in CVPIA managed watersheds. The terms *natural production* and *naturally produced* refer to salmon that are produced by adults spawning in the wild regardless as to their origin. For instance, the offspring of a wild and a hatchery origin adult salmon is considered "naturally produced." Maximizing this metric would ultimately help lead to larger wild populations as well as more Central Valley fall-run Chinook salmon towards the CVPIA doubling goal. I identified two means objectives that would address the fundamental objective: increase the amount of spawning habitat and increase the amount of rearing habitat. These means objectives were used to identify the decision alternatives available to the decision maker.

Decision Alternatives

The decision alternatives available to the decision maker were derived from the means objectives identified above. The construction of dams and overall habitat degradation has left many of the watersheds in the Central Valley lacking suitable spawning and/or juvenile rearing habitats. In this analysis I consider two of the main habitat restoration techniques that are used by managers in the Central Valley: spawning gravel additions and floodplain excavation. Many CVPIA watersheds have dams on them that have halted natural alluvial processes such as gravel recruitment. This has led to a decline of suitable spawning habitats. Spawning gravel additions involved placing large amounts of gravel (>1000 m^3) in a reach of a stream to provide additional spawning habitat. Land use changes and a high demand for water in some CVPIA watersheds has created systems where historic floodplains are no longer inundated with any regular frequency. Floodplain excavations lower the elevation at which floodplains become activated which provides additional, off-channel rearing habitat for juvenile salmon (Jeffres et al. 2008). Both these habitat restoration alternatives were available alternatives in each watershed along with an option to do nothing.

The effect size (the mount of habitat added) that both the decision alternatives have on their respective target habitats in each watershed was determined by through expert elicitation and evaluating previous habitat projects in the Central Valley (Table 3.2). Cost was indirectly incorporated by choosing effect sizes that represent projects that would cost the same to implement. In the case that a decision alternative has equal utility to the “do nothing” option, the do nothing option is the de facto optimal decision.

Salmon decision model

The underlying Chinook salmon population dynamics for this decision model was a salmon life cycle model, similar to many previous salmon life history modeling efforts (Bartholow et al. 1997, Satterthwaite et al. 2010). A life history approach was desirable because it allowed me to directly evaluate the effects of different habitat restoration projects that target different stages of the Chinook life cycle. Most of the previous modeling efforts require not only a lot of data but also data at a very small temporal and spatial resolution (e.g., daily temperatures and reach specific estimates of habitat). Unfortunately, these types of data do not exist for many of populations of Central Valley Chinook Salmon. I developed a life cycle model that could incorporate both the available empirically derived data and the expert derived data, both occur at large temporal and spatial scales.

Model inputs

The primary inputs for the decision model were watershed level estimates of habitat availability and several measures of stream conditions as they relate to Chinook salmon. A majority of the model parameters and inputs were estimated using expert elicitation due to the lack of empirical information available for many watersheds. Empirical data is always preferable when parameterizing a model; however data from expert elicitation can serve as a starting point when it comes to prioritizing data needs. The amount of spawning, in-stream rearing, and floodplain rearing habitats were provided by experts and managers from each watershed (Table 3.3). Habitat availability is often related to stream flows (Beakes et al. 2014). Generally, in years with little precipitation and a shallow snow pack (“dry years”), there is less water available when compared to years with lots of precipitation and a deep snow pack ("wet years"). The effect of wet and dry years is especially noticeable in the amount of available floodplain habitat. The variation of available habitat due to precipitation is reflected in the amount of spawning and juvenile rearing habitats in the population model. For now, I assume that dry and wet years are equally probable. Other model inputs include watershed specific measures of water quality, stream flows, and other habitat conditions (Tables 4-7).

The model can be broken down into roughly seven sub-models (Figure 3.3). The model began with the *ocean harvest and in-river survival* sub-model which was initiated with a starting number of adult Chinook salmon, of both natural and hatchery origin, in the ocean. Chinook salmon typically reside in the ocean for 2 to 5 years before migrating to their natal streams to spawn. Fish that were ready to spawn then experienced mortality related to ocean harvest, recreational harvest, and in-river conditions as they migrated to their respective spawning grounds. Once on the spawning grounds, the *reproductive success* sub-model was applied, which simulated redd creation and egg-to-fry survival. Next, there were several transitions that occur for newly hatched fish: *fry survival, parr survival,* and *pre-smolt survival*. In each of these sub-models if there were more fish than suitable habitat, excess fish migrated downstream towards the ocean. Thus, it was possible to migrate to the ocean as a fry, parr, pre-smolt. Fish that did not migrate remained to survive to the next life stage until they become smolts, after which they migrated to the ocean. The *fry, parr, pre-smolt and smolt migration success* sub-model was then used to calculate life stage specific juvenile-to-adult survival rates. These rates were applied to outmigrating fish to determine the number of ocean dwelling adults produced. Lastly, there was the *hatchery smolt migration success* sub-model which determined the contribution of hatchery fish to the number of ocean dwelling adults.

1 - *Ocean harvest and in-river survival*

The model started with a spawning cohort of adult salmon ($X_{ocean,j}$) from a single watershed (j) that returned from the ocean to spawn in their natal streams. Fall run salmon begin returning to their natal streams beginning in July and continue through December. Once the spawning cohort was identified, total escapement ($X_{escape,j}$), the number of salmon that arrive to the spawning areas was estimated as,:

[1] $X_{escape,j} = X_{ocean,j} \cdot s_{comm,j} \cdot s_{rec,j} \cdot s_{adult,j}$,

where $s_{comm,j}$ was the probability of surviving ocean commercial fishing, $s_{rec,j}$ was the probability of surviving freshwater recreational angling, and $s_{adult,j}$ was baseline survival. The commercial and recreational survival rates varied by watershed and were random draws from a beta distribution whose mean and standard deviation are provided in Table 3.1. Due to a lack of other information, the beta distribution was parameterized using method of moments estimation. The survival rate $s_{adult,j}$ was calculated using logistic regression:

[2] $logit(s_{adult,j}) = \boldsymbol{X}_{adult,j}\boldsymbol{\beta}_{adult}$,

where $\boldsymbol{X}_{adult,j}$ was a random vector of independent environmental covariates for the adult survival in watershed j and $\boldsymbol{\beta}_{adult}$ was a random vector of independent regression coefficients for adult survival. The values and distributions used to parameterize the elements of these vectors can be found in Table 3.4 for $\boldsymbol{X}_{adult,j}$ and Table 3.7 for $\boldsymbol{\beta}_{adult}$. Finally, the value of $s_{adult,j}$ as found using the inverse logit function:

[3] $s_{adult,j} = \left(e^{X_{adult,j}\boldsymbol{\beta_{adult}}}\right) \Big/ \left(1 + e^{X_{adult,j}\boldsymbol{\beta_{adult}}}\right)$

Run Timing

Run timing was incorporated into the model as a means to incorporate the effect of environmental factors (e.g. temperature) that can delay returning adult migration. Run timing was modeled using a triangle distribution that is parameterized using dates for the start, peak, and end of the run (Table 3.1). The peak of the run was assumed to be the mid-point between the beginning and the end of the run (Table 3.1). The model tracked three groups of salmon: early, mid, and late spawners. These groups will correspond to the 0-33%, 33-66% and 66-100% tertiles respectively.

Migration delays cause more salmon to enter natal watersheds at the same time, which may affect adult survival and spawning success. Run delays (in weeks) were calculated using a simple linear equation:

[4] $delay_j = \boldsymbol{X_{delay,j}} \cdot \boldsymbol{\beta_{delay}}$

where $\boldsymbol{X}_{delay,j}$ was a vector of environmental predictors for watershed *j* where the first element equal to 1 (Table 3.4), $\boldsymbol{\beta}_{delay}$ was a vector of linear coefficients, and *delay* is the number of weeks a run may be delayed (Table 3.7). The value of *delay* was added to the value of the start date of the run and a new triangle distribution was calculated. The original tertile cutoffs were retained and still used to determine the early, mid and late groups of salmon. This process ensures that if a run delay occurred, more fish were pushed into the mid and late groups, which created more competition during the escapement process for spawning habitat.

For sake of simplicity, I will only describe the remainder of the model in terms of single run timing group, however the model did track all three groups in unison within each watershed. The model followed the cohorts of offspring that were produced by each run timing group, thus the model allows run timing groups to influence each other. For instance, if fish in the early group occupy habitat, it is unavailable to fish in the mid and late groups.

2 - *Reproductive success*

Spawning typically occurs from early October through late December. Once the number of escaped adults was set, the number of fry produced (fry_j) by those adults was estimated as:

[5] $fry_j = redd_j \cdot fecund_j \cdot s_{egg,j}$

where $redd_j$ was the number of redds produced in watershed j, $fecund_j$ was fecundity, and $s_{egg,j}$ was the egg-to-fry survival in watershed j. Fecundity ($fecund_j$) was a random sample from the distribution (Mills et al. 2004):

[6] $fecund_j \sim Normal(5522{,}1104)$

The value of $redd_j$ was calculated by dividing the total amount of suitable spawning habitat in each watershed ($Hab_{spawn,j}$, m^2) by the mean redd size ($reddsize_j$, m^2) to determine each watershed, j, redd capacity ($reddcap_j$). The value of $Hab_{spawn,j}$ was dependent on if it's a "wet" or "dry" scenario, each occurred with an equal probability. The variable $reddsize_j$, was a random sample from a normal distribution with mean 12.38 and a standard deviation 2.48.

The number of viable redds created, $redd_j$, follows:

[7] $$redd_j = \begin{cases} reddcap_j, & X_{escape,j} \cdot p_{female} > reddcap_j \\ X_{escape,j} \cdot p_{female}, & otherwise \end{cases}$$

where p_{female} was the proportion of females in the population. Equation 7 represented the process of how redds can be superimposed on top of one another (Gallagher and Gard 1999). The assumption is that if the entire spawning habitat was occupied, another salmon could dig a new redd on top of an existing redd, effectively destroying the first redd. This process occurred across run timing groups, with later spawning groups super imposing redds on top of earlier run timing groups. Lastly, the variable $s_{egg,j}$ was calculated using the same process outlined in equations 2-3. The vectors $\boldsymbol{X}_{egg,j}$, and $\boldsymbol{\beta}_{egg}$ were parameterized using the relevant values from tables 4-8.

3 - *Fry habitat and fry survival*

At this point, fry could either remain in freshwater to rear to parr or migrate to the ocean (Figure 3.3). This portion of the model represents the first two months after hatching (January – February). This process was directly regulated by the amount of available fry habitat. The number of parr produced ($parr_j$) at this step was calculated as:

[8] $$parr_j = rearfry_j \cdot s_{fry,j},$$

where $rearfry_j$ as the number of fry that remain in watershed j to rear, and $s_{fry,j}$ was the fry-to-parr specific survival rate. The calculation of $s_{fry,j}$ used the same process outlined by equations 2-3. However, for this calculation the vectors $\boldsymbol{X}_{fry,j}$ and $\boldsymbol{\beta}_{fry}$ were parameterized using the relevant values from tables 4-8.

The number of salmon fry that remained in the stream to rear to parr ($rearfry_j$) and the number of fry that migrated out of their natal watershed as fry ($migfry_j$) were calculated using the following rule set:

[9] $$migfry_j = \begin{cases} fry_j - frycap_j, & fry_j > frycap_j \\ 0, & otherwise \end{cases}$$

[10] $$rearfry_j = \begin{cases} frycap_j, & fry_j > frycap_j \\ fry_j, & otherwise \end{cases}$$

where $frycap_j$ was the habitat carrying capacity for fry in watershed j. Habitat carrying capacity was calculated as:

[11] $$frycap_j = \frac{hab_{fry,j} + FloodHab_{fry,j}}{terr_{fry,j}}$$

where $hab_{fry,j}$ was the amount of in-stream fry habitat in watershed j, $FloodHab_{fry,j}$ was the amount of floodplain fry habitat in watershed j (Table 3.3) and $terr_{fry,j}$ was the average amount of territory a fry occupies. The value of $hab_{fry,j}$ was dependent on if it was a “wet” or “dry” scenario, each occurred with an equal probability. To calculate $terr_{fry,j}$ I used the fork length – territory size relationship found in Grant and Kramer (1990):

[12] $$terr_{fry,j} = L_{fry}{}^{2.61} \cdot 10^{-2.83}$$

where $L_{fry,j}$ was the fork length of a fish (cm). For this calculation, I assumed that fry were 3.75 cm in length (Mills et al. 2004).

The last component of the fry rearing process was routing outmigrant fry through their respective downstream rearing habitats. Juveniles that originated upstream of the Lower-mid Sacramento or the San Joaquin were allowed to rear for 2 months in these habitats as they passed through. The total number of migrant fry above the lower-mid

Sacramento and the San Joaquin was calculated and was compared to the total fry capacity in each downstream rearing stream. The number of individuals allowed to stay and rear to parr and the number of fry that were forced to continue their journey to the ocean was determined using the same procedures outlined in equations 8 – 12 but with habitat values from the lower-mid Sacramento and the San Joaquin.

4 - *Parr habitat and parr survival*

The parr to pre-smolt transition used an identical set of rules as the fry to parr transition, but with parr specific habitat and fish length values. This portion of the model represents another two months (March – April) following the fry submodel. In this step, parr could either remain in the watershed to rear to pre-smolts or migrate to the ocean as a parr. The parr to pre-smolt transition was calculated by:

[13] $presmolt_j = rearparr_j \cdot s_{parr,j}$

where $rearparr_j$ was the number of parr that remained in the watershed to rear to pre-smolts and $s_{parr,j}$ was parr-to-pre-smolt transition rate. The calculation of $s_{parr,j}$ used the same process outlined by equations 2-3. However for this calculation, the vectors $\boldsymbol{X}_{parr,j}$ and $\boldsymbol{\beta}_{parr}$ were parameterized using the relevant values from Tables 4-8.

The number of rearing parr, $rearparr_j$, depended on the amount of parr habitat, $parrhab_j$, available in each watershed j. Specifically, this relationship used the rule set:

[14] $$migparr_j = \begin{cases} parr_j - parrcap_j, & parr_j > parrcap_j \\ 0, & otherwise \end{cases}$$

[15] $$rearparr_j = \begin{cases} parrcap_j, & parr_j > parrcap_j \\ parr_j, & otherwise \end{cases}$$

where $parrcap_j$ was the habitat carrying capacity for parr in watershed j and was calculated as:

$$[16] \quad parrcap_j = \frac{hab_{parr,j} + FloodHab_{parr,j}}{terr_{parr,j}}$$

where $hab_{parr,j}$ was the amount of parr habitat in watershed j, $FloodHab_{parr,j}$ was the amount of floodplain parr habitat in watershed j (Table 3.3) and $terr_{parr,j}$ was the average amount of territory a parr occupies. The value of $hab_{parr,j}$ was dependent on if it’s a “wet” or “dry” scenario, each occurred with an equal probability. Parr territory size was calculated using eq. 12, except using the average length of a parr, L_{parr} (4.2 cm ,(Mills et al. 2004)).

$$[17] \quad terr_{parr,j} = {L_{parr}}^{2.61} \cdot 10^{-2.83}$$

The last component of the parr rearing process was routing outmigrant parr through their respective downstream rearing habitats. Juveniles originating upstream of the Lower-mid Sacramento or the San Joaquin were allowed to rear for two months in these habitats as they passed through. The total number of migrant fry above the lower-mid Sacramento and the San Joaquin was calculated and was compared to the total fry capacity in each downstream rearing stream. The number of individuals allowed to stay and rear to presmolts and the number of parr that were forced to continue their journey to the ocean was determined using the same procedures outlined in equations 13 – 17 but with habitat values from the lower-mid Sacramento and the San Joaquin.

5 - *Presmolt habitat and presmolt survival*

The pre-smolt to smolt transition was the last of the in-stream rearing processes in a given year. This process takes place across two months during May – June. After a juvenile Chinook becomes a smolt they cease rearing and immediately begin their migration out of their natal stream into the ocean. The transition from pre-smolt to smolt follows and identical rule set as the previous rearing transitions. The number of migrating smolts is calculated by applying a survival rate to the number of rearing pre-smolt juveniles in watershed j:

[18] $smolt_j = rearpresmolt_j \cdot s_{presmolt,j}$

where $rearpresmolt_j$ was the number of pre-smolts that remain in the watershed to rear to smolts and $s_{presmolt,j}$ was pre-smolt-to-smolt transition rate. The calculation of $s_{presmolt,j}$ used the same process outlined by equations 2-3. However for this calculation the vectors $\boldsymbol{X}_{presmolt,j}$ and $\boldsymbol{\beta}_{presmolt}$ were parameterized using values from tables 4-8.

The number of rearing pre-smolts, $rearpresmolt_j$, was calculated based on the amount of habitat available for pre-smolts to rear in. Similar to the rearing processes in the previous sections, the calculation of $rearpresmolt_j$ follows:

[19] $$migpresmolt_j = \begin{cases} presmolt_j - presmoltcap_j, & presmolt_j > presmoltcap_j \\ 0, & otherwise \end{cases}$$

[20] $$rearpresmolt_j = \begin{cases} presmoltcap_j, & presmolt_j > presmoltcap_j \\ presmolt_j, & otherwise \end{cases}$$

where $presmoltcap_j$ was the habitat carrying capacity for pre-smolts in watershed j and was calculated as:

[21] $$presmoltcap_j = \frac{hab_{presmolt,j} + FloodHab_{presmolt,j}}{terr_{presmolt,j}}$$

where $hab_{presmolt,j}$ was the amount of pre-smolt habitat in watershed j, $FloodHab_{parr,j}$ was the amount of floodplain parr habitat in watershed j (Table 3.3) and $terr_{presmolt,j}$ was the average amount of territory a pre-smolt occupies. The value of $hab_{presmolt,j}$ was dependent on if it's a "wet" or "dry" scenario, each occurred with an equal probability. Pre-smolt territory size was calculated using eq. 12, except using the average length of a parr, L_{parr} (7.2 cm; Mills et al. 2004).

[22] $$terr_{presmolt,j} = {L_{presmolt}}^{2.61} \cdot 10^{-2.83}$$

The last component of the presmolt rearing process was routing outmigrant presmolt through their respective downstream rearing habitats. Juveniles originating upstream of the Lower-mid Sacramento or the San Joaquin were allowed to rear for two months in these habitats as they passed through. The total number of migrant fry above the lower-mid Sacramento and the San Joaquin was calculated and was compared to the total fry capacity in each downstream rearing stream. The number of individuals allowed to stay and rear to smolts and the number of presmolts that were forced to continue their journey to the ocean was determined using the same procedures outlined in equations 18 – 22 but with habitat values from the lower-mid Sacramento and the San Joaquin.

7 - *Fry, parr, pre-smolt, and smolt migration and ocean survival*

There were four classes out-migrant juveniles at this point in the model, $migfry_j$, $migparr_j$, $migpresmolt_j$ and $smolt_j$. Each of out-migrant size class migrated from their natal watershed, j, to the ocean to grow into adults. The total number of naturally produced adults from each watershed j was calculated as:

[23] $$adult_{natural,j} = adult_{fry,j} + adult_{parr,j} + adult_{presmolt} + adult_{smolt,j}$$

where $adult_{fry,j}$, $adult_{parr,j}$, $adult_{presmolt,j}$, and $adult_{smolt,j}$ were the number of adults produced by each of the juvenile out-migrant life stage. The juvenile-to-adult transition is calculated by applying a life stage specific out-migrant survival rate to each of the juvenile out-migrant classes:

[24] $adult_{fry,j} = migfry_j \cdot s_{frymig,j}$

[25] $adult_{parr,j} = migparr_j \cdot s_{parrmig,j}$

[26] $adult_{presmolt,j} = migpresmolt_j \cdot s_{presmoltmig,j}$

[27] $adult_{fry,j} = smolt_j \cdot s_{smoltmig,j}$

The calculations of $s_{frymig,j}$, $s_{parrmig,j}$, $s_{presmoltmig,j}$, and $s_{smoltmig,j}$ use the life stage relevant vectors $\boldsymbol{X}$ and $\boldsymbol{\beta}$ were parameterized using the relevant estimates in tables 4-8.

Hatchery smolt migration success

A few watersheds (American, Feather, Battle Creek, and Mokelumne Rivers) have hatcheries that supplement their populations of Chinook salmon. These hatcheries release smolts both into their respective streams and directly into the delta, where they then migrate to the ocean. Annual releases range from just over 7 million to just under 3 million on average between all three hatcheries. This process is represented by:

[28] $adult_{hatchery,j} = smolt_{hatch,j} \cdot s_{smoltmig,j} \cdot hatchadj$

where $adult_{hatchery,j}$ was a random variable that represents the number of hatchery origin smolts, $smolt_{hatch,j}$, and $hatchadj$ were a survival adjustment parameter. The adjustment parameter was a constant value and represents the comparatively lower survival hatchery origin smolts typically experience (Quinn 1993). Currently $hatchadj_j$ takes a value of 0.14.

7 - *Adult Age Structure*

Next the number of naturally produced adults, $adults_{natural,j}$, and the number of hatchery origin adults, $adults_{hatch,j}$, were assigned ages that they will return to freshwater to spawn. In the Central Valley fall-run Chinook salmon spend between two to five years in the ocean before returning to their natal stream to spawn. The majority of fall-run Chinook salmon spend three or four years residing in the ocean. This process is modeled using a multinomial distribution:

[29] $$\boldsymbol{x}_{ocean,j,l} \sim multinomial\left(\left(adults_{natural,j} + adults_{hatch,j}\right), \boldsymbol{p}_{return}\right)$$

[30] $$\boldsymbol{p}_{\boldsymbol{return}} = [0.13\ 0.85\ 0.015\ 0.005]$$

where $\boldsymbol{x}_{ocean,j,l}$ was a vector where each element represents the number of ocean adults from watershed j in the ocean residence class l= 2, 3, 4, or 5 years and $\boldsymbol{p}_{return}$ was the associated probability vector for each class l (Palmer-Zwahlen and Kormos 2015).

Initial Conditions and Simulations

The model was initiated using escapement values from 2009 – 2013 (California Department of Fish and Wildlife 2015). Because of the lag caused by ocean residence times, the model required to be seeded with five years of escapement data. This was also the rationale for letting the model run for at least 6 years during any model evaluation or sensitivity analysis.

The base population model was simulated 50,000 times at each time step to ensure the system uncertainty was adequately captured. In each simulation, new values for every random process were sampled. The sampling distributions for each randomly distributed parameter are found in tables 1 – 8. The results of the simulations for each year were averaged before any relevant information (e.g. run size, proportion hatchery fish, ect…) was passed into the next time step. At every time step the relevant information to calculate each component of the utility function was also reported.

Model Calibration

The model was calibrated to ensure the estimated escapement in was relatively accurate for of each watershed. The calibration was necessary because without it the model reproduced unrealistic population dynamics (e.g. exponential growth) in several of the watersheds. To ensure that the model was able to produce reasonable population dynamics, I chose to calibrate the intercept terms on all the out-migration survival rates. The utility value that I wanted to minimize during the calibration was the absolute difference between the estimated escapement value in 2014 and the actual escapement values for that same year summed across all the watersheds. I seeded the model with escapement values in each watershed from 2009 to 2013 to estimate the 2014 escapement values. This was necessary to allow fish from each age class to contribute to the estimated escapement in 2014.

I used a genetic algorithm found in the R package *rgenoud* (Mebane and Sekhon 2011) to derive intercept values for the migratory survival rates that was used in each watershed. A total of three parameters were subject to the calibration optimization. A heuristic method such as a genetic algorithm is ideal for solving this kind problem that requires simultaneous fitting of several interdependent parameters. I constrained the optimization to only consider combinations of parameters that would result in $s_{frymig} <$

$s_{parrmig} < s_{smolt}$. This constraint meant that the baseline outmigrant survival rate would increase as the size of the outmigrant also increased. I used the default number of generations, iterations, and population size found in the *rgenoud* package.

Utility Calculation

For this decision problem, the primary utility is the total number of naturally produced adult equivalents per escapee:

$$[31] \quad U_t = {\sum_j adults_{natural,j}}\Big/{\sum_j X_{escape,j}}$$

where U_t is the total utility at time step t. This utility was the metric that I maximized during policy optimization. It should also be noted that the parameter $X_{\text{escape,j}}$ includes both wild and natural origin escapees. In the utility value the total number of adult equivalents produced was standardized by the total number of escapees so the utility value represented a mean per capita production rate. This utility definition prevented any differences in escapement from influencing optimal restoration strategies.

Policy Optimization

I structured this decision problem as Markovian Decision Process and used dynamic programming to derive a set of optimal policies. The goal of solving an MDP is to find a set of decisions or actions that maximize the cumulative utility value through time while simultaneously accounting for various inherent sources of stochasticity. In addition, they are computationally more consistent and efficient than heuristic methods or grid search optimization routines.

These problems can be generally formalized in discrete time as:

[32] $$\max_{[\boldsymbol{d}(t)\in\boldsymbol{D}]} \sum_{t=t_0}^{t_f} \gamma^t \cdot F(\boldsymbol{x}, \boldsymbol{d}, \boldsymbol{z}, t) + F_T\left[\boldsymbol{x}\left(t_f\right)\right]$$

subject to:

$$\boldsymbol{x}(t+) = \boldsymbol{x}(t) + f(\boldsymbol{x}, \boldsymbol{d}, \boldsymbol{z}, t)$$

[33] $$\boldsymbol{x}(t_0) = \boldsymbol{x_0}$$

$$\boldsymbol{x}(t) \in \boldsymbol{X}$$

where $F()$ is a time specific utility function, $F_T()$ assigns a terminal value to the system, $\boldsymbol{x}$ is a vector of system states, $\boldsymbol{d}$ is a vector of time-specific decisions or actions, $\boldsymbol{z}$ is a vector of random variables influencing dynamics but not under decision control, γ is a discount factor and $f()$ describes system dynamics. In other words, we want to maximize the function $F()$ over time steps t_i for $i = 0,1,\ldots, f$, given system dynamics in the function $f()$. I assumed the parameter γ to have a constant value of 0.99 for these analyses. As the constraints in equation 33 indicate, this is a Markov process, meaning that the value of $\boldsymbol{x}(t+1)$ is only dependent on the value of $\boldsymbol{x}$(t) and the system dynamics, $f(\boldsymbol{x},\boldsymbol{d},\boldsymbol{z},t)$, at time t. Thus, we can invoke the principle of optimality (Bellman 1957) and use backwards induction to optimize our utility function. Consider the Hamilton-Jacobi-Bellman (HJB) equation:

[34] $$J^*[\boldsymbol{x}(t), t] = \max_{[\underline{d}(t)\in\underline{D}]} [F(\boldsymbol{x}, \boldsymbol{d}, t) \cdot \gamma^t + J^*(\boldsymbol{x}(t+1), t+1)]$$

Equation 34 states that a decision at time t (assuming time steps of 1) is only optimal if all the remaining decisions are also optimal. Under this framework, we can derive an entire set of optimal decisions by finding the optimal decision at the final time step, t_f, then working backwards to find the optimal decision at t_{f-1}. This process is repeated until an entire set of optimal decisions is found for the entire time series $[t_0,t_f]$. In the end, this process guarantees an optimal decision set when they are implemented forwards in time. If this process is repeated over a long enough time frame, the vector $\boldsymbol{d}(t,x)$ may converge to a set of a set of stationary, state-specific optimal decisions. This process of is known as policy iteration because it provides the optimal decision for each possible system state. Given the unintuitive nature of inductive reasoning, the formal proof can be found in either Bellman's (1957) article or Bathers (2000) text.

To simplify solving equation 34 and deriving a time-specific set of optimal decisions, we can define the HJB equation as using transition probabilities to create a Markov chain of system dynamics. If we define the conditional probability of being in state $\boldsymbol{x}_{t+1}$ at time t+1 as:

[35] $\pi(\boldsymbol{x}_{t+1}|\boldsymbol{x}_t,\boldsymbol{d}_t)$

then the HJB equation can be rewritten as:

[36] $$J^*[\boldsymbol{x}(t),t] = \max_{[\underline{d}(t)\in\underline{D}]}\begin{bmatrix}\overline{F}(\boldsymbol{x},\boldsymbol{d},t)\cdot\gamma^t + \\ \sum_{x_{t+1}}\pi(\boldsymbol{x}_{t+1}|\boldsymbol{x}_t,\boldsymbol{d}_t)J^*(\boldsymbol{x}(t+1),t+1)\end{bmatrix}$$

where $\overline{F}(\boldsymbol{x},\boldsymbol{d},t)$ is the expected utility for the next immediate time step.

The dynamic programming approach for solving a MDP described above provides the framework I used to solve the decision problem in this chapter. The utility function ($F(\boldsymbol{x},\boldsymbol{d},t)$) for this problem was the same as equation 31. Next, I derived transition probability matrices ($\pi(\boldsymbol{x}_{t+1}|\boldsymbol{x}_t,\boldsymbol{d}_t)$) using the salmon decision model for a single time step. I chose to define the system state as discrete combinations of fry rearing habitat and spawning habitat in an individual watershed (see section below). Using this definition of system states, I was able to generate optimal management alternatives for any given watershed given its current habitat configuration.

System State Definition

I chose to define the system state as the configuration of two different habitat types in a single watershed. The system state for any watershed was made up of three pieces of observable information: the number of spawning females, the total amount of spawning habitat (m^2), and the total amount of juvenile rearing habitat (m^2). A combination of these variables defined the two dimensional state-space as a whole:

[37] $$x_{s,w} = \left[\frac{Spawnhab_{s,w}}{Redd}, \frac{FryHab_{s,w}}{Redd}\right],$$

where *s* represented whether the watershed was composed of a large or small tributary, and *w* represented the salmon diversity watershed grouping (Fig. 2). The indexing in equation 37 meant that a separate policy was derived for watersheds with both large and small tributaries in each salmon evolutionary diversity group. Tributary size was important to consider in the system-state definition because populations in small and large tributaries may respond differently to habitat restoration projects. The salmon diversity grouping provided a way to incorporate a spatial component to the system state definition. It's more likely that streams that are in close proximity and share similar characteristics will react in similar ways to habitat restoration projects. Additionally, the salmon diversity grouping is a metric already used by local managers. The combinations of tributary size and salmon diversity groupings resulted in a total of 7 policies (the Northwestern California diversity grouping was only included watersheds with large tributaries).

This definition of the system state required discretize values, rather than continuous to implement the HJB equation presented above. I discretized both the habitat dimensions of the defined states into bins of 50 in the range of 0 to 1000+ (21^2 total habitat states). This range and binning was chosen so the effect of each decision (or no decision) would have an effect on future system states and it also reflected the potential range of state values possible in CVPIA administered watersheds.

Under these state definitions, I calculated both transition matrices (π) and the reward function ($\overline{F}(\boldsymbol{x}, \boldsymbol{d}, t)$) for each combination of watershed size and salmon diversity group. To calculate the transition matrices, I simulated a single time step for every system state configuration. The new system state configurations was recorded after decision was implemented. This process was repeated 10,000 times for each decision alternative and allowed to me determine state specific transition probabilities for a given management action. Simultaneously, I calculated the utility (total number of naturally produced adults) after implementing each decision. These values were averaged across the system states, x, to determine the expected state-specific reward for each decision $\overline{F}(\boldsymbol{x}, \boldsymbol{d}, t)$. I assumed the discount parameter, γ, was equal to 0.99. All analyses were programmed and run in the statistical program *R* (R Core Team 2018).

Forward Simulation

I simulated 50 years of decision making using the salmon decision model described above. In each simulation year, the optimal decision in each watershed was identified using the relevant optimal policy for each watershed. The current amount of habitat in each watershed was assumed to be known and observable. The number of redds present in particular watershed, for a given year was not likely to be directly observable in time to implement a decision in the same year. Typically, the number of redds in watershed are estimated using carcass counts, aerial photography, or another escapement based estimation process after the spawning season (Williams 2001, Gallagher and Gallagher 2005). I calculated the mean redd count over the previous five years in each watershed to account for the lag in redd estimation and the variability in redds that occur between years. The mean redd count was used with the habitat information to determine the optimal decision in each watershed using the appropriate policy. The optimal decision was identified in each of the 25 watersheds, which resulted in a set of 25 decision alternatives. The single decision that maximized the utility was chosen from that set to be implemented in that year. The single decision alternative that was implemented was the one that maximized the utility function. This process was repeated for every year of the simulation. A complementary set of simulations was performed where no actions were implemented across the same time horizon to provide a comparative control. Each simulation began with the same initial starting parameters with 10,000 simulations taken for each year.

Sensitivity Analyses

One-way sensitivity analysis

I ran a one-way sensitivity analysis by estimating the utility value while varying the mean value of each of the population model's parameters (Tables 1 - 8) by +50% and -50% while holding all the remaining model parameters at their expected values. The utility value was calculated after a six time steps for every parameter perturbation. This process isolates the influence that each individual parameter can have on the utility function value and demonstrates how influential parameters are relative to one another. If a mean value wasn't available (e.g. due to the multinomial distribution used to determine predator prevalence), it was varied across its full range of effects (e.g. low and high). A parameter is considered influential if the utility value responds while the parameter is varied between +50% and -50% of its original value. Due to the large number of parameters in this model (+100), I divided the parameters into two groups: environmental inputs and biological parameters (Tables 1 – 8). Environmental inputs are reflect environmental conditions whereas biological parameters are parameters that are used to estimate survival and transition rates. Additionally, in this sensitivity analysis I perturbed the parameter of interest across all 27 watersheds simultaneously to gage the parameter's influence at the full spatial extent of the model rather than just an individual watershed.

Survival sensitivity analysis

I also performed sensitivity analysis to determine juvenile in-river survival and outmigrant survival influence the number of naturally produced adult equivalents given current habitat conditions. The goal of this analysis was to provide some insight on how these groups of influential parameters interact with one another. This analysis was a two-way sensitivity analysis but instead perturbing two individual parameters, I'm perturbed two groups of parameters. The survival rates were divided into two groups: in-river survival (s_{fry}, s_{parr}, $s_{presmolt}$) and outmigrant survival (s_{frymig}, $s_{parrmig}$, $s_{smoltmig}$). The total number of naturally produced adults was estimated in a single time step while these groups of parameters were varied across ±50% of their estimated mean value. The survival rates were perturbed across all the watersheds during this analysis. All the other model parameters and inputs were held constant at their mean values.

Response Profiles

A response profile sensitivity analysis evaluates how the identity of optimal decisions vary across a range of values of one or more parameters. A one-way response profile sensitivity analysis is similar to the one-way sensitivity analysis, in that a single parameter is perturbed at a time. However, instead of focusing how different parameters affect the utility, these analyses evaluate how the optimal decision alternative may change across a range of parameter values. In other words, it answers the question, "would your optimal decision be different if this individual parameter took a different value?" I varied the value of each parameter in the model across a range of ±50% of its mean value using 5% intervals while all the other parameters were held at their expected values. For every value of the parameter being varied, all the decision alternatives were applied and the decision with the greatest utility value was reported. So for any given parameter, I can determine if the optimal decision changes across a range of its values and where (at what value) those changes occur in that range.

Results

Population Model Performance

In general, the population model was able to represent target the population dynamics within all 26 populations at the watershed level, however the calibration was unable to exactly match the target escapement levels. The model overestimated escapement for watersheds with lower targets and underestimated escapement for watersheds with higher targets (Figure 3.4). This was due to interactions among the watersheds in the model. Many of the watersheds shared the downstream rearing habitats (lower-mid Sacramento and San Joaquin Rivers), which made some of the watersheds highly dependent on each other. Also, the parameters I chose to calibrate ended up being highly sensitive parameters (see below). Small perturbations in these values had large impacts on escapement and natural production levels. Despite these issues I believe the calibration provided escapement estimates that are adequate for the purposes of this study.

Simulated escapement levels were constant with little fluctuation due to density dependence induced by habitat limitations in several watersheds (Figure 3.5 -3.7). However, the current simulated production estimates show that production was still well below the doubling goal of 750,000 fish (Figure 3.8). The streams with the largest estimated escapement were the American and Feather Rivers in the Sacramento Basin and Merced River in San Joaquin Basin. Many of the watersheds sustained escapement levels that are almost nonexistent such as Bear Creek or Paynes Creek. Additionally, the number of adult equivalents produced in each year followed very similar patterns (Figures 5 -7). The population model was stable (e.g., populations are not unexpectedly increasing or decreasing exponentially), which allowed me to evaluate the influences of decision alternatives effectively. Current habitat conditions and mean survival rates were used in the model and did not move through time. This is the primary reason why the population model appears to be so stable.

All of the juvenile out-migrant life history strategies were also represented in the population model and contributed to the overall production of adult equivalents (Figure 3.9 and 3.10). The model estimated that juvenile fall-run Chinook salmon migrate to the ocean as fry, parr or smolts to some degree in almost all of the CVPIA streams. However, the vast majority of juveniles were estimated to leave their natal watersheds as fry. The extent to which each life history strategy contributes to natural production changed from watershed to watershed based on watershed specific outmigration survival rates.

Policy Optimization

The policy optimization identified a habitat based, state-dependent optimal policy for a watershed with each combination of watershed tributary size and salmon diversity group. Five of the seven policies had very similar shapes across the different values of spawning habitat per redd and juvenile habitat per redd (Figure 3.11). In these policies the optimal decision was to implement a gravel addition project at the lowest values of spawning habitat per redd. The optimal decision was to implement a floodplain excavation project at the highest values of spawning habitat per redd in these policies as well. The policies derived for watersheds in Southern Sierra Nevada salmon diversity group were no similar to the other policies. In these streams the optimal decision wasn't determined by the amount of juvenile habitat per spawner, instead the value of spawning habitat per spawner solely determined the optimal decision. Additionally, the decision to "do nothing" was only optimal in small tributaries in the Southern Sierra Nevada grouping. The differences in the derived policies highlights how differences in survival rates can influence what the optimal decision is for a particular combination of habitats.

Forward Simulation

The forward simulation using the optimal policies resulted in both types of habitat restoration projects being implemented across several different watersheds (Figure 3.12). Only 9 different watersheds were selected to have projects implemented in them using the policies. Stony Creek had the most habitat projects implemented (9) while Antelope Creek had the fewest (1). Spatially, projects were not concentrated in a single region or area. In almost half the years (23) projects were implemented in watersheds in the Norther Sierra Nevada salmon diversity group. Watersheds belonging to the Northwest California diversity group had the next largest number of projects (18), followed by watersheds in the Southern Sierra Nevada diversity group (5) and watersheds in the Basalt and Porous Lava diversity group (4). Implementing a floodplain excavation project was only optimal in seven of the 50 years simulated with gravel additions being the optimal decision in other 43 years of the simulation.

Implementing the optimal policy resulted in large gains in both escapement and natural production during the 50 year simulation (Figure 3.8). At the end of the simulation where the optimal policies were used total natural production had climbed to just under 500,000 adults and total escapement has increased almost 300,000 total individuals. Both these metrics represent large increases relative to the simulation where no actions where implemented. This means that on average the number of natural origin adults produced by each escapee increased as a result from implementing the optimal policy (Figure 3.13).

Sensitivity Analyses

One-way sensitivity analysis

The one-way sensitivity analyses on the model parameters showed that baseline fry outmigration rate (s_{frymig} intercept, Table 3.8) had the largest influence on the utility value (Figure 3.14). The effect of this single parameter was several times greater than any other model parameter in the model, which isn't surprising given how many outmigrant fry are produced system wide. The next most influential parameter was the baseline adult survival rate ($\mathrm{s}_{\mathrm{adult}}$ intercept, Table 3.8). Four of the six most influential parameters were all related intercept parameters used to calculate juvenile in-river or out-migration survival rates.

As mentioned above, two separate one-way sensitivity analyses to evaluate the environmental inputs, one for a wet year (high precipitation) and one for dry year (low precipitation; Figures 15 - 16). The top five most influential environmental parameters were identical in both the wet and dry conditions. The most influential parameter in both cases was the amount of spawning habitat. This was followed closely by the parameter that represents the proportional size of the pulse of water that occurs when fry are out-migrating from the system. The next three most influential parameters were the instream temperature during presmolt rearing, the amount of fry habitat, and the amount of fry floodplain habitat. Three of the five most sensitive parameters are used to calculate fry out-migration survival or are related to fry habitat. For comparison, the amount of parr and presmolt habitats were all in the bottom quarter of the most influential parameters.

None of the parameters used to calculate reproductive success or adult survival were very influential to the utility value (Figure 3.14). The early life history portions of the model (e.g. fry survival) seemed to have the largest influence on the overall utility value for these populations. The one-way sensitivity analysis of model inputs (Figure 3.15 – 3.16) indicated that fry rearing temperature and fecundity are the most influential environmental parameters. Surprisingly, none of the temperature effects on out-migrant juveniles had much influence on the overall utility value. The parameter that resulted in the largest increase in utility from the one-way analysis was the fry rearing temperature and the parameters that resulted in the largest decrease in utility values was fecundity and the amount of stream available for anadromous species. The one-way sensitivity analysis for estimated model parameters showed that the effect of temperature on fry survival and parr survival were the most influential on production. Overall, the environmental parameters appear to have a much larger influence over utility values than the estimated biological parameters.

Survival Analysis

The two-way survival sensitivity analysis showed that increases to outmigrant survival are more likely to achieve the natural production recovery goal compared to increases to in-river survival (Figure 3.17). The influence of in-river juvenile survival rates decreases as outmigration survival increases. At the current rates of survival, total natural production appeared to be more sensitive to outmigrant survival compared to in-river survival rates. Figure 3.17 demonstrates that under the current habitat conditions and configurations it may be possible to reach the doubling goal with increases to either class of juvenile survival.

Response Profiles

The response profile identified 7 model components that were influential changing the optimal decision in a single time step (Table 3.9). The single most influential component was the logistic intercept term used to calculate s_{frymig}. The optimal decision changed a total of three times across ±50% of its original mean value (Figure 3.18). When s_{frymig} has a small value the optimal decision was to implement gravel additions in one of two different watersheds. At larger values, the optimal decision switches to a floodplain excavation project in a third watershed. The amount of spawning habitat was the only influential habitat component. In both wet and dry scenarios the optimal decision changed one, but only at the very low end of the values I evaluated (Figure 3.19). All the other parameters had no influence on the optimal decision across the ranges of values evaluated.

Discussion

In this study, I demonstrated how a dynamic programming approach could be used to derive polices to guide restoration strategies for fall-run Chinook salmon in California's Central Valley. The results of the policy optimization suggest that focusing efforts on single watershed is an effective habitat restoration strategy. During the forward simulation, the optimal strategy included the implementation of a specific decision alternative in a single watershed for several years at a time. This suggests that spreading efforts across multiple watersheds (e.g. implementing a decision in a new watershed every year) was a suboptimal strategy when maximizing natural production for fall-run Chinook salmon. Allocating restoration efforts to a different watershed only occurred after a specific habitat limitation was fully resolved. Also, during a fifty year simulation there were some watersheds that were never selected for restoration. In fact, only a small number (9) of watersheds were selected for restoration during the forward simulation. This suggests that future habitat restoration activities for Chinook salmon in the Central Valley should be intensively focused on a small number of watersheds.

The appeal of the SDM approach is in its ability to identify key model components and assumptions that are able to alter optimal decision making (Possingham et al. 2001, Conroy and Peterson 2013). All of the parameters that were used to calculate survival rates in this model were parameterized by expert opinion rather than from empirical sources (Table 3.1-3.7). Thus, identifying influential parameters and processes is important when prioritizing future monitoring efforts. Through several sensitivity analyses, I've identified several key parameters whose measures of uncertainty influences optimal decision making for fall-run Chinook salmon in the Central Valley. In the one-way sensitivity analyses, I perturbed the value of a single parameter across all 26 watersheds simultaneously. It's important to keep in mind that these analyses provide a look at how a single parameter may influence natural production at the full spatial extent of this decision problem. I would expect slightly different results if a similar analysis was performed at the individual watershed scale due to the different watershed specific parameter values. Four of the six most influential parameters in the one-way sensitivity analyses were all related intercept parameters used to calculate juvenile in-river or out-migration survival rates. These parameters are influential because they are essentially shifting the entire baseline survival rate for a given life stage. However, if we ignore these intercept parameters, the estimated parameter effects that had the largest effects were all temperature related. Specifically, the in-river 10-day average stream temperature that influences in-river survival was influential to total production. These results suggest that future monitoring should be focused on estimating baseline juvenile survival rates in all the CVPIA streams. Thus future monitoring efforts should be made to minimize the uncertainty around those parameters.

The single fundamental objective in this decision model represents the primary goal of the stakeholders in this decision problem. Ultimately, objectives reflect the values of the stakeholders or decision makers (Conroy and Peterson 2013). The SDM framework provides the opportunity to incorporate and evaluate multiple objectives if necessary. Multiple objectives can be combined into a single utility by using relative weights for different model outputs that represent other objectives. For instance, the scope of this analysis was limited to fall-run Chinook salmon. However, the managers that implement the CVPIA have obligations to other three other runs of Chinook salmon and several other anadromous species. It’s likely that these additional runs and species would be influenced by the decision alternatives evaluated in this analysis and their incorporation into this decision making process would likely yield different strategies for habitat and stream restoration work in the Central Valley.

Broad scale restoration strategies can be difficult to develop due to the high amounts of uncertainty that exist at large spatial extents. In natural resource management, uncertainty often manifests itself as a lack of empirical information. A lack of information can paralyze decision making, resulting in no decisions being implemented. In this study, I addressed the lack of information by making use of expert judgement. Expert judgment may be biased or highly variable, but it still enables managers to model their decision making process. This is important because decision models allow managers to identify the portions of their model that are the most influential to the decision making process. Expert participation also creates more confidence in the final model which results in a decision tool that managers are more likely to use. Identifying influential parameters is essential to prioritizing future study and monitoring. In this study I had to parameterize most the model with expert judgement, but a decision model on this scale would not be possible without it. Instead, I was able to identify several parameters that are highly influential to this decision making process.

Decision problems that operate at large spatial scales often require data to be summarized at large spatial extents and grains. Most freshwater fisheries data and assessment methods are focused on much finer resolutions such as at a reach level (Lewis et al. 1996, Frissell et al. 2001). Data observed at smaller spatial resolutions (e.g. reach or tributary) has to be aggregated when objectives occur at larger spatial scales (e.g. population or watershed; Wager et al. 2006). Aggregating data or processes spatially ignores any heterogeneity present in a system and tends to lead to higher levels of variance and bias in parameter estimates (Clark and Avery 1976). This is referred to as "ecological bias," in which a lot of fine scale data and/or processes (e.g. juvenile rearing and migration) are homogenized in order to be represented at a coarser scale (Greenland and Morgenstern 1989). It's essential that the variance associated with aggregating data is accounted when evaluating decision alternatives. One strength of the SDM process is it can facilitate a quantitative evaluation of the potential of those uncertainties to influence the optimal decision.

The observability of the current system state is a key assumption in dynamic decision problems and should be a consideration when implementing any large scale optimal policy. System states can be classified as being either fully observable or only partially observable to decision makers in dynamic decision problems (Williams 2011, Alpaydin and Bach 2014). In this analysis, I assumed the current system states were fully observable. However, there could arise situations where this assumption would not be valid. For instance, incomplete habitat estimates due to a lack of resources or redds not being estimated in due to the remoteness of the sampling site are situations that could lead to partial observability. Our ability to accurately identify large scale system states can become more difficult if they depend on aggregating fine scale monitoring data. Partially observable Markov decision processes (POMDPs) are an approach to dynamic decisions problems that account for partially observable system states (Monahan 1982, Fackler and Pacifici 2014). POMDPs are extensions of hidden Markov processes, which are like traditional Markov processes except the current system state isn't known with complete accuracy (Ross 2014). The partially observable system states are handled by putting a probability distribution on the system states themselves. POMDPs may be especially useful in large scale decision problems in natural resource management due to the increased levels of environmental uncertainty and potential difficulties of monitoring system states across large areas. However, deriving optimal strategies using a POMDP can be difficult due to a more complex state space, which can limit the complexity of the problem that can be evaluated (McDonald-Madden et al. 2011).

MDPs have some limitations in the application to natural resource decision problems. Infinite horizon MDPs, such as the one presented here, require stationary reward vectors and transition matrices. The stationarity assumption is violated when state-specific transition rates or reward values shift through time. In this analysis I assumed habitat transition rates and the number of salmon produced from decision alternatives were static through time. Climate change is an example of a large scale stressor that could influence those parts of this decision problem. Non-stationary resource dynamics create new issues in decision optimization and dynamic programming (Nichols et al. 2011, Williams 2011). Heuristic approaches (e.g. reinforcement learning, genetic algorithms) can handle nonstationary decision problems, but they do not provide always provide the optimal decision set. Another solution is to assume stationarity for short periods of time and revising solutions optimal solutions periodically (Nichols et al. 2011, Williams and Johnson 2013).

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Tables

Table 3.1 - Descriptions of the 26 watersheds administered by the CVPIA in California's Central Valley . Values for freshwater angler harvest rate, commercial ocean harvest rate, and hatchery smolt release represent the mean with the standard deviation in parenthesis. Values of s_{rec} and s_{comm} used in simulations of the population model were sampled from a beta distribution parameterized using Method of Moments. Simiarly, values of $smolt_{hatch}$ used in simulations of the popualtion model were sampled from a normal distribution.

	Diversity Group	**Run Beginning**	**Run End**	**Watershed Area (ha)**	**Freshwater Angler Harvest Rate**	**Commerical Ocean Harvest Rate**	**Hatchery Smolt Release**
					s_{rec}	s_{comm}	$smolt_{hatch}$
Sampling Distribution					Beta(α,β)	Beta(α,β)	Gamma(α,β)
Watershed							
American River	Northern Sierra Nevada	Sept.	Sept.	490803	0.45 (0.23)	0.4 (0.1)	4709043.33 (371232.55)
Antelope Creek	Northern Sierra Nevada	Oct.	Oct.	31857	0.1 (0.05)	0.4 (0.1)	0 (0)
Battle Creek	Basalt and porous lava	Aug.	Aug.	93240	0.1 (0.05)	0.4 (0.1)	0 (0)
Bear Creek	Basalt and porous lava	Oct.	Oct.	93240	0.1 (0.05)	0.4 (0.1)	0 (0)
Bear River	Northern Sierra Nevada	Sept.	Sept.	75628	0.1 (0.05)	0.4 (0.1)	0 (0)
Big Chico Creek	Northern Sierra Nevada	Aug.	Aug.	18648	0.1 (0.05)	0.4 (0.1)	0 (0)
Butte Creek	Northern Sierra Nevada	Aug.	Aug.	38850	0.1 (0.05)	0.4 (0.1)	0 (0)
Calaveras River	Northern Sierra Nevada	Sept.	Sept.	103600	0.2 (0.1)	0.4 (0.1)	0 (0)
Clear Creek	Northwestern California	Sept.	Sept.	61642	0.1 (0.05)	0.4 (0.1)	0 (0)
Cosumnes River	Northern Sierra Nevada	Sept.	Sept.	191659	0.1 (0.05)	0.4 (0.1)	0 (0)
Cottonwood Creek	Northwestern California	Sept.	Sept.	242941	0.1 (0.05)	0.4 (0.1)	0 (0)
Cow Creek	Basalt and porous lava	Sept.	Sept.	110074	0.1 (0.05)	0.4 (0.1)	0 (0)
Deer Creek	Northern Sierra Nevada	Sept.	Sept.	59311	0.1 (0.05)	0.4 (0.1)	0 (0)
Elder Creek	Northwestern California	Oct.	Oct.	-	0.1 (0.05)	0.4 (0.1)	0 (0)
Feather River	Northern Sierra Nevada	Sept.	Sept.	952080	0.2 (0.1)	0.4 (0.1)	7005944.67 (3940843.92)
Lower-mid Sacramento River	-	Aug.	Aug.	-	0.05 (0.1)	0.4 (0.1)	0 (0)
Merced River	Southern Sierra Nevada	Sept.	Sept.	329705	0.1 (0.03)	0.4 (0.1)	0 (0)
Mill Creek	Southern Sierra Nevada	Sept.	Sept.	34706	0.1 (0.05)	0.4 (0.1)	0 (0)
Mokelumne River	Southern Sierra Nevada	Sept.	Sept.	171198	0.1 (0.05)	0.4 (0.1)	2945667.33 (2588701.62)
Paynes Creek	Southern Sierra Nevada	Oct.	Oct.	-	0.1 (0.05)	0.4 (0.1)	0 (0)
San Joaquin River	-	Sept.	Sept.	3506067	0.05 (0.05)	0.4 (0.1)	0 (0)
Stanislaus River	Southern Sierra Nevada	Sept.	Sept.	278424	0.1 (0.03)	0.4 (0.1)	0 (0)
Stony Creek	Northwestern California	Oct.	Oct.	191659	0.1 (0.05)	0.4 (0.1)	0 (0)
Thomes Creek	Northwestern California	Oct.	Oct.	48692	0.05 (0.05)	0.4 (0.1)	0 (0)
Tuolumne River	Southern Sierra Nevada	Sept.	Sept.	398858	0.1 (0.03)	0.4 (0.1)	0 (0)
Upper-mid Sacramento River	Basalt and porous lava	Oct.	Oct.	-	0.2 (0.05)	0.4 (0.1)	0 (0)
Yuba River	Northern Sierra Nevada	Sept.	Sept.	346799	0.1 (0.05)	0.4 (0.1)	0 (0)

Table 3.2 - The 3 different decision alternatives and their effects for fall-run Chinook Salmon population model fo the Central Valley, CA. Each of the decisions can be implimented on any of the 28 different watersheds/populations. The Effect sizes represent cost equivalent projects.

Decision	**Description**	**Model Component(s) Affected**	**Effect Size**
1.) Gravel Addition	Gravel is added to watershed to increase the total amount of suitable spawning habitat.	*SpawnHab* (wet and dry scenarios)	1194 m^2 increase in spawning habitats
2.) Excavate Floodplain	River banks are excavated to lower the elevation that floodplains are activated at and creates additional floodplain rearing habitat for juvenile Chinook salmon.	$FloodHab_{fry}$, $FloodHab_{parr}$, and $FloodHab_{presmolt}$ (wet and dry scenarios)	7031 (m^2) increase in floodplain rearing habitats.
3.) Do Nothing	No habitat restoration prc	-	-

Table 3.3 - Habitat estimates for fall-run Chinook salmon in each of the 26 CVPIA watersheds. All estimates are in m^2 except holding habitat which is expressed in number of holding pools in each watershed. Habitat values are considered to be constant in popualtion model and are differentiated into wet or dry years.

Watershed	**Holding**	**Spawning**		**Fry**		**Parr**		**Fry Floodplain**		**Parr Floodplain**		**Presmolt Floodplain**	
		Hab_{spawn}		Hab_{fry}		Hab_{parr}		$FloodHab_{fry}$		$FloodHab_{parr}$		$FloodHab_{presmolt}$	
		Wet	Dry	Wet	Dry	Wet	Dry	Wet	Dry	Wet	Dry	Wet	Dry
American River	53	81551	81008	392933	392933	956654	956654	50721	45649	45649	45649	15216	22824
Antelope Creek	240	22666	22666	131680	131680	142473	142473	23876	17509	23876	16714	7163	0
Battle Creek	149	5850	7421	27034	27889	50356	58077	13597	8498	11473	11473	8923	3824
Bear Creek	152	7504	7504	43595	43595	47169	47169	7365	5261	7891	6313	789	0
Bear River	33	15648	15648	0	0	235	235	17941	17941	37676	18838	0	0
Big Chico Creek	87	8728	8728	50705	50705	54861	54861	7891	4856	9105	4553	0	0
Butte Creek	810	61405	61405	503578	503578	721967	721967	29569	22177	33265	24949	11088	2772
Calaveras River	33	33451	33451	107785	107785	78051	78051	35450	23634	22157	17725	0	0
Clear Creek	561	18367	15696	43707	45589	29562	27579	0	0	0	0	0	0
Cosumnes River	27	204259	204259	1186649	1186649	1283915	1283915	143124	114499	300560	150280	42937	42937
Cottonwood Creek	377	2889	3670	127536	120962	91105	86246	82246	63266	47449	56939	0	9490
Cow Creek	166	40180	40180	243225	257311	157510	153009	39470	28193	42290	33832	4229	0
Deer Creek	256	12187	12187	70799	70799	76602	76602	11898	6799	15297	10198	5099	3824
Elder Creek	28	12484	12484	72527	72527	78472	78472	11399	8768	6576	7891	1315	1315
Feather River	114	117375	117375	406899	406899	2128396	2128396	482399	438545	723599	460472	394690	263127
Lower-mid Sacramento River	372	0	0	4746594	4746594	5135660	5135660	70280	63252	73794	52710	10542	10542
Merced River	487	263822	263822	389854	389854	598361	598361	75757	46620	52447	52447	87412	52447
Mill Creek	990	8141	8141	47298	47298	51175	51175	7365	3966	8498	5949	6799	2550
Mokelumne River	13	44179	44179	1878973	1878973	326858	394299	82421	63401	133142	76081	123632	66571
Paynes Creek	49	2490	2490	14466	14466	15652	15652	2630	1403	1315	789	0	0
San Joaquin River	7	0	0	3231871	3231871	3496778	3496778	1098655	894410	3793688	2804899	1214422	1214422
Stanislaus River	386	102777	109361	97963	97963	78146	78146	35963	107889	242751	269723	107889	134862
Stony Creek	7	11303	11303	65664	65664	71047	71047	8755	6367	3581	4775	0	0
Thomes Creek	27	22351	22351	129848	129848	140491	140491	20342	14083	16430	11736	4694	2347
Tuolumne River	56	50226	50226	291787	291787	315704	315704	112988	112988	317780	190668	148297	127112
Upper-mid Sacramento River	229	264699	289527	101435	104115	44586	48547	1611932	1518193	1301308	1257198	0	0
Yuba River	120	85604	83400	27765	27861	17767	16565	283091	202208	394306	242650	212319	121325

Table 3.4 - Below are the environmental variables that are used to estimate s_{adult} and *delay* for Chinook Salmon in the Central Valley, CA for each watershed. The small tributary variable is an indicator variable. The Prob. Mig. Corridor Temp columns represent the probability of the migratory corrridor for each watershed is between 20-25°C or greater than 25°C. These probabilities are used in a multinomial distribution with a single trial to create a respective indicator variable. Number of migration barriers include things such as passable dams, diversions, or other obsticles. The Pulse column represents the mean (sd) of proportion increase in the base flow that is created while adults are migrating.

	Small Tributary	**Temperature Probability of Migration Corridor**			**# migration barriers**	**Pulse Flow**	**Prob. Scouring Flow**
		≤ 20°C	**> 20°C & ≤ 25°C**	**> 25°C**			
Sampling Distribution	Constant		Multinom(***p***)		Constant	Normal(μ ,σ)	Binomial(p)
Watershed							
American River	0	0.596	0.381	0.023	0	0.656 (0.165)	0.01
Antelope Creek	1	0.596	0.381	0.023	0	0.827 (2.801)	0.04
Battle Creek	1	0.581	0.381	0.038	1	0.88 (0.274)	0.04
Bear Creek	1	0.596	0.381	0.023	0	1.936 (4.484)	0.04
Bear River	1	0.596	0.381	0.023	0	0.896 (0.91)	0.04
Big Chico Creek	1	0.581	0.381	0.038	2	1.179 (0.532)	0.03
Butte Creek	1	0.581	0.381	0.038	3	1.003 (0.512)	0.03
Calaveras River	1	0.426	0.501	0.073	4	3.852 (3)	0.05
Clear Creek	1	0.596	0.381	0.023	1	1.973 (0.319)	0.05
Cosumnes River	1	0.426	0.501	0.073	1	4.639 (4.328)	0.02
Cottonwood Creek	1	0.596	0.381	0.023	0	1.279 (0.564)	0.01
Cow Creek	1	0.596	0.381	0.023	0	3.613 (2.902)	0.04
Deer Creek	1	0.596	0.381	0.023	2	4.092 (4.957)	0.05
Elder Creek	1	0.596	0.381	0.023	1	1.427 (33.5)	0.00
Feather River	0	0.596	0.381	0.023	0	0.592 (0.286)	0.20
Lower-mid Sacramento River	0	0.596	0.381	0.023	0	1.703 (0.107)	0.01
Merced River	1	0.426	0.501	0.073	0	1.506 (0.824)	0.04
Mill Creek	1	0.596	0.381	0.023	0	3.065 (1.321)	0.03
Mokelumne River	1	0.426	0.501	0.073	1	1.427 (2.701)	0.04
Paynes Creek	1	0.596	0.381	0.023	0	1.257 (4.484)	0.04
San Joaquin River	0	0.426	0.501	0.073	0	1.039 (0.501)	0.01
Stanislaus River	0	0.426	0.501	0.073	0	1.936 (0.404)	0.04
Stony Creek	1	0.596	0.381	0.023	0	1.427 (2.398)	0.05
Thomes Creek	1	0.596	0.381	0.023	1	1.348 (2.558)	0.03
Tuolumne River	1	0.426	0.501	0.073	1	1.042 (1.082)	0.05
Upper-mid Sacramento River	0	0.596	0.381	0.023	0	0.785 (0.286)	0.18
Yuba River	0	0.596	0.381	0.023	1	0.498 (0.189)	0.02

Table 3.5 - Environmental parameters used to calculate rearing survival probabilities ($s_{fry,j}$, $s_{parr,j}$, and $s_{presmolt,j}$) for juvenile life stages for each watersheds. Note any value followed by a second number in parenthesis represents the mean and standard deviation respectively. The sampling distribution assocaited with each variable indicated how random samples were generated during simulations of the population model. The Predator prevelance columns are used in a multinomial distribution with a single trial to create a respective indicator variable.

	# Unscreened Diversions	**# of Operating Diversions**	**# TMDL violations**	**Probability of Predator Prevelance**			**Prob. Fry Stranding**	**Prob. Parr Stranding**	**Prob. Presmolt Stranding**
				Low	**Medium**	**High**			
Sampling Distribution	Poisson(μ)	Poisson(μ)	Constant		Multinom($\boldsymbol{p}$)		Binomial(p)	Binomial(p)	Binomial(p)
Watershed									
American River	1	1	3	0.070	0.730	0.200	0.018	0.014	0.011
Antelope Creek	1	3	0	0.330	0.500	0.170	0.150	0.075	0.025
Battle Creek	7	7	0	0.070	0.830	0.100	0.086	0.025	0.010
Bear Creek	7	8	4	0.330	0.500	0.170	0.150	0.075	0.025
Bear River	15	15	1	0.000	0.330	0.670	0.158	0.134	0.150
Big Chico Creek	3	3	4	0.070	0.870	0.070	0.191	0.022	0.010
Butte Creek	146	85	5	0.070	0.870	0.070	0.095	0.035	0.007
Calaveras River	153	145	1	0.170	0.330	0.500	0.050	0.020	0.010
Clear Creek	3	3	1	0.000	0.000	1.000	0.100	0.073	0.029
Cosumnes River	22	16	0	0.170	0.500	0.330	0.129	0.044	0.008
Cottonwood Creek	10	2	3	0.130	0.600	0.270	0.147	0.090	0.025
Cow Creek	25	35	0	0.270	0.570	0.170	0.229	0.171	0.050
Deer Creek	5	4	0	0.557	0.330	0.113	0.068	0.019	0.010
Elder Creek	4	4	7	0.130	0.600	0.270	0.189	0.112	0.043
Feather River	81	60	6	0.000	0.277	0.723	0.311	0.259	0.200
Lower-mid Sacramento River	517	441	6	0.000	0.000	1.000	0.000	0.011	0.006
Merced River	196	190	7	0.170	0.500	0.330	0.157	0.155	0.271
Mill Creek	2	3	0	0.557	0.330	0.113	0.166	0.217	0.305
Mokelumne River	104	97	6	0.170	0.500	0.330	0.020	0.021	0.078
Paynes Creek	14	15	0	0.330	0.500	0.170	0.150	0.075	0.025
San Joaquin River	449	378	8	0.000	0.170	0.830	0.498	0.500	0.500
Stanislaus River	51	44	5	0.000	0.170	0.830	0.036	0.016	0.010
Stony Creek	5	4	4	0.500	0.500	0.000	0.080	0.045	0.020
Thomes Creek	6	9	0	0.130	0.600	0.270	0.150	0.100	0.040
Tuolumne River	123	96	6	0.330	0.330	0.340	0.317	0.237	0.355
Upper-mid Sacramento River	187	95	4	0.087	0.613	0.300	0.323	0.238	0.217
Yuba River	17	14	1	0.000	0.830	0.170	0.119	0.152	0.371

Table 3.6 - Temperature and water diversion parameters used to calculate rearing survival probabilities ($s_{fry,j}$, $s_{parr,j}$, and $s_{presmolt,j}$) for juvenile life stages for each watersheds. Note any value followed by a second number in parenthesis represents the mean and standard deviation respectively. The sampling distribution assocaited with each variable indicated how random samples were generated during simulations of the population model. The water diversion estimates are given for both wet (high precipitation) and dry (low precipitation) years.

	Fry High Temp (°C)	**Parr High Temp (°C)**	**Presmolt High Temp (°C)**	**Fry Water Diversion (% of total flow diverted)**		**Parr Water Diversion (% of total flow diverted)**		**Presmolt Water Diversion (% of total flow diverted)**	
				Dry	**Wet**	**Dry**	**Wet**	**Dry**	**Wet**
Sampling Distribution	Normal(μ,σ)	Normal(μ,σ)	Normal(μ,σ)	Constant	Constant	Constant	Constant	Constant	Constant
Watershed									
American River	12.134 (1.112)	15.041 (1.261)	16.747 (1.628)	0.0561	0.0808	0.0621	0.0866	0.0941	0.0966
Antelope Creek	9.879 (3)	11.035 (4)	18.815 (6)	0.0000	0.0000	0.0300	0.0450	0.3070	0.4149
Battle Creek	9.176 (3)	9.222 (4)	16.845 (6)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Bear Creek	9.176 (3)	9.222 (4)	16.845 (6)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Bear River	9.355 (2)	13.239 (4)	15.958 (4)	0.0000	0.0000	0.0000	0.0000	0.1072	0.1099
Big Chico Creek	14.288 (7.075)	11.353 (2.377)	24.52 (4.561)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Butte Creek	8.216 (1.189)	12.677 (2.523)	19.248 (1.469)	0.0362	0.0460	0.3067	0.4488	0.7283	0.4595
Calaveras River	15.215 (3)	16.138 (2)	20.958 (4)	0.1210	0.2419	0.4550	0.5345	0.9599	0.9582
Clear Creek	9.176 (2)	9.222 (3)	16.845 (6)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Cosumnes River	15.215 (3)	16.138 (4)	20.958 (4)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Cottonwood Creek	9.176 (3)	9.222 (4)	16.845 (6)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Cow Creek	9.176 (3)	9.222 (4)	16.845 (6)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Deer Creek	8.61 (0.747)	13.368 (2.197)	24.637 (5.371)	0.0000	0.0000	0.0362	0.0669	0.3330	0.4655
Elder Creek	9.879 (3)	11.035 (4)	18.815 (6)	0.0014	0.0043	0.0106	0.0166	0.0572	0.0754
Feather River	9.45 (0.598)	15.639 (2.3)	19.509 (4.35)	0.0124	0.0096	0.2252	0.3176	0.5297	0.5278
Lower-mid Sacramento River	15.482 (1.356)	17.021 (3.201)	25.564 (3.629)	0.0244	0.0209	0.1576	0.1986	0.5213	0.5948
Merced River	11.385 (2.543)	16.905 (6.532)	25.909 (2.723)	0.0029	0.0094	0.1812	0.3493	0.3547	0.5050
Mill Creek	15.215 (1.47)	16.138 (3.149)	20.958 (2.756)	0.0000	0.0000	0.0493	0.0848	0.3118	0.4237
Mokelumne River	9.879 (3)	11.035 (4)	18.815 (4)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Paynes Creek	15.708 (3)	19.551 (4)	23.98 (6)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
San Joaquin River	12.46 (1.968)	14.991 (2)	18.879 (4.174)	0.5419	0.4414	0.4034	0.4754	0.8070	0.7571
Stanislaus River	9.176 (2.298)	9.222 (1.921)	16.845 (3.073)	0.0000	0.0000	0.0045	0.0285	0.0884	0.1013
Stony Creek	9.879 (2)	11.035 (3)	18.815 (6)	0.0016	0.0000	0.2056	0.2589	0.4620	0.5622
Thomes Creek	11.87 (3)	12.991 (4)	15.41 (6)	0.0021	0.0029	0.0106	0.0152	0.0524	0.0804
Tuolumne River	11.111 (0.957)	11.753 (1.943)	11.587 (3.078)	0.0000	0.0006	0.0037	0.0268	0.0539	0.1536
Upper-mid Sacramento River	10.591 (2)	15.233 (4)	20.796 (4)	0.0002	0.0002	0.0097	0.0219	0.0569	0.0511
Yuba River	9.259 (2)	10.838 (4)	12.407 (4)	0.0239	0.0239	0.0835	0.1758	0.5209	0.7775

Table 3.7 - Environmental parameters used in the calculating out-migration survival for each of the juvenile life stages. Note any number followed by a second number in parenthesis is the mean and (sd).

	Fry Pulse Flow	**Parr/Presmolt Pulse Flow**	**Smolt Pulse Flow**	**Fry Mig. High Temp**	**Parr/Presmolt Mig. High Temp**	**Smolt Mig. High Temp**
Sampling Distribution	Normal(μ ,σ)	Normal(μ ,σ)	Normal(μ ,σ)	Normal(μ ,σ)	Normal(μ ,σ)	Normal(μ ,σ)
Watershed						
American River	1.334 (0.692)	1.21 (0.512)	0.782 (0.172)	15.341 (3.786)	20.141 (3.629)	21.708 (1.078)
Antelope Creek	1.837 (1)	1.256 (1)	0.5 (0.25)	13.155 (2.144)	18.489 (3.122)	21.067 (3.058)
Battle Creek	1.114 (0.3)	0.982 (0.14)	0.703 (0.108)	13.155 (2.144)	18.489 (3.122)	21.067 (3.058)
Bear Creek	1.261 (1)	1.011 (1)	0.622 (0.25)	10.591 (1.356)	15.233 (3.201)	20.796 (3.629)
Bear River	6.832 (9.11)	0.782 (0.303)	0.635 (0.411)	13.155 (2.144)	18.489 (3.122)	21.067 (3.058)
Big Chico Creek	1.711 (0.767)	0.708 (0.306)	0.548 (0.059)	13.155 (2.144)	18.489 (3.122)	21.067 (3.058)
Butte Creek	1.515 (0.755)	0.865 (0.172)	0.615 (0.139)	13.155 (2.144)	18.489 (3.122)	21.067 (3.058)
Calaveras River	1.453 (1)	1.025 (1)	0.527 (0.25)	15.708 (1.968)	19.551 (3)	23.98 (4.174)
Clear Creek	1.125 (0.302)	0.919 (0.213)	0.649 (0.133)	13.155 (2.144)	18.489 (3.122)	21.067 (3.058)
Cosumnes River	1.766 (0.862)	0.913 (0.419)	0.403 (0.158)	15.708 (1.968)	19.551 (3)	23.98 (4.174)
Cottonwood Creek	1.518 (1.087)	1.102 (0.929)	0.575 (0.178)	10.591 (1.356)	15.233 (3.201)	20.796 (3.629)
Cow Creek	1.286 (0.707)	1.042 (0.899)	0.56 (0.194)	10.591 (1.356)	15.233 (3.201)	20.796 (3.629)
Deer Creek	1.081 (0.095)	1.143 (0.26)	1.071 (0.463)	10.591 (1.356)	15.233 (3.201)	20.796 (3.629)
Elder Creek	1.837 (1.803)	1.256 (1.065)	0.5 (0.167)	10.591 (1.356)	15.233 (3.201)	20.796 (3.629)
Feather River	1.415 (0.584)	0.843 (0.225)	1.264 (0.478)	13.155 (2.144)	18.489 (3.122)	21.067 (3.058)
Lower-mid Sacramento River	2.798 (0.301)	1.124 (0.3)	0.393 (0.21)	15.708 (1.356)	19.551 (3.201)	23.98 (3.629)
Merced River	1.445 (1.932)	0.849 (0.503)	0.613 (0.137)	13.155 (1.968)	18.489 (3)	21.067 (4.174)
Mill Creek	1.14 (0.343)	1.138 (0.165)	0.65 (0.091)	17.595 (2.144)	21.913 (3.122)	24.243 (3.058)
Mokelumne River	1.837 (0.759)	1.256 (0.549)	0.5 (0.291)	10.591 (1.968)	15.233 (3.304)	20.796 (3.609)
Paynes Creek	1.47 (1)	1.101 (1)	0.624 (0.25)	13.155 (1.356)	18.489 (3.201)	21.067 (3.629)
San Joaquin River	1.519 (0.931)	1.54 (0.326)	0.563 (0.12)	15.708 (2.144)	19.551 (3.122)	23.98 (3.058)
Stanislaus River	1.261 (0.952)	1.011 (0.673)	0.622 (0.173)	13.155 (1.968)	18.489 (3)	21.067 (4.174)
Stony Creek	1.837 (0.5)	1.256 (1)	0.5 (1)	10.591 (2.144)	15.233 (3.122)	20.796 (3.058)
Thomes Creek	1.993 (1)	1.041 (1)	0.362 (0.25)	15.708 (1.356)	19.551 (3.201)	23.98 (3.629)
Tuolumne River	0.972 (1.83)	1.22 (0.931)	0.972 (0.19)	15.341 (1.968)	20.141 (3)	21.708 (4.174)
Upper-mid Sacramento River	1.109 (0.268)	0.924 (0.39)	0.925 (0.195)	10.591 (3.786)	15.233 (3.629)	20.796 (1.078)
Yuba River	1.362 (0.573)	0.999 (0.369)	0.875 (0.517)	13.155 (2.144)	18.489 (3.122)	21.067 (3.058)

Table 3.8 - The coefficients used to in the logistic regression functions to calculate different survival parameters. The values represent the mean followed by the (sd). These parameters are used to sample values from a normal distribution, which populate the $\boldsymbol{\beta}$, coefficient vector. The description column describes the environmental model parameter that matches these coefficients. Intercepts for the some of the survival rates differed between watersheds and can be found on table 7. All parameters were estimated by expert opinion except those fit during the calibration process

Parameter	**Description**	**mean (sd)**
delay	Intercept	0.1419 (0.0823)
	Small tributary	0.9647 (0.5272)
	Temperature migratory coord > 25	1.4972 (0.7172)
	Temperature migratory coord 20-25	0.4087 (0.2205)
	No of barriers	0.1994 (0.1015)
	Pulse flow*small trib	-0.2379 (0.1385)
	pulsed flow squared* small trib	0.011 (0.0059)
$s_{adult,j}$	Intercept	3.5783 (0.8946)
	Adult holding habitat density	-0.0033 (0.0008)
	Water temperature 20-25 C	-1.2171 (0.3043)
	Water temperature >25 C	-1.9486 (0.4872)
	Passage delay (weeks)	-0.5063 (0.1266)
$s_{egg,j}$	Intercept	-0.5914 (0.1183)
	Hatchery fish interactions	0.5332 (0.2133)
	Scouring flow	-0.6554 (0.1311)
dewater	Intercept	2.113 (0.382)
	Discharge ratio	-6.656 (0.271)
$s_{fry,j}$	Intercept	2.6541 (0.5308)
	Number of unscreened diversions	-0.0102 (0.0034)
	No. diversions operating during rearing and outmigration	-0.0295 (0.0105)
	Stranded	-0.8465 (0.211)
	Moderate predator prevalence	-0.9304 (0.254)
	High predator prevalence	-2.2771 (0.7942)
	10-day maximum temperature during rearing	-0.2042 (0.0808)
	Water quality impairments	-0.0484 (0.0173)
$s_{parr,j}$	Intercept	5.4358 (1.0872)
	Number of unscreened diversions	-0.0081 (0.0024)
	No. diversions operating during rearing and outmigration	-0.03 (0.0079)
	Stranded	-0.72 (0.3165)
	Moderate predator prevalence	-0.9047 (0.3938)
	High predator prevalence	-1.6575 (0.4574)
	10-day maximum temperature during rearing	-0.2222 (0.0853)
	Water quality impairments	-0.0842 (0.0347)
$s_{presmolt,j}$	Intercept	7.6015 (1.5203)
	Number of unscreened diversions	-0.0042 (0.001)
	No. diversions operating during rearing and outmigration	-0.0155 (0.0031)
	Stranded	-0.219 (0.0889)
	Moderate predator prevalence	-0.81 (0.2577)
	High predator prevalence	-1.56 (0.6835)
	10-day maximum temperature during rearing	-0.2687 (0.0555)
	Water quality impairments	-0.078 (0.0268)
$s_{frymig,j}$	Intercept†	-4.958 (0.9916)
	10-day maximum temperature during migration	-0.15 (0.0413)
	Pulsed flow during outmigration	0.198 (0.0594)
$s_{parrmig,j}$	Intercept†	-1.951 (0.36)
	10-day maximum temperature during migration	-0.175 (0.0481)
	Pulsed flow during outmigration	0.2188 (0.0656)
$s_{smolt,j}$	Intercept†	-1.07 (0.214)
	10-day maximum temperature during migration	-0.175 (0.0481)
	Pulsed flow during outmigration	0.2975 (0.0893)

Table 3.9 - Results from the response profile analysis for the salmon decision model. The response profile analysis identifed how many times the optimal decision would change across a range of values (±50% of the original mean value) for each parameter in the model. Only the parameters that had the optimal decision change more than once are reported.

Parameter	**Description**	**Type**	**# Optimal Decisions**	**# Decision Changes**
s_{frymig}: intercept	Baseline fry migration survival	Biological Parameter	3	3
s_{egg}: intercept	Baseline reproductive success probability	Biological Parameter	2	2
s_{frymig}: pulsed flow	Effect of that the migration water pulse has on fry outmigration survival	Biological Parameter	2	2
s_{smolt}: intercept	Baseline smolt migration survival	Biological Parameter	2	2
SpawnHab (wet)	Amount of spawning habitat during a wet year	Environmental Input	2	2
SpawnHab (dry)	Amount of spawning habitat during a dry year	Environmental Input	2	2
Fry Pulse Flow	The relative increase of flow during fry outmigration	Environmental Input	2	2

Figures

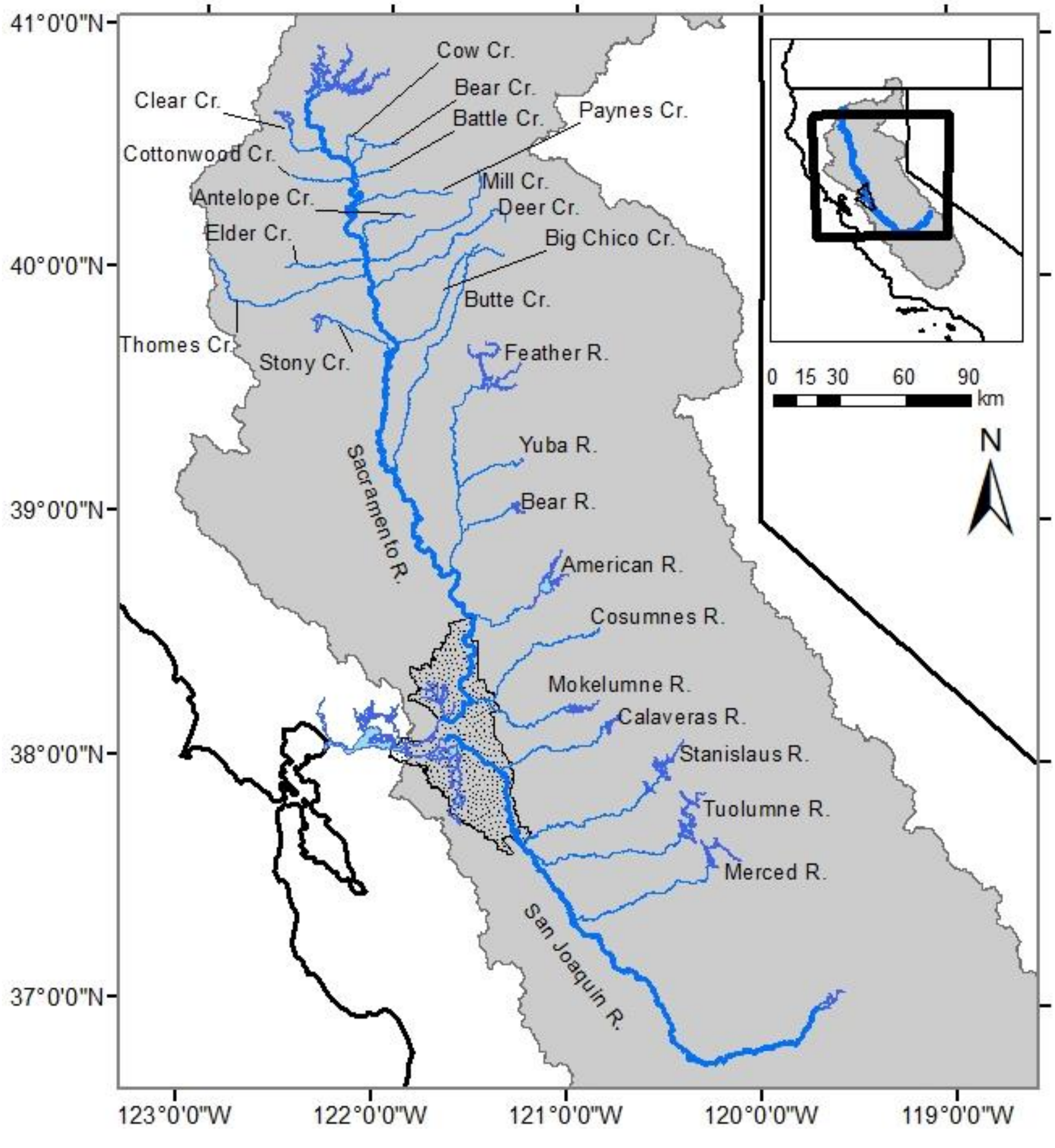

Figure 3.1 – A map of the primary watersheds that make us the Central Valley, CA. Shasta Lake is not considered part of this analysis since it is not open to anadromy. In this analysis, the mainstem of the Sacramento river is divided into two reaches, upper and lower, with the dividing line at Red Bluff Dam.

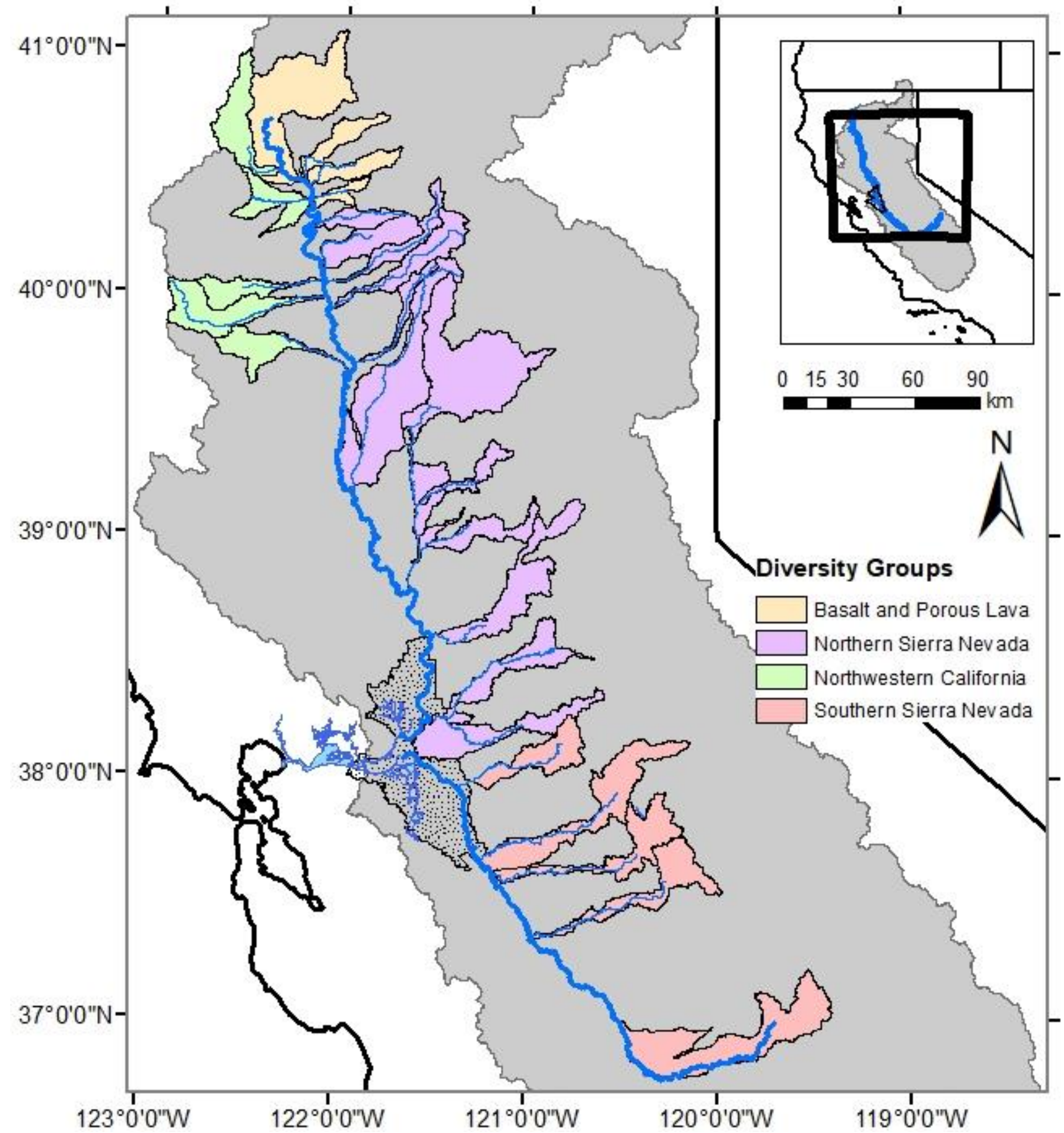

Figure 3.2 – A map of the 4 different Chinook salmon diversity groups for the CVPIA.

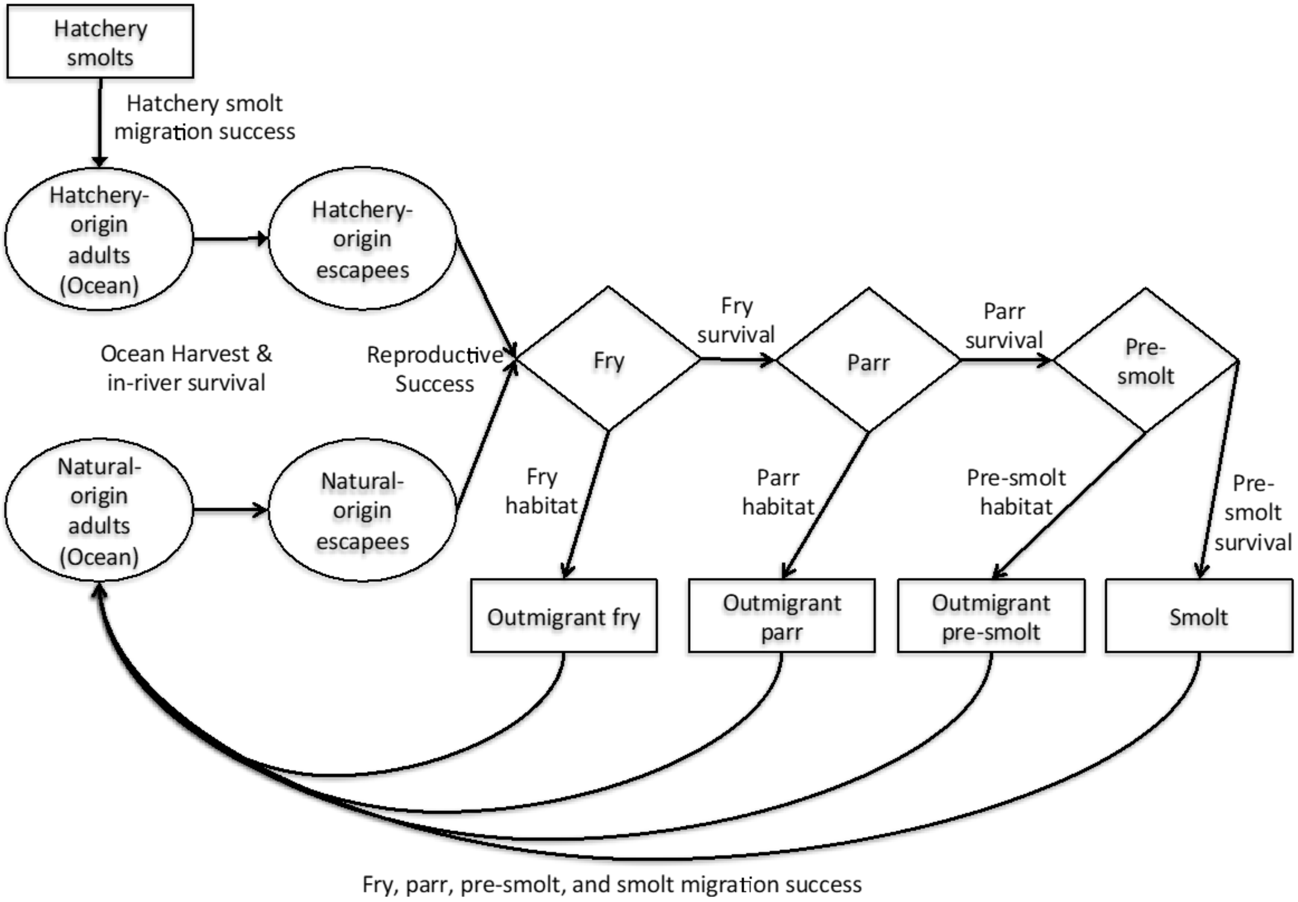

Figure 3.3 – Conceptual diagram of the life history of a fall-run Chinook salmon in the Central Valley, CA. Circle nodes represent mature adult fish, diamonds represent freshwater juvenile stages, and boxes represent outmigrant juvenile life stages. Each arrow represents a different survival or reproductive process.

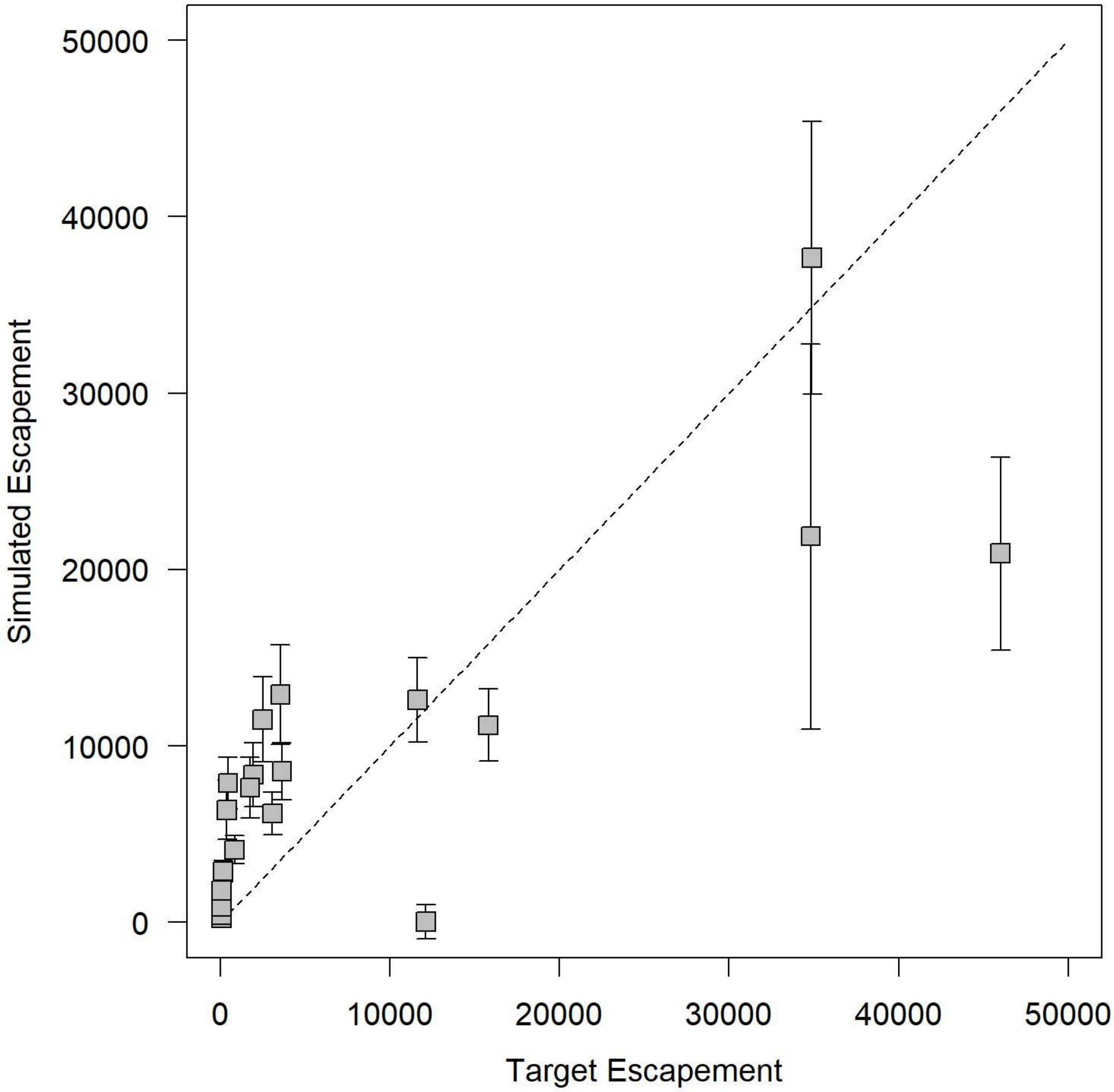

Figure 3.4 –Each point represents how close the simulated escapement sizes were to their target escapement sizes for every watershed after the calibration. The calibration adjusted the baseline survival rates for each of the outmigrant size classes. The line represents a 1:1 relationship. Points above the line were over-estimated and points below the line were under-estimated.

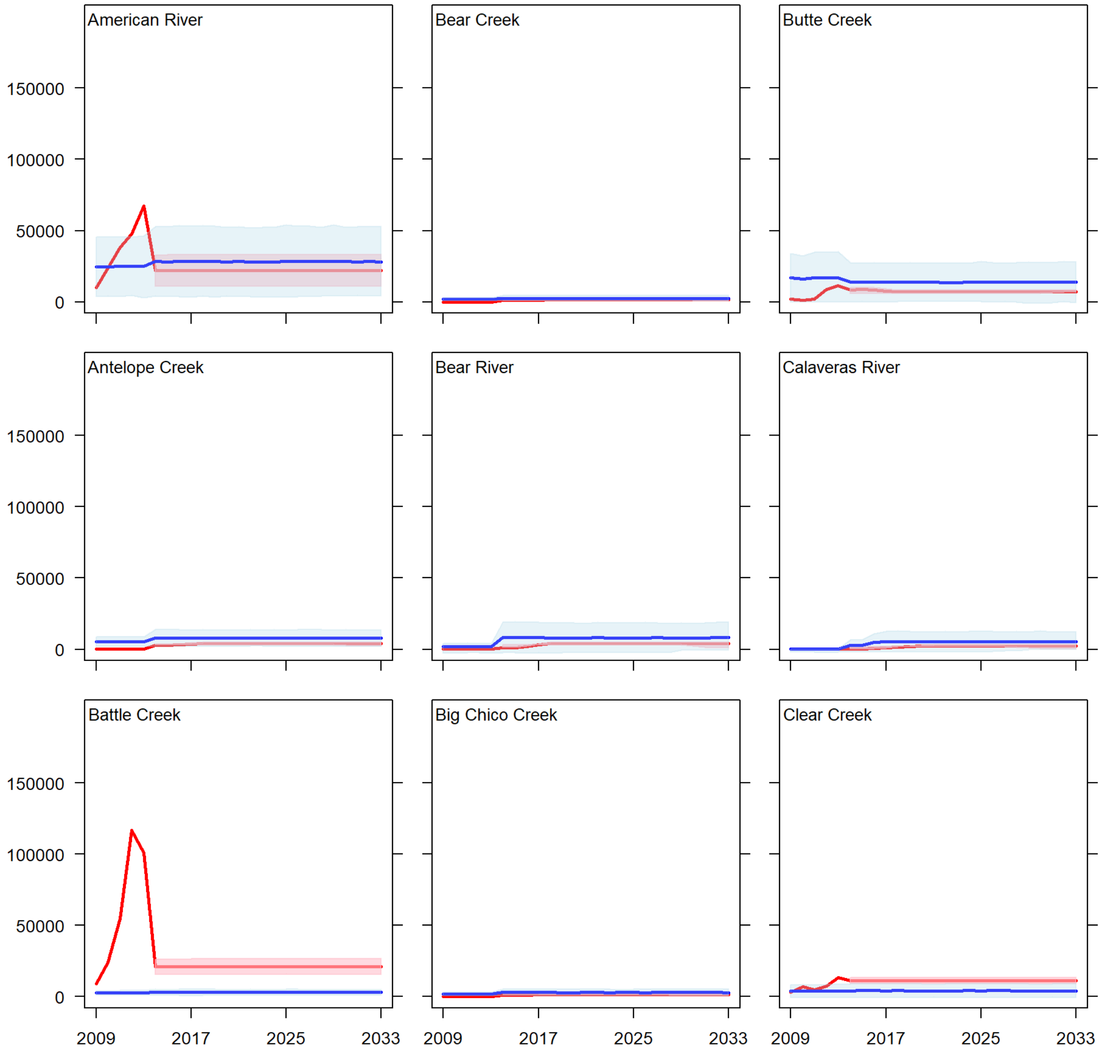

Figure 3.5 – Simulated mean escapement (red) and mean total natural production (blue) of fall-run Chinook salmon for 9 of the 26 CVPIA watersheds. Shaded areas represent ± 1 standard deviation. Simulations were ran for 25 years total, starting in 2009.

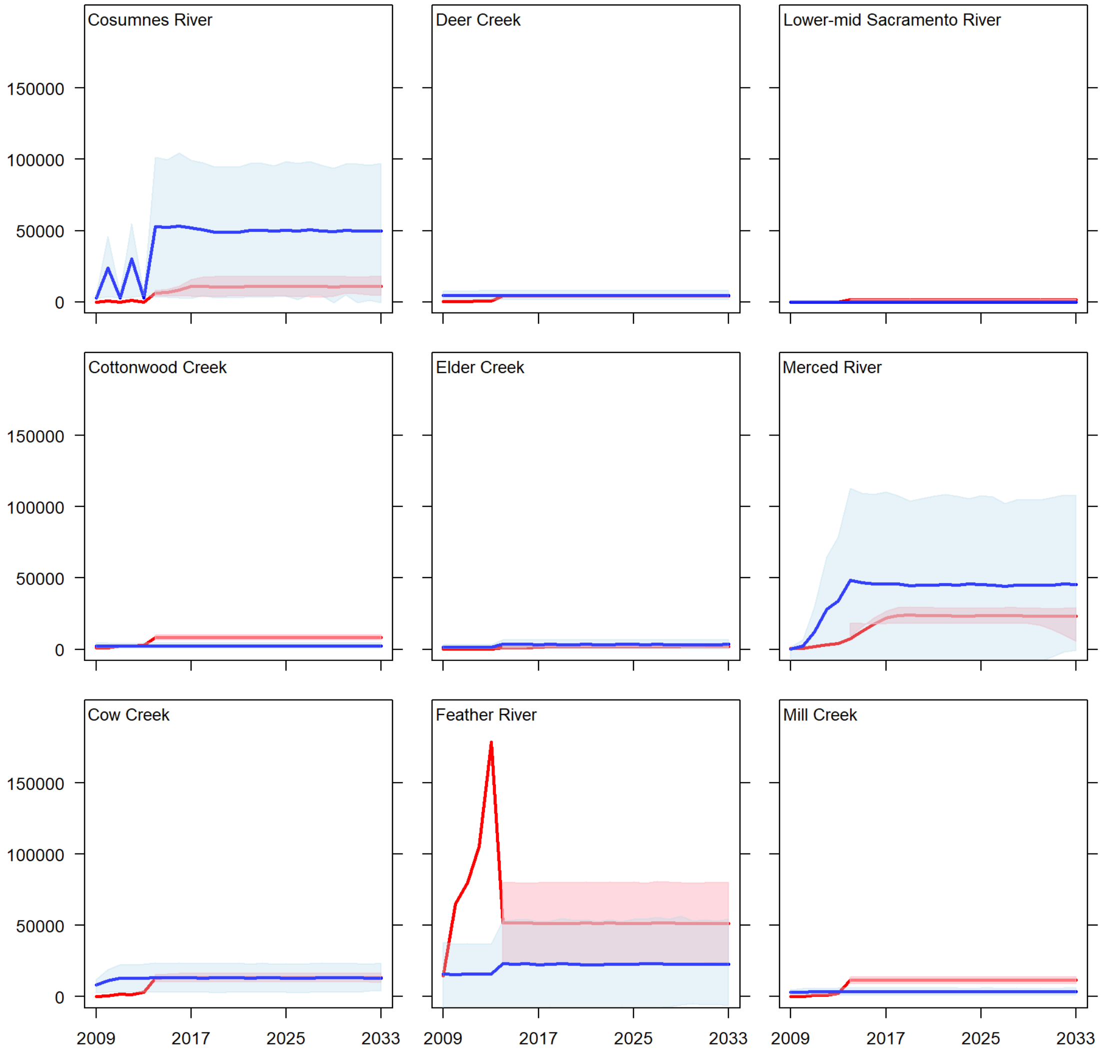

Figure 3.6 – Simulated mean escapement (red) and mean total natural production (blue) of fall-run Chinook salmon for 9 of the 27 CVPIA watersheds. Shaded areas represent ± 1 standard deviation. Simulations were ran for 25 years total, starting in 2009.

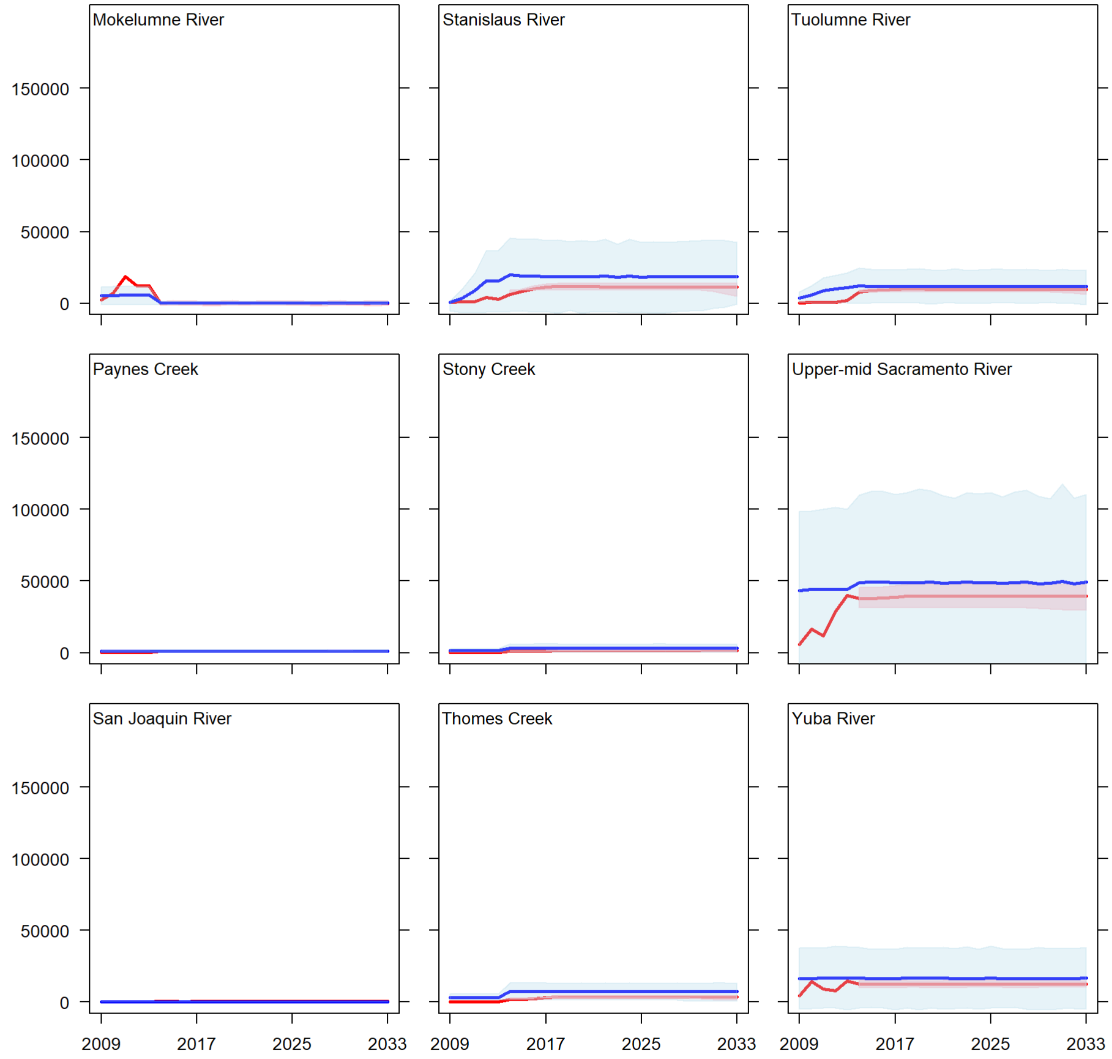

Figure 3.7 – Simulated mean escapement (red) and mean total natural production (blue) of fall-run Chinook salmon for 9 of the 27 CVPIA watersheds. Shaded areas represent ± 1 standard deviation. Simulations were ran for 25 years total, starting in 2009.

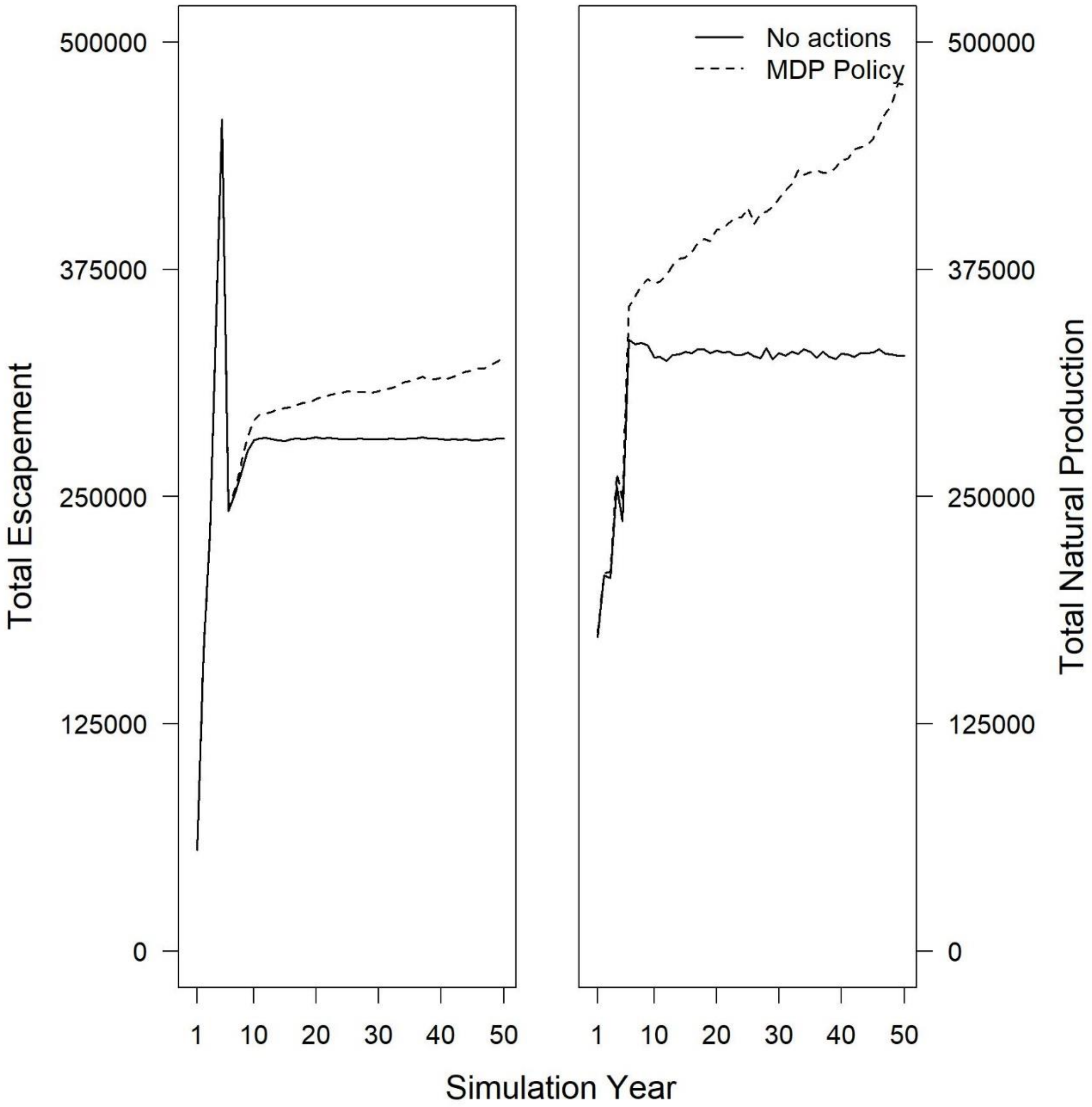

Figure 3.8 – Results from the forward simulation of the population model for fall-run Chinook salmon in the Central Valley, CA while applying the strategies derived from the optimization routines. Lines represent the estimated mean values of total (system wide) escapement (left) and production of adult equivalents (right). The solid black line represents abundance and production levels when no action is implemented, the dashed lines represent the same metrics but after optimal management alternatives are implemented.

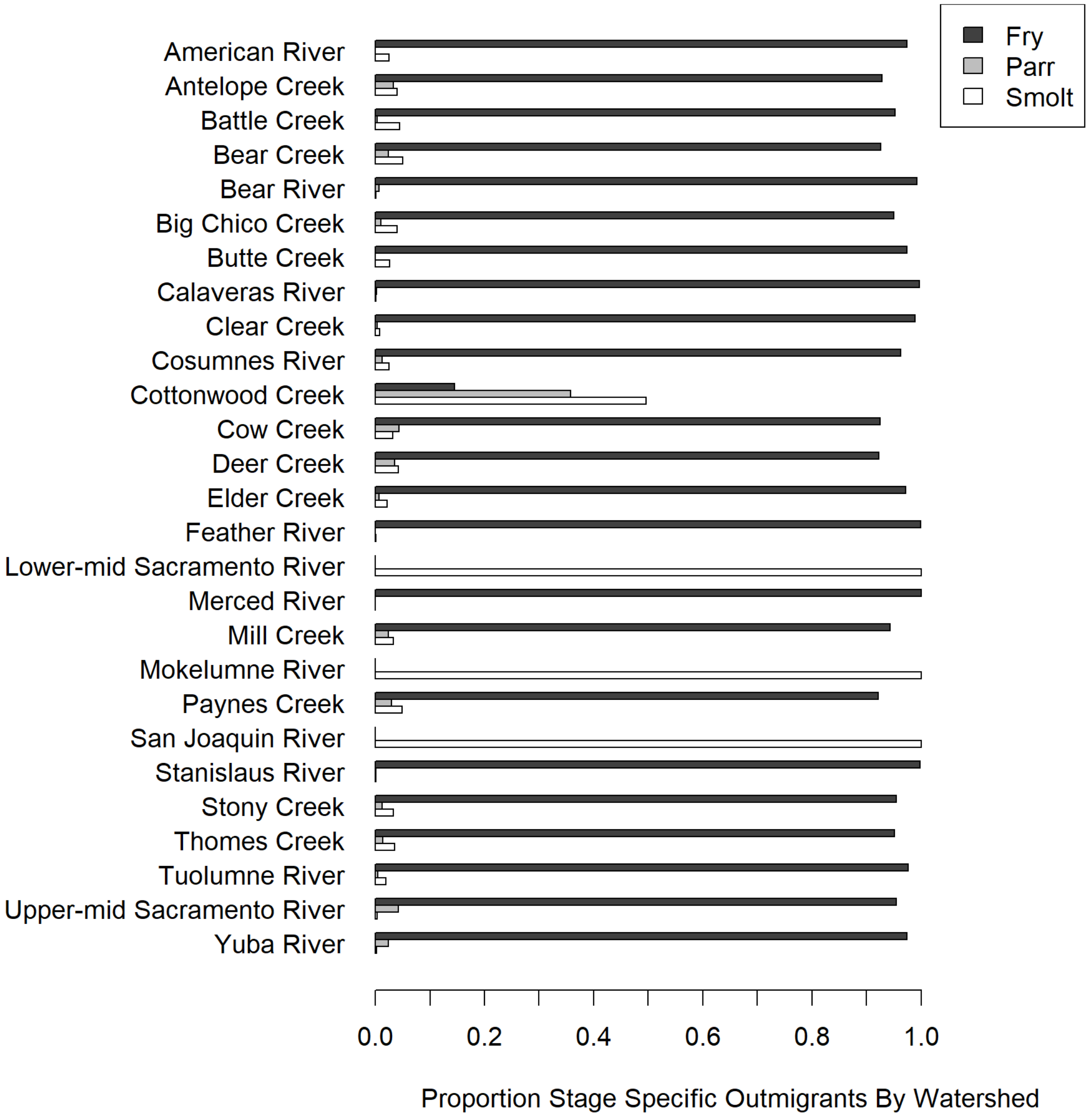

Figure 3.9 – Each bar presents the proportion of total juvenile fall-run Chinook salmon outmigrants produced by life stage for each watershed in the CVPIA. For instance, over 90 percent of the juvenile outmigrants produced in the American River leave as fry while the remainder leave as smolt. These data were produced by letting the population model run for 6 years, to account for population momentum from known escapement values. The model suggests that in almost all the CVPIA streams most Chinook salmon leave their natal streams as fry.

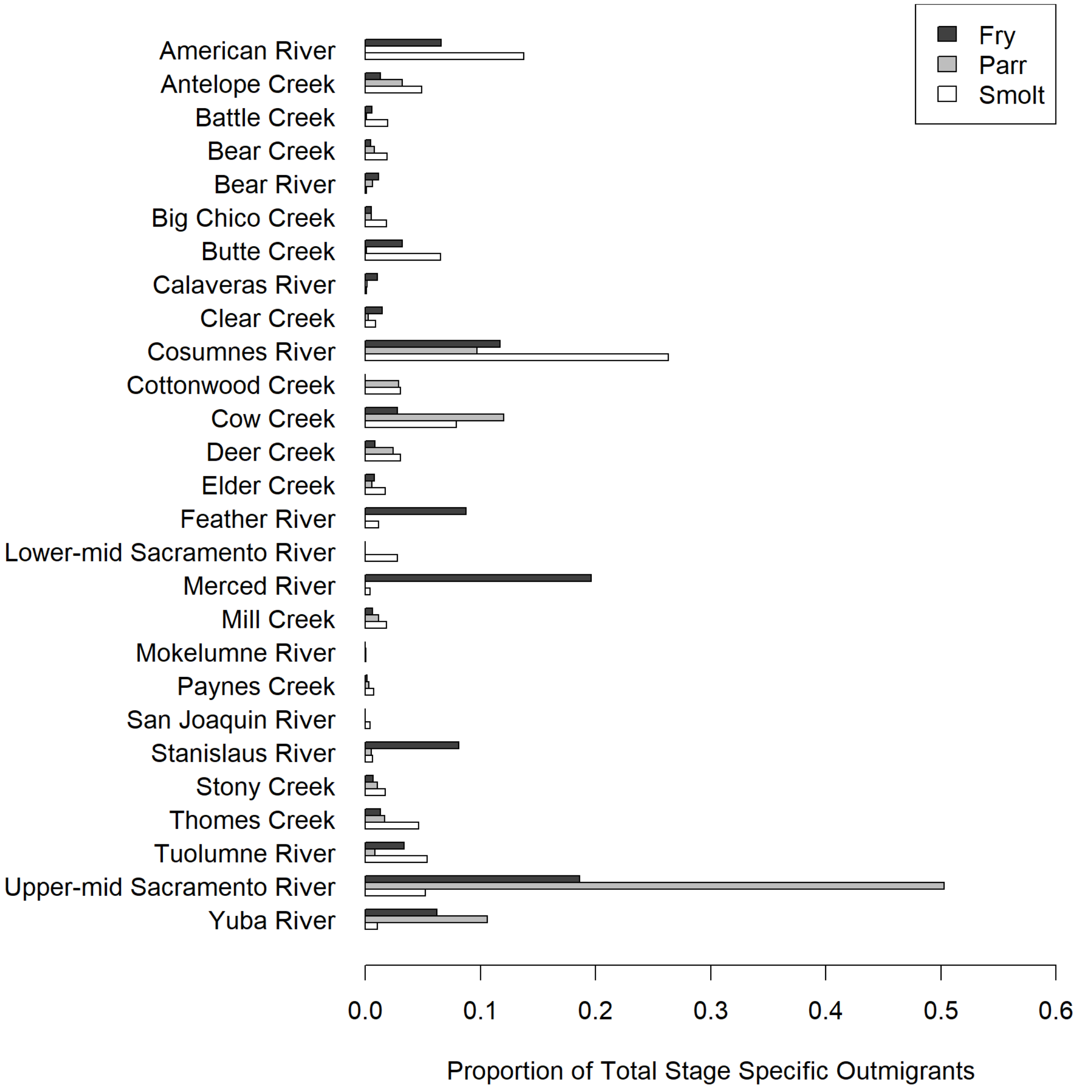

Figure 3.10 – Each bar presents the proportion of the total number of each stage specific outmigrant that was produced in each CVPIA watershed. For instance, the model estimates that approximately 50 percent of all parr outmigrants produced in the entire Central Valley originated from the Upper-mid Sacramento. These data were produced by letting the population model run for 6 years, to account for population momentum from known escapement values.

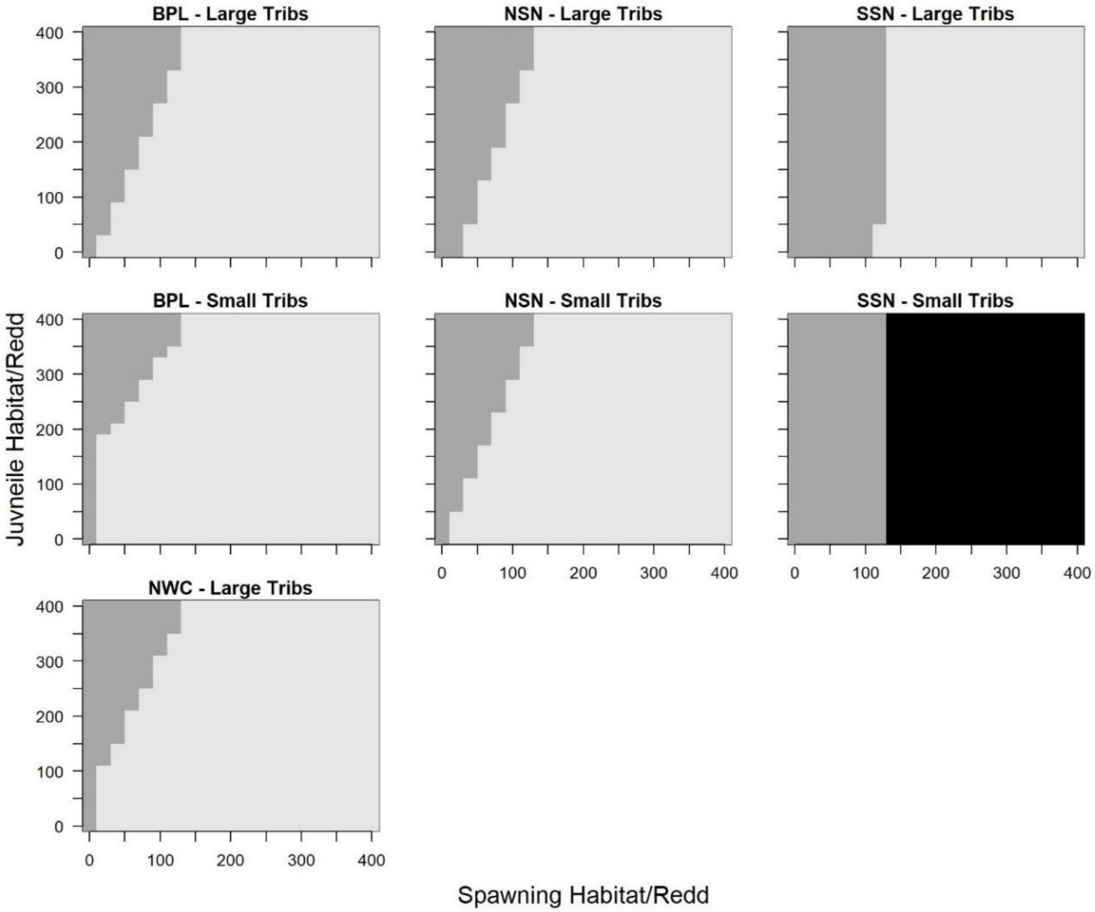

Figure 3.11 – Optimal policies that were derived from framing the decision problem as a MDP. Policies were derived for different combinations of tributary size (large and small) and evolutionary diversity groupings (BPL – Basalt and Porous Lava, NSN – Northern Sierra Nevada, SSN – Southern Sierra Nevada, and NWC – Northwest California) The different colors represent state space configurations where the optimal decision was different. Light grey represents floodplain excavations, dark grey represents gravel additions and black represents the do nothing option.

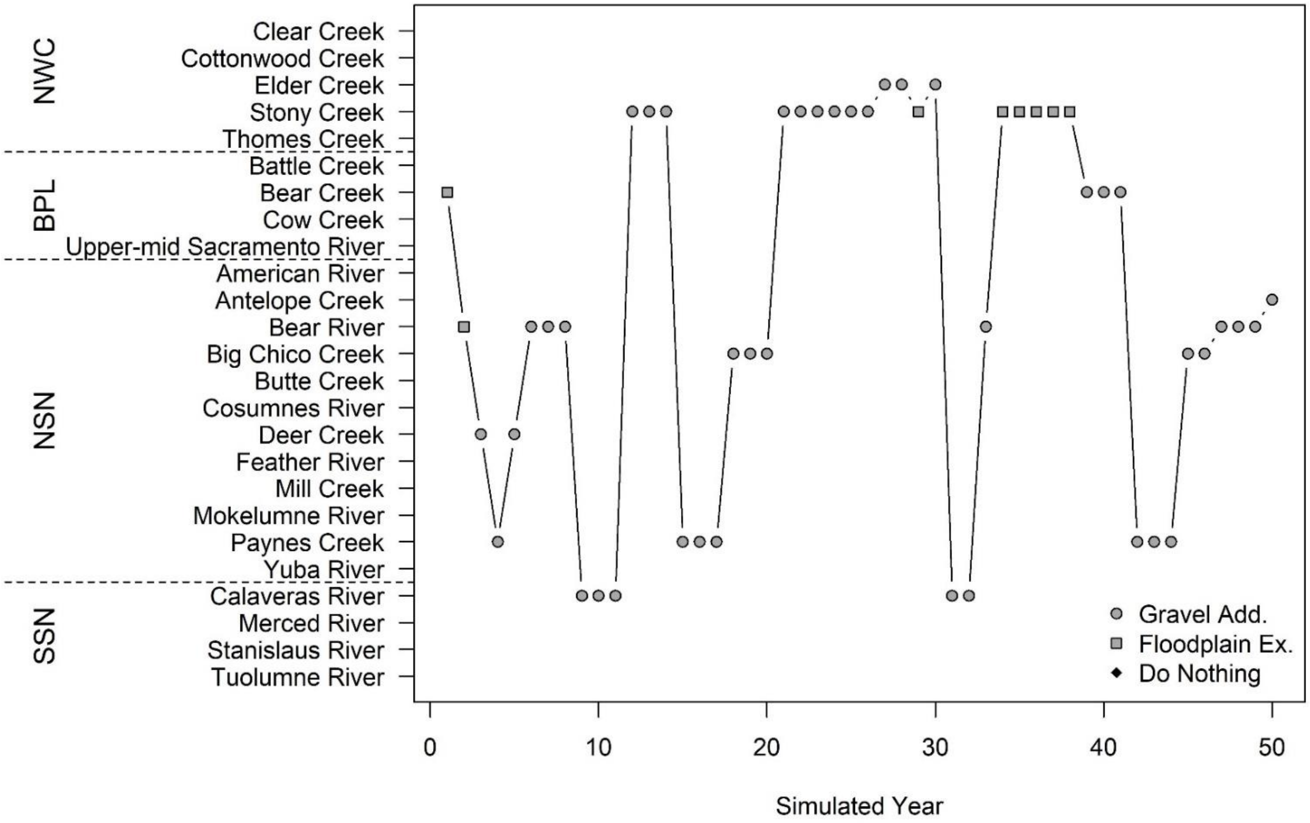

Figure 3.12 – The optimal decision was determined in each time step of the forward simulation and reported here. The watersheds are grouped into their evolutionary diversity groups (BPL – Basalt and Porous Lava, NSN – Northern Sierra Nevada, SSN – Southern Sierra Nevada, and NWC – Northwest California) on the y-axis.

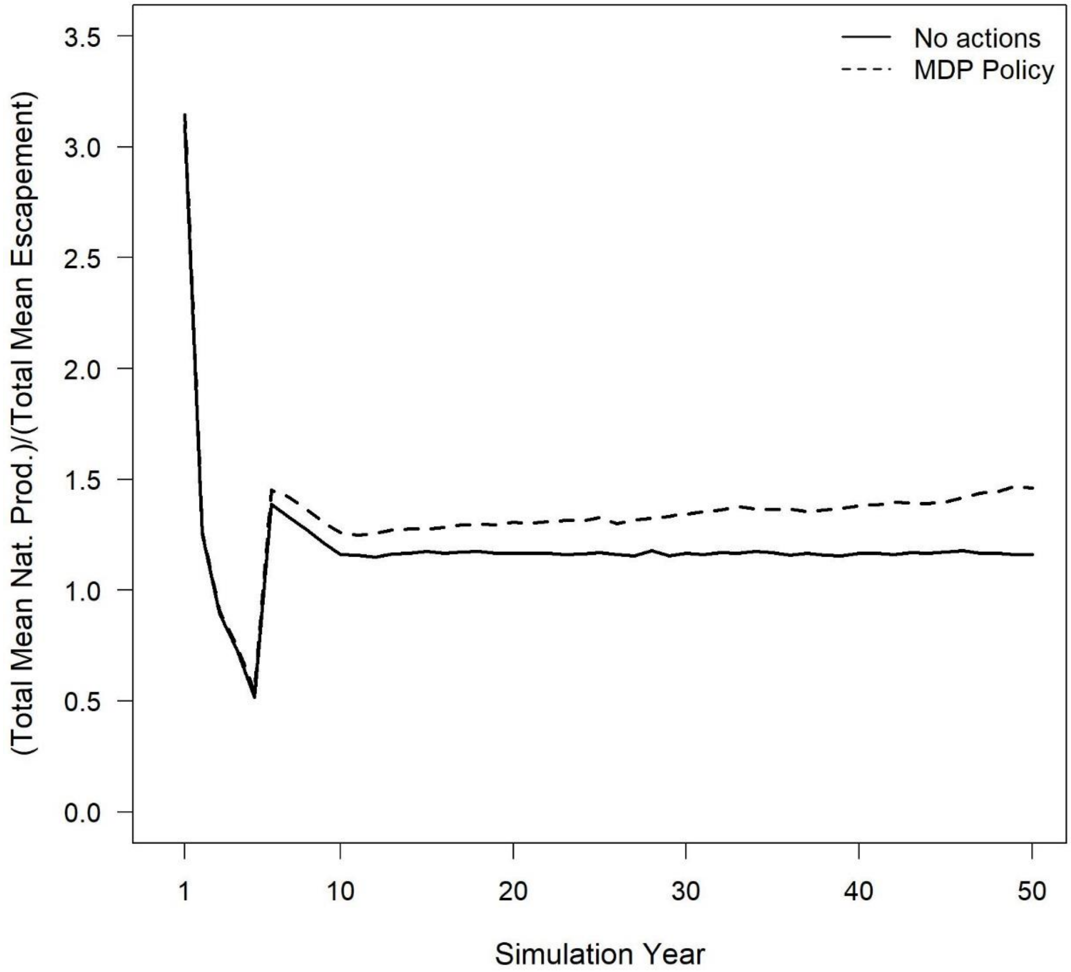

Figure 3.13 –The dashed line represents the change in utility during the forward simulation when the optimal policies were implemented. The solid line represents the utility if no actions were implemented during the 50 year time horizon.

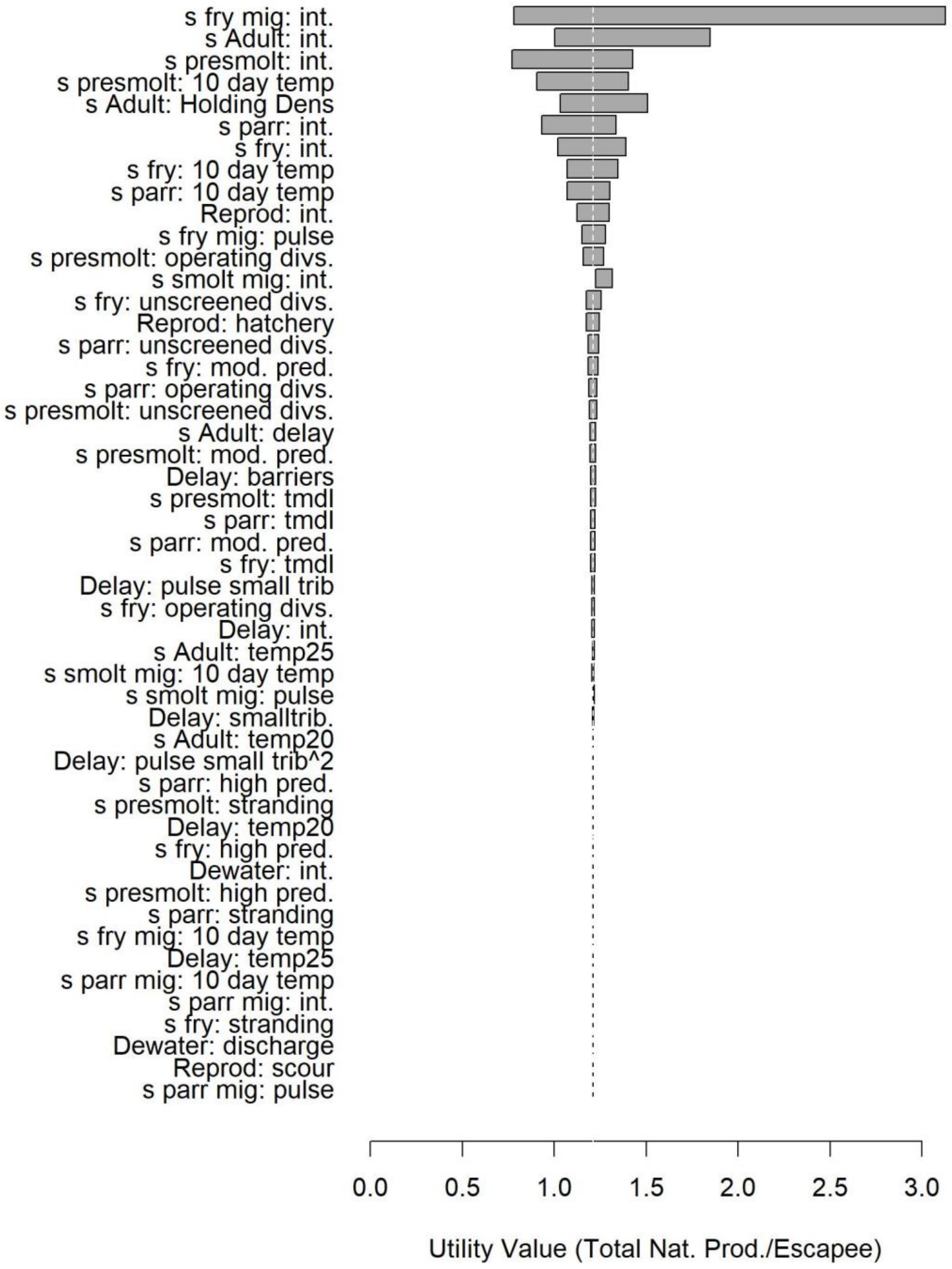

Figure 3.14 – Tornado diagram showing the results from the one-way sensitivity analysis for the biological parameters in the population model.

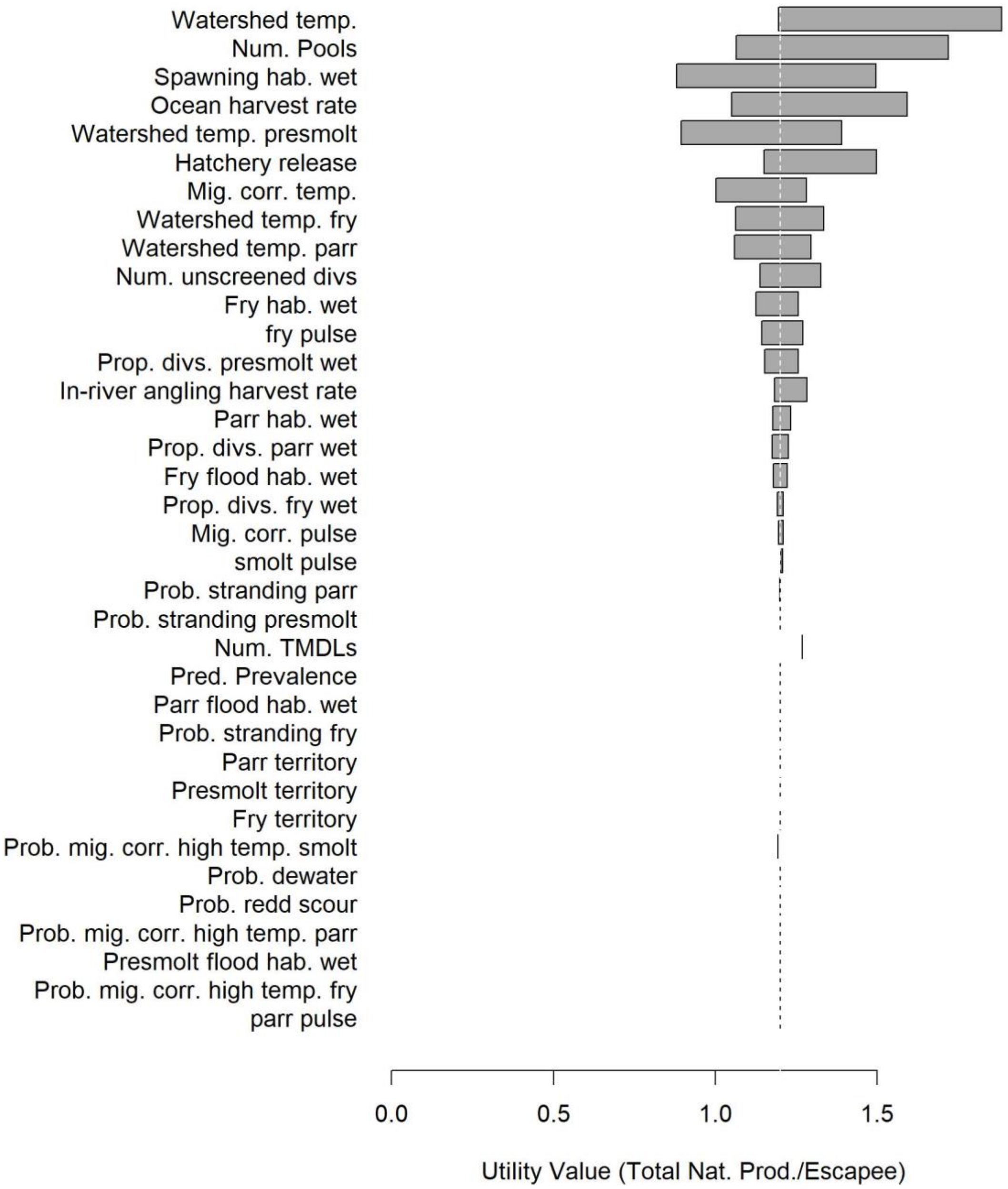

Figure 3.15 – Tornado diagram showing the results from the one-way sensitivity analysis for the environmental parameters during a “wet” scenario in the population model.

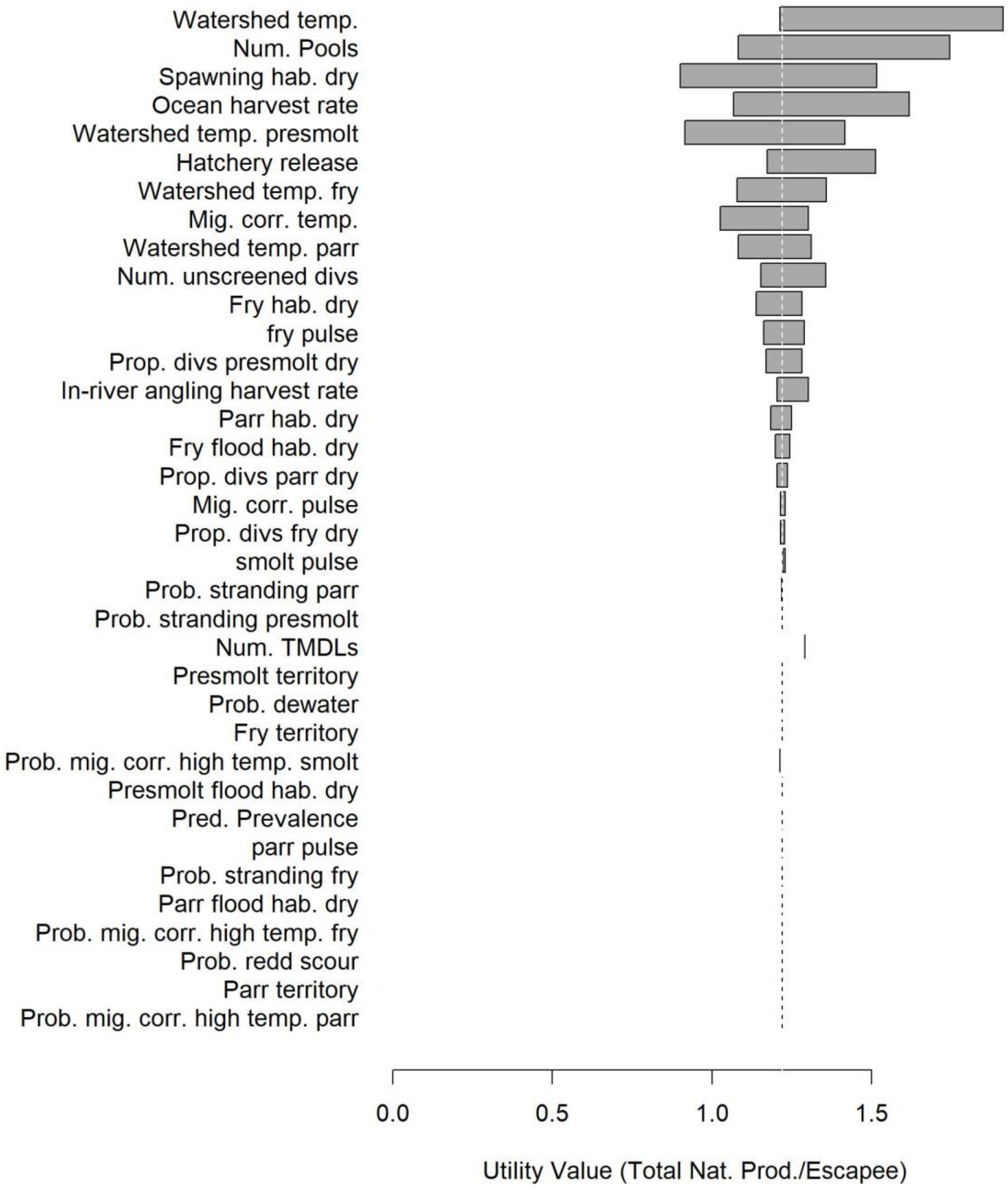

Figure 3.16 – Tornado diagram showing the results from the one-way sensitivity analysis for the environmental parameters during a “dry” scenario in the population model.

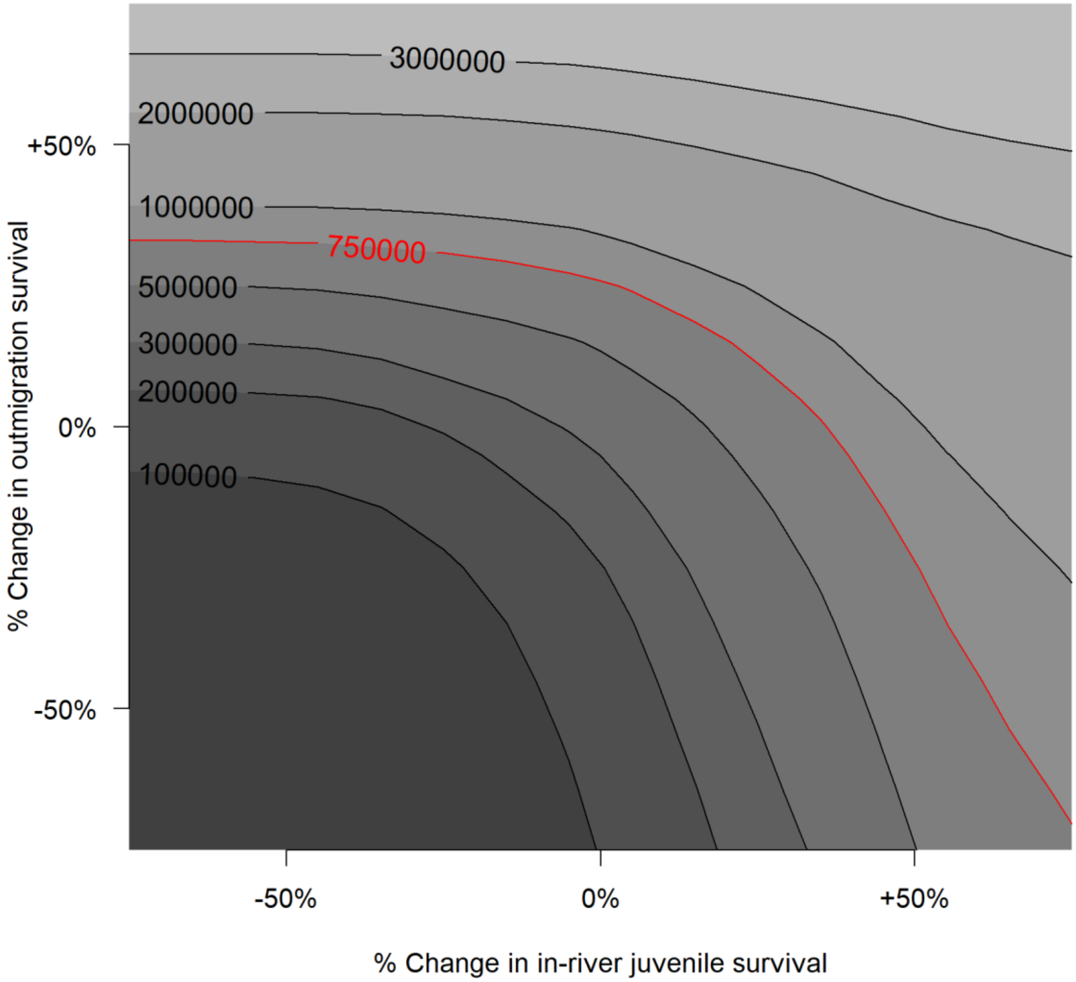

Figure 3.17 – Results from the two-way sensitivity analysis between the outmigration survival (s_{frymig}, $s_{parrmig}$, $s_{smoltmig}$) and in-river survival (s_{fry}, s_{parr}, $s_{presmolt}$) rates for fall-run Chinook salmon in CVPIA administered streams. The contours represent the mean total natural production as each of these parameters are varied by ± 50% of their original mean value. The red contour line represent the CVPIA system wide "doubling goal." The mean natural production was estimated using the population model and running the model for a single year for each combination of parameter values.

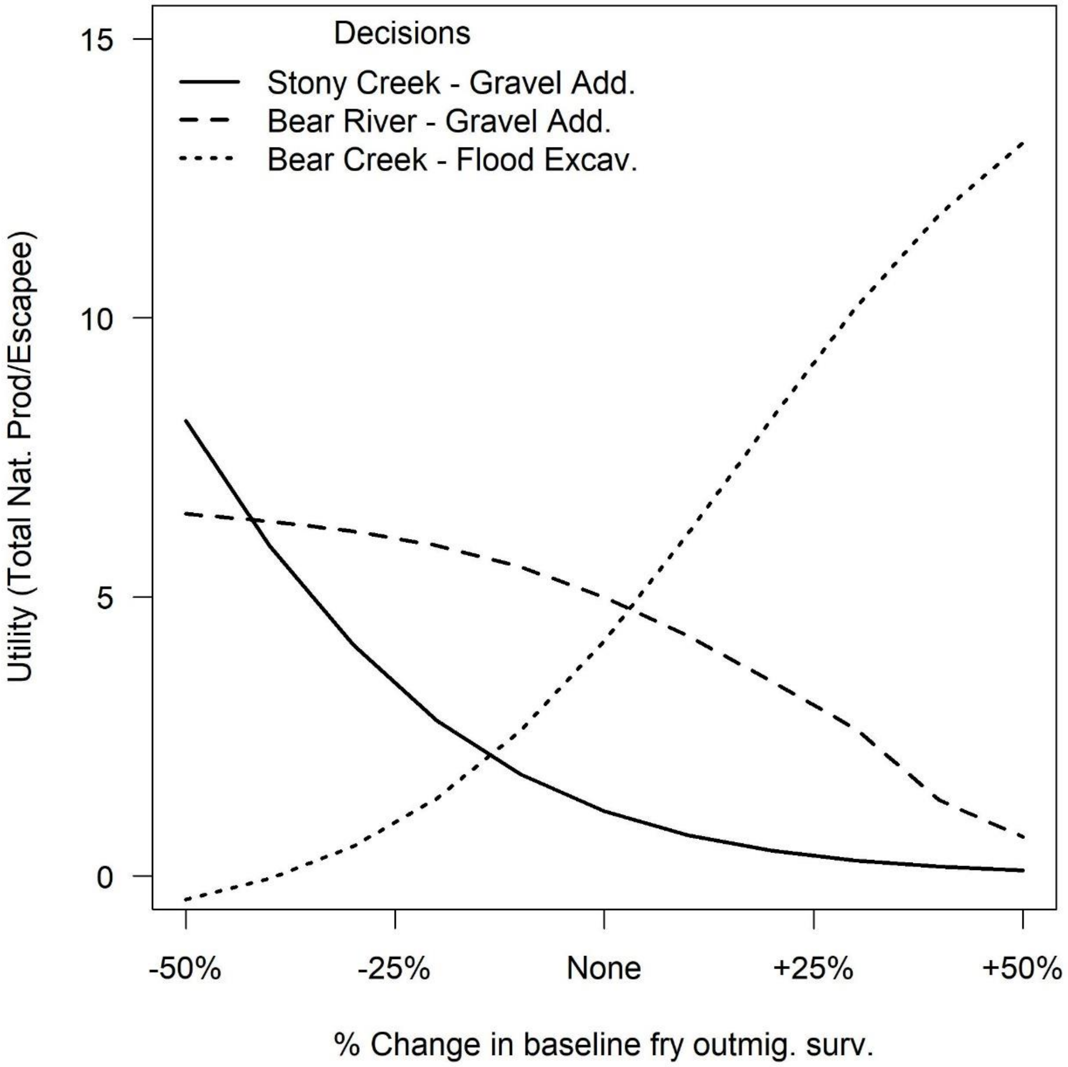

Figure 3.18 – The response profile analysis identified the baseline survival rate for outmigrating fry (the intercept term for calculating s_{frymig}) as the most influential parameter in the decision model. Each line represents how the utility of a specific decision changes across a range of parameter values. The optimal decision changes three times in total.

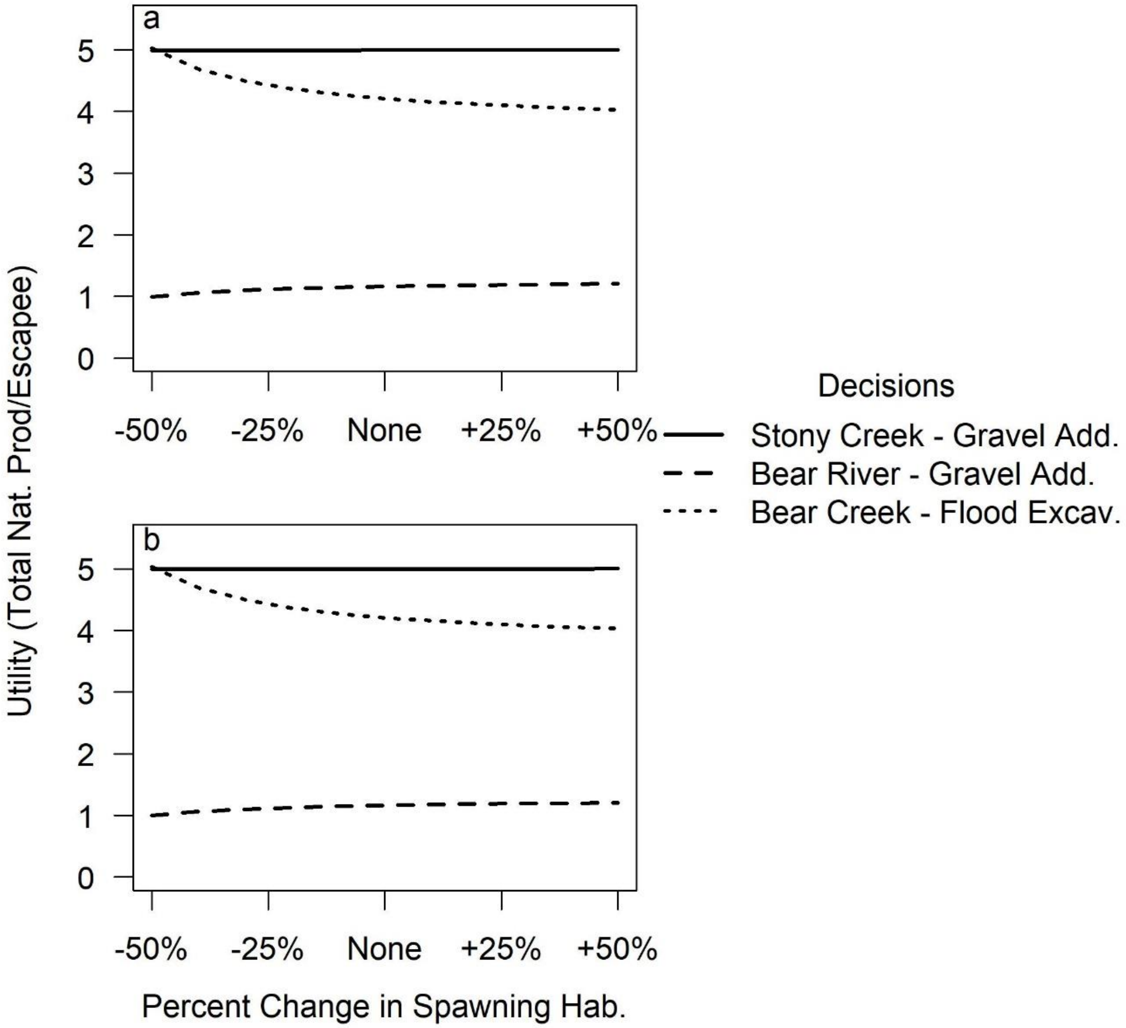

Figure 3.19 - The response profile analysis identified the amount of spawning habitat as the most influential habitat component of the decision model. Each line represents how the utility of a specific decision changes across a range of parameter values. Spawning habitat in both a wet (a) and dry (b) scenario was evaluated. The optimal decision changes twice for both habitat measures.

CHAPTER 4: QUANTITATIVE DECISION ANALYSIS FOR IDENTIFYING THE OPTIMAL ALLOCATION OF CHINOOK SALMON HABITAT RESTORATION PROJECTS IN A CALIFORNIA CENTRAL VALLEY STREAM

Abstract

Effective management of natural resources requires decision makers to embrace uncertainty and understand how different types of uncertainty can influence the decision making process. A determining factor of the types of uncertainty a decision problem has is the scale that it exists at. Most stream restoration efforts are implemented on a small spatial, often on reaches less than 1km. I used a population of Chinook salmon from a stream in California's Central Valley to develop a structured decision model to derive a state-specific stream restoration strategy. The fundamental objective of the decision maker in the decision problem was to maximize the production of natural origin adults. The model was a spatially explicit, habitat based life cycle that simulated adult migration into freshwater, spawning, juvenile rearing, and juvenile outmigration. Two habitat based decision alternatives were considered in the decision model: spawning gravel additions and floodplain excavations. The decision problem was represented as Markov decision problem and I used dynamic programming to derive a state-specific, optimal policy for individual reaches within the study stream. The optimal policies depended on four pieces of observable information in a given reach: the amount of spawning habitat, the amount of juvenile rearing habitat, the average number of redds present, and the temperature suitability of the reach. Implementing the optimal policy during a 100 year simulation resulted in significant increases in natural production compared to a scenario where no actions were taken over the same time horizon. Sensitivity analyses were

performed on the decision model to identify model inputs that could influence the decision making process. Structured decision modeling and dynamic programming provide a frame work and tools that can break a complex problem down to more manageable components which can inform future decision making.

Introduction

Uncertainty is a key feature of decision making in natural resource management. Effective management requires decision makers to embrace uncertainty and understand how different types of uncertainty can influence the decision making process (Mowrer 2000). Almost all uncertainty comes from the natural variation inherent in nature or from the inability to perceive systems correctly (Nichols et al. 2011, Williams and Johnson 2013). Structured decision making (SDM) provides a quantitative approach to fish and wildlife management and decision making that transparently incorporates uncertainty into decision making models (Holling 1978, Walters and Hillborn 1978, Walters 1986). SDM is comprised of just three basic components. The first is explicit, quantifiable objectives, the second is a set of explicit management alternatives, and the third is a model that is able to predict the effect of the management alternatives on the resource (Possingham et al. 2001, Martin et al. 2009, Conroy and Peterson 2013). The biggest strength of SDM is its ability to transparently identify how different sources of uncertainty can influence optimal decision making.

Decision problems are especially difficult if they require a decision maker to make a series of decisions through time. Sequential decision making often means that decisions are not independent through time (i.e., a decision at time t can affect a decision at time *t*+1). These problems are typically framed as Markov decision problems (MDPs) due to the Markovian property of the decisions and system. MDPs frame a sequential decision problem as a set of discrete state transition matrices and reward vectors where the probability of being in any given system state is only dependent on the system state at the previous time step (Ross 2014). The goal of a MDP is to find the optimal sequence of decision alternatives that maximize some utility function. Dynamic programming is one of the most common approaches to solve MDPs. The system stochasticity is captured in the transition matrices where the state-specific transition rates influence the expected reward value for each discrete state. Dynamic programing results in state-specific optimal policies through a backwards inductive computation procedure (Bellman and Dreyfus 1962, Bather 2000, Puterman 2009). The ability of dynamic programing to capture large amount of uncertainty and deconstruct a decision problem down to its essential elements makes it a great approach for sequential resource decision problems.

Streams are highly dynamic systems that makes stream habitat restoration decision problems a great example of a natural resource management issue that would benefit from structured approaches. In the last 100 years, anthropogenic fragmentation and degradation of in-stream fish habitat across North America has led to an increase in stream restoration activities. Past activities that have directly destroyed fish habitat include unsustainable mining and forestry practices and artificial channelization (Nehlsen et al. 1991, Lichatowich 1999). Some activities such as the construction of impoundments and irrigation diversions acted to deny fish access to historic habitats (Yoshiyama et al. 1998). These actions have caused populations of many freshwater fish species to decline across North America. This is especially true for highly migratory fish, such as Pacific salmon (*Oncorhynchus* spp.), whose life history requires access to multiple types of habitat. The degradation of fish habitats has led to the development and implementation of stream restoration programs to rehabilitate these streams and hopefully the fish populations that depend on them.

Scale is an important consideration when attempting to solve any decision problem. There are two primary components to scale: extent and grain. Extent refers to the broadest spatial and temporal dimensions over which decisions are made (e.g., a management area or the time horizon) and grain refers to the finest spatial and temporal resolution that the decisions and observations (e.g., monitoring) are conducted (Peterson and Dunham 2010). Stream habitat restoration is an example of a decision problem can vary largely in both their scale and complexity. Some restoration projects occur on very large scales and can take years to accomplish. An example of this is large dam removal (e.g., Elwa River, Washington; McHenry and Pess 2008, East et al. 2015) or a complete stream restoration from headwaters to confluence (e.g. Clear Creek, CA; Cummings et al. 2008). In contrast, some restoration efforts might occur at smaller scales, such as placing a few trees into a stream reach to increase the amount of woody debris habitat or through connecting a river channel to an off-channel habitat. Despite the wide range of spatial and temporal scales that restoration activities can occur, most stream restoration actions take place at spatial scales smaller than a 1 km reach (Bernhardt et al. 2005). Actions that occur at these small scales are usually due to limited available funds or personnel, limited stream access, and/or complicated permitting processes. In addition, landowner cooperation can be difficult to obtain. Thus, projects may be limited to locations where access is assured, regardless if that location is optimal for a given restoration activity or not. For these reasons, effective, large-scale restoration activities can be prohibitively expensive or too logistically complex to achieve (Roni et al. 2002, Beechie et al. 2008).

Unfortunately, stream restoration projects are often implemented in an ad-hoc manner due to the opportunistic nature of natural resource management. Systemic uncertainty and other key uncertainties also can result in managers pursuing smaller projects where the outcomes are more certain. Uncertainty creates a risk adverse decision making environment for natural resource managers (Thompson 2002, Cullen and Small 2004). That is, the perceived risk of an unintentional negative outcome resulting from an action or set of actions is so great that managers many choose not to pursue said management action even if it has the potential to achieve their objectives. This generally results in inaction or mangers pursuing less than optimal management actions. Management actions that are implemented in an unstructured or ad-hoc manner often lead to suboptimal outcomes that do not achieve their intended effect. The previous work that has been done on prioritizing stream habitat restoration has mostly focused on qualitative approaches where stakeholders use ranking systems to evaluate alternative habitat projects (Beechie et al. 2008, Roni et al. 2018). Although these approaches are useful for gaging support for different alternatives within a stakeholder group, they do not quantitatively connect management alternatives with models of system dynamics. Thus, stream restoration activities may benefit from employing a transparent, structured approach to decision making (Hobbs and Norton 1996, Suding 2011).

Restoration of Chinook salmon populations in the California's Central Valley provides a great opportunity to evaluate decision alternatives in fine scale decision problem. Chinook salmon occur in four distinct runs in the Central Valley which are identified by the time of year that spawners migrate into freshwater: Fall, Late-fall, Winter, and Spring (Vogel and Marine 1991, Fisher 1994). The fall-run is the largest run of Chinook salmon in the Central Valley and in turn it supports large commercial and recreation fisheries (Moyle 1994, Yoshiyama et al. 1998). Chinook salmon were once abundant throughout the Central Valley but since the turn of the 20^{th} century their numbers have been in decline (Yoshiyama et al. 2000). The decline of Chinook salmon populations in the Central Valley was primarily due to overharvest, habitat degradation and dams (Yoshiyama et al. 1998, Lichatowich 1999). In 1992 the Central Valley Improvement ACT (CVPIA) was passed by the U.S. Congress to restore anadromous fish populations to their historic population levels in the tributaries throughout the Central Valley, CA. The CVPIA became a necessary piece of legislation due to the serious decline of these Chinook salmon populations in the two decades leading up to its passage (Nehlsen et al. 1991, Cummins et al. 2008b). One of the primary provisions of the CVPIA is to double the abundance of anadromous species in the Central Valley from their 1992 levels. Specifically, the doubling goal seeks to increase the number of naturally produced (non-hatchery origin) Chinook salmon in the watersheds it oversees. The primary tool of the CVPIA has been habitat restoration to restore and improve habitats that would benefit Chinook salmon. These projects typically occur on a reach scale within a watershed. A quantitative approach to prioritizing habitat restoration projects within a watershed would benefit the management of Chinook because it would directly evaluate which uncertainties influence.

I developed a decision model that is able to replicate the fine-scale system dynamics of a population of fall-run Chinook salmon in a stream in California’s Central

Valley. The goal of the model was to accurately portray system dynamics and how managers implement management alternatives to benefit fall-run Chinook salmon. The model presented here is able to incorporate available habitat data, stream dynamics, management alternatives, and salmon life history to develop optimal habitat restoration policies. The model operates at a fine spatial grain (individual reaches) across an entire stream. The model was used as part of a SDM approach to evaluate how an optimal habitat restoration strategy could be used to increase fall-run Chinook production.

The primary objective of this chapter was to demonstrate how a quantitative decision analysis approach could be used to prioritize habitat restoration projects at a fine scale resolution. I used a structured approach and dynamic programming to derive optimal strategy for a habitat restoration problem in a Central California Chinook salmon stream. The habitat restoration strategy considers current values of two different kinds of habitat (spawning and fry rearing) to determine the optimal management alternative at a reach scale. The secondary objective of this chapter was to identify key uncertainties that drive the decision making process. Creation of a decision model at such a fine scale provides insight into what decisions are Chinook salmon management and how sensitive those optimal decisions are at this decision making scale.

Methods

Study Site

The American River is a 120 mile long tributary to the Sacramento River, whose confluence is in the city of Sacramento (Figure 4.1). The headwaters of the American River begin in Sierra Nevada Mountains in the Eldorado and Tahoe national forests. The

American River is made up of three primary branches (North, Middle, and South) that flow into Lake Folsom. Lake Folsom is created by Folsom Dam, which has blocked upstream passage for anadromous fish since its construction in 1956. Since no fish passage mitigation was provided at Folsom Dam, only the lowest 35.4 kilometers of stream are currently accessible to Chinook salmon (Williams 2001) and included in my analysis. This portion of the river is known as the Lower American River (LAR). The LAR watershed covers 4,856 km^2 and consists primarily of developed and urbanized land cover. In this study, the spatial extent of the decision was the length of the LAR and the grain consisted of 87 sections of the LAR that were approximately 400 m (0.25 mi) long beginning at Folsom Dam. The 400 m grain size was chosen to reflect the average size of past restoration projects, current monitoring, and hydraulic modeling.

The LAR supports one of the single largest populations of fall-run Chinook salmon in the Central Valley. In the last decade, approximately over 40,000 adult salmon have returned to the LAR on average. Wild and hatchery-origin fish are represented in the run, with the majority of the fish being hatchery origin in any given year (Palmer-Zwahlen and Kormos 2015). The Nimbus Fish Hatchery was built shortly after the construction of Folsom Dam and located just downstream of the dam. The Nimbus Hatchery releases and average of 4.7 million fall-run Chinook salmon smolts every year in late summer to minimize any overlap between hatchery and wild origin juvenile Chinook salmon. Currently, the hatchery does not release any other life stages of Chinook salmon into the river.

The construction of Folsom Dam has altered the hydrology and flow regimes in the LAR and contributed to the decline of suitable salmon habitats in the LAR. High levels of urbanization along the stream bank combined with high flows and the elimination of coarse sediment inputs have caused the river to excise into its channel (James 1997). This has effectively cut the river off from its historic floodplains throughout much of the river. The slow moving, off channel habitats associated with floodplain inundation are believed to be necessary for rearing juvenile salmonids (Sommer et al. 2001, Jeffres et al. 2008). In addition, the construction of Folsom Dam has interrupted the delivery of gravels and sediment from the headwaters into the LAR (Fairman 2007). This degraded and reduced the amount of suitable spawning habitat for adult Chinook salmon.

Decision Problem

This decision problem was framed from the point-of-view of the CVPIA implementing agencies: the U.S. Bureau of Reclamation and the U.S. Fish and Wildlife Service. These two agencies act jointly as the primary decision makers regarding habitat restoration activities in the LAR. They are tasked with developing and implementing habitat restoration actions that would best benefit the fall-run Chinook salmon population in the LAR. As a CVPIA stream, the LAR is also bound by a legislatively mandated "doubling goal" regarding the natural production of Chinook salmon. The term "natural production" refers to salmon that are produced by adults spawning in the river regardless as to their origin. For instance, the offspring of a wild and a hatchery origin adult salmon is considered "naturally produced." The legislative mandate means that the decision makers implement restoration actions that they think will achieve Chinook salmon natural production that is double that observed in 1991.

In 2013, the representatives of the implementing agencies and their collaborators participated in a series of workshops to develop an SDM framework for this decision problem. The workshops included the decision makers and other stakeholders including fisheries and hydrology experts from local state, federal, and private entities. The result of this workshop was the identification of the decision maker's fundamental and mean objectives, management alternatives, data sources, and the framework for a Chinook salmon decision model that would serve as the quantitative link between their potential management actions and objectives.

Objectives

One of the most important steps of SDM processes is the identification and structuring of both fundamental and means objectives. A fundamental objective is an objective that relates to the core values of the decision maker(s) or stakeholder(s), while a means objective is an objective that contributes to a fundamental objective without directly contributing to the fundamental objective (Conroy and Peterson 2013). In other words, a fundamental objective answers the question, "why is this important," and a means objective answers the question, "how do I accomplish that?" Typically, means objectives help achieve fundamental objectives.

The decision makers identified a single fundamental objective based on their legislative mandate, which was to maximize the number of naturally produced fall-run adult Chinook salmon. They hypothesized that increasing this measure would ultimately help lead to a more stable wild population as well as move the Chinook population towards its CVPIA doubling goal. Since a single fundamental objective was identified, the number of naturally produced adult Chinook salmon served as the utility (the metric that will be optimized) for the decision model. The decision makers also identified two means objectives that they hypothesized would help accomplish the fundamental objective of maximizing the number of naturally produced fall-run Chinook salmon. The first means objective was to increase the amount of spawning habitat available to returning adult salmon. The second means objective was to increase the amount of rearing habitat available to juvenile Chinook salmon. Although there may be other means of increasing the number of naturally produced Chinook salmon (e.g., decreasing in-stream temperatures or increasing pulse flows at critical times), the means objectives identified are aspects of the LAR that the decision makers could influence given their available resources and oversight.

Management Alternatives

The decision alternatives that the decision makers identified were derived from their means objectives. The two management alternatives considered were to add gravel to the stream channel or to excavate the stream bank to lower the floodplain, actions that have been previously performed in the LAR. The decision makers noted that these types of management actions are generally implemented on river reaches approximately 400 m (0.25 miles) long. They also decided that due to monetary and permitting constraints only a single restoration action could occur in a single year. Both management alternatives and their implementation were assumed to be cost equivalent based on previous work. Lastly, the decision makers chose not to evaluate management actions in the lowest 6.2 km of the LAR. From their previous experience, this stretch of river rarely holds either spawning adults or rearing juveniles due to seasonally high stream temperatures.

The first alternative the decision makers wanted to evaluate the effect of adding roughly 9000 m^3 of gravel into a single 400 m section (henceforth, reach) of the LAR. This volume represented a typical amount of gravel material that was added in previous gravel addition projects. During a gravel addition, gravel is trucked to the site and placed into the stream channel using heaving machinery. Ideally, the gravel is able to settle into the contours of the stream channel and thus provide spawning habitat. The whole process takes approximately two weeks to complete. The change in salmon spawning and juvenile rearing habitat availability resulting from a gravel addition to each reach was determined using 1-D hydrodynamic model (Table 4.1). The hydrodynamic model incorporated the effect of streambed contour, stream flows, and the channel shape of each reach to determine how a gravel addition would be distributed in an individual reach (Hammersmark 2014, Hammersmark and Tu 2015). Since the gravel is subject to the scouring flows, a gravel project may decay over time as gravel is scoured and transported downstream during high flow events. Thus, gravel additions do not permanently alter the stream channel or the amount of habitat. Previous studies on the LAR have shown that under low flows spawning gravel additions may have a life span of roughly 20 years (Horner 2015). Given this information, I decided that these projects would experience an exponential decay with a decay rate of 0.23 based on the recommendations of local experts (C. Hammersmark, CBEC eco engineering; T. Horner, Sacramento State University). This rate translates to an 85% reduction in suitable spawning area approximately five years after a gravel project was implemented.

The *excavate a stream bank* decision requires heavy machinery to manually excavate a volume of earth to lower the effective floodplain to create juvenile rearing habitat with slower currents with more cover. These are the types of habitats that juvenile Chinook salmon require to avoid predation and efficiently feed (Sommer et al. 2001). Previous excavation projects in the LAR have excavated an area of soil roughly 400 m long and 10 m wide adjacent to the river channel. These projects also excavate to a depth were the water depth in the new habitat is roughly 0.3-0.9 m. To estimate the extent of excavation needed to lower the floodplain, I used stream bank height data derived from a digital elevation model. The average stream bank height within 15.2 m of the stream edge at a discharge of 56.6 m^3/s was calculated for each stream reach. I assumed that this height corresponded to the excavation depth plus an additional 1m depth to create suitable juvenile habitat. Because bank height varied from reach to reach, the exact dimensions and volume required for excavation varied among the stream reaches. I also assumed that the habitat created from the excavation projects would be available to all juvenile salmon (fry and parr) in that reach. These projects are much more resilient than the spawning gravel projects (C. Hammersmark, personal communication). Thus, I assumed that any excavation project decay was negligible.

Salmon decision model

The model framework I used was developed during the stakeholder workshops and reflects participants' beliefs regarding system dynamics and how management alternatives change the system. The model operates on an annual time step beginning with adult Chinook salmon returning to the LAR to spawn and ending with juvenile

Chinook salmon exiting the LAR on their way to the ocean. A single management alternative can be implemented in each time step of the model. When implemented, the habitat changes occur that same year and were experienced by the adult salmon returning in that time step and their progeny. The model required several inputs that included: three types of habitat data, spawning, in-channel rearing and off-channel rearing; the probability of a wet year (high flow) versus a dry year (low flow); and survival rates for returning adult salmon and the juveniles produced. At the end of each time step, I estimated the expected number of wild adults produced for that cohort of out-migrating Chinook salmon. This metric represented the number of naturally produced adults that would be produced from single cohort of out-migrating juvenile salmon (i.e., natural production: the fundamental objective). Henceforth, I define this metric as adult equivalents.

A life history based population model was used to represent the dynamics of the fall-run Chinook salmon population in the LAR. Although salmon life history models have been developed for a large variety of applications in the past, these models are often data intensive and work at incompatible spatial scales (Bartholow et al. 1997, Satterthwaite et al. 2010). As such, I developed a model that used the available data and simulated the dynamics of the LAR fall-run Chinook population in response to restoration actions and external population drivers. The primary inputs for the model were initial adult escapement, habitat data, adult spawning success rates, juvenile survival rates, and juvenile-to-adult outmigration and survival rates. The primary outputs of the model were the number of naturally and hatchery produced adult equivalents for a given cohort.

A single time step (annual) of the population dynamics model consisted of six sub-models: *escapement, reproductive success, fry rearing and habitat, parr rearing and habitat, hatchery migration success,* and *fry, parr and smolt migration success* (Figure 4.2). I define a fry as a juvenile salmon <65mm in total length, a parr juvenile salmon between >65mm and <90mm, and a smolt as a juvenile salmon >90mm. The *escapement* sub-model simulated adult Chinook salmon in the ocean that migrated from the ocean into the LAR. These migrating individuals experience mortality from ocean harvest and recreational angler harvest. After entering freshwater, adult salmon fish are distributed throughout the reaches in the LAR. The escapees then dig redds and produce fry in the *reproductive success* sub-model. The *fry rearing and habitat* and *parr rearing and habitat* sub-models simulate the juvenile rearing process. During these sub-models, individuals either find habitat, grow, and survive or they migrate to the ocean as fry or parr. If habitat is not immediately available to a fish, they do have the opportunity to move downstream in an attempt to rear. Fish that survive both rearing processes ultimately become smolts, after which they migrate to the ocean. The hatchery component of the LAR is simulated in the *hatchery migration success* sub-model where hatchery origin smolts are released from the Nimbus Fish Hatchery. Lastly, the *fry, parr, and smolt migration success* sub-model applies a juvenile-to-adult survival rate. This rate is dependent on which life stage a juvenile fish migrates out of the watershed.

Escapement

The escapement submodel begins with adult salmon returning from the ocean to the LAR to spawn, $X_{ocean,j}$, where j represented the current time step (annual). These fish are then exposed to several sources of mortality before they are available for spawning:

[1] $X_{escape,j} = X_{ocean,j} \cdot s_{comm.,j} \cdot s_{rec.,j} \cdot s_{adult,j}$

where $X_{escape,j}$ is the number of escaped adults available for spawning, $s_{comm.,j}$ is the survival associated with commercial fishing in the ocean, $s_{rec.,j}$ is the survival attributed to freshwater recreational angling, and $s_{adult,j}$ is the freshwater survival rate of migrating adults (Table 4.2). Stochasticity was imposed by randomly sampling all of the above survival rates from beta distributions, whose shape and scale parameters were calculated via method–of-moments estimation.

Spawning adults were distributed within the river using a multinomial distribution:

[2] $spawn_{j,k} = multinomial(X_{escape,j}, \boldsymbol{p})$

where $spawn_{j,k}$ is the number of spawners in reach *k* at time step *j* and $\boldsymbol{p}$ is a probability vector of length *k*. Reaches in the LAR closer to the dam are colder and tended to be favored by spawning adults. In addition, hatchery origin adults have an affinity for areas closer to Nimbus hatchery (Williams 2001). To account for this behavior, the probability that an individual attempted to spawn in a specific reach of the river was related to the distance from the dam. This relationship was represented using the following exponential decay function:

[3] $p_k = {}^{1}\!/_{(1 + e^{-2.4+0.36*damdist_k})} \cdot nc$

where $damdist_k$ is the distance from Folsom Dam reach *k* is, *nc* is a normalizing constant to ensure that function integrates to one over the support of [0,35] river kilometers. I integrated equation 3 over each reach to determine the total probability of an individual adult spawning within that reach *k*. The value of *k* was calculated as the river kilometer at the upstream boundary for each 400 m reach that serve as the grain for this analysis.

Reproductive success

After the number of spawning adults (escapees) in each reach has been determined [eq. 2], females create redds and spawn to produce viable eggs. I assume that if there were more female spawners in a given reach than space for redds, those fish superimposed redds on top of one another destroying the original redd. This process reflected the density dependent relationship between spawning habitat and the total number of spawners. Soon after spawning, the adult fish died due to the energetic costs of freshwater migration and spawning. If these eggs experienced suitable temperatures and are undisturbed, they hatched to produce fry. This process occurred in each 400 m reach, *k*, and was approximated by:

[4] $$fry_{k,j} = ConRedd_{k,j} \cdot fecund_j \cdot s_{egg,j}$$

where $fecund_j$ was a random variable that represented the average fecundity in the population, $s_{egg,j}$ was a random variable that represented egg-to-fry survival and $ConRedd_{k,j}$ was the number of contributing redds at reach *k* (Tables 4.2 and 4.3). The value of $ConRedd_{k,j}$ was determined by:

[5] $$ConRedd_{k,j} = \begin{cases} reddcap_{k,j}, & redd_{k,j} > reddcap_{k,j} \\ redd_{k,j}, & otherwise \end{cases},$$

where $reddcap_{k,j}$ was the redd capacity in reach *k* and $redd_{j,k}$ was the potential number of redds produced in reach *k*. The potential number of redds in each reach *k*, $redd_{k,j}$ was determined using:

[6] $redd_{j,k} = X_{spawn,k,j} \cdot sex_j$

[7] $X_{spawn,k,j} = X_{escape,j} \cdot p_k$

where $X_{spawn,k,j}$ was the number of spawners in reach *k*, sex_j was the proportion of females and p_k was the probability of spawning within the reach with the upper boundary *k* (Table 4.3).

Lastly, the redd capacity of each reach was calculated by dividing the amount of spawning habitat (m^2) by the average redd size (m^2):

[8] $reddcap_{k,j} = {}^{spawnhab_{k,j}}\!/_{reddsize_j}$

where $spawnhab_{k,j}$ was amount of spawning habitat in each reach *k*, and $reddsize_j$ was the average redd size (Table 4.3). Also, the amount of spawning habitat varied depending on the amount of flow in the river (Table 4.4). Stream flows in the LAR are largely under the control of managers during spawning provided there is sufficient storage above Nimbus dam. Therefore, two flow conditions during spawning were included in the model, high (56.6 m^3/s), which represented typical LAR spawning flows when storage is sufficient and low (32.6 m^3/s), which represented storage-limited flow conditions. The candidate restoration actions were designed to have maximal benefits (i.e., most habitat available) between these flows. Both flows are equally probable in the model and were applied to every reach *k*.

Fry survival and fry habitat

In this sub-model, the fry produced in each reach *k*, rear to become parr if rearing habitat is available or begin to migrate downstream to look for available habitat. This portion of the model represented a roughly three-month period after larval swim-up. If downstream habitat was not available, migrating fry left the watershed and began their migration to the ocean. Fry that remained to rear survived as they transitioned from fry to parr. The number of parr produced in each reach *k*, $parr_{k,j}$, was calculated by applying a survival rate to the fry that reared in each reach:

[9] $$parr_{k,j} = rearfry_{k,j} \cdot s_{fry,j}$$

where $rearfry_{k,j}$ was the number of fry that will rear in reach *k*, and $s_{fry,j}$ was the fry-to-parr survival rate (Table 4.2). This survival rate was then applied to rearing fry in all the reaches.

The number of fry that remained to rear to parr, $rearfry_{k,j}$, included the fry that were able to find available habitat initially in the reach they were hatched in as well as those fry that migrated downstream and find available habitat. This process was modeled as:

[10] $$\boldsymbol{rearfry}_j = \boldsymbol{stayfry}_j + \boldsymbol{migfry}_j$$

where $\boldsymbol{stayfry}_j$ was a vector formulization of the fry that found habitat initially after hatching and $\boldsymbol{migfry}_j$, was a vector formulization of the excess fry that were unable to find available habitat after hatching but found habitat downstream. In the vector format above, the first element in the vector represented the furthest upstream reach and each subsequent element represented the next adjacent downstream reach.

The values of the elements in both $\boldsymbol{stayfry}_j$ were derived using the following habitat driven rule set:

[11] $$movefry_{k,j} = \begin{cases} fry_{k,j} - frycap_{k,j}, & fry_{k,j} > frycap_{k,j} \\ 0, & otherwise \end{cases}$$

$$[12]\quad stayfry_{k,j} = \begin{cases} fry_{k,j} - migfry_{k,j}, & fry_{k,j} > frycap_{k,j} \\ fry_{k,j}, & otherwise \end{cases}$$

where $frycap_{k,j}$ was the carrying capacity of reach k and $movefry_{k,j}$ was the excess fry that were unable to find available habitat in reach k. This rule set represented the hypothesis that if there was insufficient habitat for every fry in reach k to rear, excess fry become migratory and search for available habitat downstream. However, if all the downstream habitat was occupied the excess fry migrated directly to the ocean. The value of $frycap_{k,j}$ was determined based on the amount of habitat in each reach and the average size of a fry territory:

$$[13]\quad frycap_j = \frac{Fryhab_{k,j} \cdot temp_k \cdot qual_{fry}}{FryTerr_j}$$

$$[14]\quad temp_k = (1/(1 + exp(-(0.6 + damdist_k \cdot 0.39 - 0.018 \cdot damdist_k{}^2))))$$

$$[15]\quad FryTerr_j = L_{fry}{}^{2.61} \cdot 10^{-2.83}$$

where $Fryhab_{k,j}$ was the amount of fry habitat (m^2) available in reach k, $FryTerr_j$ was the average size of an individual fry's required territory (m^2), $temp_k$ was a coefficient from stream reach k, and $qual_{fry}$ was a measure of the fry habitat quality throughout the LAR. The $qual_{fry}$ parameter was a calibrated parameter (see *Survival Rates and Model Calibration* section below) that was necessary to reproduce the diversity of outmigrants by life stage (fry, parr, or smolt). Fry territory size was determined using an allometic that related fry territory size to fork length (Grant and Kramer 1990). Thermal suitability (eq. 14) was based on expert opinion of the stakeholders and represented reaches in the LAR with thermal regimes that were most suitable for juvenile rearing and growth. The quadratic shape of the function shows depicted the hypothesis that reached immediately below the dam were too cold for juvenile rearing and reaches too far downstream it is too warm (Figure 4.3). Similar to *reproductive success* sub-model, the value of $Fryhab_{k,j}$, was flow dependent. Both high (141.4 m^3/s) and low flow (93.4 m^3/s) rearing scenarios were included, both occurred with equal probabilities, and were independent of the spawning flows.

The elements of $\boldsymbol{migfry}_j$ were calculated using a transition matrix, $\boldsymbol{Y}_{fry}$, that allowed excess fry, $movefry_{k,j}$, to move downstream to find suitable rearing habitat. Fry that are unable to find habitat were forced out of the system to begin their migration to the ocean. The elements of $\boldsymbol{migfry}_j$ were calculated by:

[16] $$\overline{\boldsymbol{migfry_j}} = \boldsymbol{movefry}_j \cdot \boldsymbol{Y}_{fry}$$

[17] $$oceanfry_{k,j} = \begin{cases} \overline{migfry_{\boldsymbol{k,j}}} - (frycap_{k,j} - stayfry_{k,j}), & \overline{migfry_{\boldsymbol{k,j}}} > (frycap_{k,j} - stayfry_{k,j}) \\ 0, & otherwise \end{cases}$$

[18] $$migfry_{k,j} = \begin{cases} \overline{migfry_{\boldsymbol{k,j}}} - oceanfry_{k,j}, & \overline{migfry_{\boldsymbol{k,j}}} > (frycap_{k,j} - stayfry_{k,j}) \\ \overline{migfry_{\boldsymbol{k,j}}}, & otherwise \end{cases}$$

where $\boldsymbol{migfry}_j$ was a 1xk vector, and $oceanfry_{k,j}$ was a scalar that represented the final number of fry to migrate out of the LAR.

The transition matrix $\boldsymbol{Y}_{fry}$ is a (k) x (k) diagonal matrix that simulated downstream migration:

$$\mathbf{Y}_{fry} = \begin{vmatrix} 0 & y_{2|1} & y_{3|1} & y_{4|1} & \cdots & y_{k-1|1} & y_{k|1} \\ 0 & 0 & y_{3|2} & y_{4|2} & \cdots & y_{k-1|2} & y_{k|2} \\ 0 & 0 & 0 & y_{4|3} & \cdots & y_{k-1|3} & y_{k|3} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & y_{k-1|k-2} & y_{k|k-2} \\ 0 & 0 & 0 & 0 & \cdots & 0 & y_{k|k-1} \end{vmatrix}$$

The rows in the transition matrix $\boldsymbol{Y}_{fry}$ represented a fry's current position and the columns represented the downstream reaches accessible to upstream fry. Each non-zero element represented a probability that a fry would land in that reach of stream given where they started. For instance, element $y_{3|1}$ is the probability a fish rears in the third reach given it started in the first reach. These probabilities were the relative proportion of unoccupied downstream habitat (after initial seeding of habitat) in each reach given a particular upstream starting point. This process resulted in reaches of river that still have more fry than allowable habitat. That is, the number of fry exceeded the carrying capacity of the habitat.

Parr survival and parr habitat

The mechanisms of the parr-to-smolt transition were identical to that of the fry-to-parr transition. Similar to the fry sub-model, this model represented another 2.5 month period that ended with smolts migrating to the ocean. As the juvenile salmon grew (e.g., fry to parr sized), they required more space to feed and survive. The parr that remained in the watershed had to establish territories and any individuals that was unable to establish a territory due to habitat limitations migrated downstream to search for territory or potentially, migrate out of the watershed and towards the ocean. This resulted in parr that reared in the river to become smolts and parr that migrated to the ocean.

The fry-to-parr transition was similar to equation 9:

[19] $smolt_{k,j} = rearparr_{k,j} \cdot s_{parr,j}$

where $rearparr_{k,j}$ was the number of fry that will reared in reach k, and $s_{parr,j}$ was the parr-to-smolt survival rate (Table 4.2). Again, the parr-to-smolt survival rate was assumed constant across all the reaches.

The number of parr that remained to rear and become smolts, *rearparr*$_{k,j}$, included the (former) fry that were able to find available habitat either in the reach they were hatched or a downstream reach. This process was modeled as:

[20] $$\boldsymbol{rearparr}_j = \boldsymbol{stayparr}_j + \boldsymbol{migparr}_j$$

where ***stayparr***$_j$ was a vector formulization of the parr that found habitat, ***migparr***$_j$, was a vector formulization of the excess parr that were unable to find available habitat but found available habitat downstream. In the vector format above, the first element in the vector represented the furthest upstream reach and each subsequent element represented the next adjacent downstream reach.

The values of the elements in ***stayparr***$_j$ were derived using the following habitat driven rule set:

[21] $$moveparr_{k,j} = \begin{cases} parr_{k,j} - parrcap_{k,j}, & parr_{k,j} > parrcap_{k,j} \\ 0, & otherwise \end{cases}$$

[22] $$stayparr_{k,j} = \begin{cases} parr_{k,j} - migparr_{k,j}, & parr_{k,j} > parrcap_{k,j} \\ parr_{k,j}, & otherwise \end{cases}$$

where *parrcap*$_{k,j}$ was the parr specific carrying capacity of reach *k* and *moveparr*$_{k,j}$ was the excess parr that were unable to find available habitat in reach *k*. The value of *frycap*$_{k,j}$ was determined based on the amount of habitat in each reach and the average size of a fry territory:

[23] $$parrcap_j = \frac{Parrhab_{k,j} \cdot temp_k \cdot qual_{parr}}{ParrTerr_j}$$

[24] $$ParrTerr_j = {L_{parr}}^{2.61} \cdot 10^{-2.83}$$

where $Parrhab_{k,j}$ was the amount of fry habitat (m^2) available in reach k, $ParrTerr_j$ was the average size of an parr territory (m^2) and $qual_{parr}$ was a measure of the parr habitat quality throughout the LAR. Similar to $qual_{fry}$, $qual_{parr}$ was a calibrated parameter (see *Survival Rates and Model Calibration* section below) that was necessary to reproduce the diversity of outmigrants by life stage (fry, parr, or smolt). Again, the value of $Parrhab_{k,j}$, was flow dependent (Table 4.4). Both high (141.4 m^3/s) and low flow (93.4 m^3/s) scenarios were included with equal occurrence probabilities. These parr rearing flows were independent of the spawning flows and fry rearing flows.

The elements of $\boldsymbol{migparr}_j$ were calculated using a transition matrix, $\boldsymbol{Y}_{parr}$, that allowed excess parr, $moveparr_{k,j}$, to move downstream to find suitable rearing habitat. Parr that were unable to find habitat left the system to begin their migration to the ocean. The calculation of $\boldsymbol{migparr}_j$ was done by:

[25] $\overline{\boldsymbol{migparr_j}} = \boldsymbol{moveparr}_j \cdot \boldsymbol{Y}_{parr}$

[26] $oceanparr_{k,j} =$

$$\begin{cases} \overline{migparr_{\boldsymbol{k,j}}} - \left(parrcap_{k,j} - stayparr_{k,j}\right), & \overline{migparr_{\boldsymbol{k,j}}} > \left(parrcap_{k,j} - stayparr_{k,j}\right) \\ 0, & otherwise \end{cases}$$

[27] $migparr_{k,j} =$

$$\begin{cases} \overline{migparr_{\boldsymbol{k,j}}} - oceanparr_{k,j}, & \overline{migparr_{\boldsymbol{k,j}}} > \left(parrcap_{k,j} - stayparr_{k,j}\right) \\ \overline{migparr_{\boldsymbol{k,j}}}, & otherwise \end{cases}$$

where $\overline{migparr_{k,j}}$ represented each element of $\overline{\boldsymbol{migparr_j}}$. This rule set was identical to that found in equations 16-18. This process mimicked excess parr moving downstream in an attempt to search for available habitat. If none was available, fish begin their out migration to the ocean.

The transition matrix $\boldsymbol{Y}_{parr}$ was a k x k diagonal matrix that simulated downstream migration:

$$\mathbf{Y}_{\text{parr}} = \left| \begin{array}{ccccccc} 0 & y_{2|1} & y_{3|1} & y_{4|1} & \cdots & y_{k-1|1} & y_{k|1} \\ 0 & 0 & y_{3|2} & y_{4|2} & \cdots & y_{k-1|2} & y_{k|2} \\ 0 & 0 & 0 & y_{4|3} & \cdots & y_{k-1|3} & y_{k|3} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & y_{k-1|k-2} & y_{k|k-2} \\ 0 & 0 & 0 & 0 & \cdots & 0 & y_{k|k-1} \end{array} \right|$$

The transition matrix $\boldsymbol{Y}_{parr}$ was parameterized using the same process as $\boldsymbol{Y}_{fry}$ where each non-zero element represented a probability that a parr would land in that reach of stream given where they started.

Outmigration

When out-migrant juvenile salmon leave the LAR they migrated through the San Francisco Bay-Delta before entering the ocean. After entering the ocean these juvenile fish survived to adults before returning to the LAR to spawn once again. In this model, the decision makers had no control of processes that affect salmon outside of the LAR watershed (e.g., harvest). Thus, I condensed the entire process into a single life stage dependent, survival metric that represented the probability of an individual fish leaving the watershed to return as an adult. Up to this point, the model created three classes out-migrant juveniles, $migfry_{k,j}$, $migparr_{k,j}$, and $smolt_{k,j}$, each of which will migrate to the ocean to transition into adults with varying degrees of success. This was accomplished by applying a life stage specific out-migrant survival rate to each of the juvenile out-migrant classes:

[28] $adult_{fry,j} = \sum_k migfry_{k,j} \cdot s_{frymig,j}$

[29] $adult_{parr,j} = \sum_k migparr_{k,j} \cdot s_{parrmig,j}$

[30] $adult_{smolt,j} = \sum_k smolt_{k,j} \cdot s_{smoltmig,j}$

[31] $adult_{natural,j} = adult_{fry,j} + adult_{parr,j} + adult_{smolt,j}$

where $adult_{fry,j}$, $adult_{parr,j}$, $adult_{smolt,j}$, were the number of adults produced after applying the respective juvenile outmigrant survival rate (Table 4.2). The variable $adult_{natural,j}$ was the total number of naturally produced adults. The contribution of the hatchery production was estimated as:

[32] $adult_{hatchery,j} = smolt_{hatch,j} \cdot s_{hatch,j}$

with $smolt_{hatch,j}$ as the number of smolts produced in time step j, and $s_{hatch,j}$, is the smolt-to-adult survival rate for hatchery origin smolts (Table 4.2).

Adult Age Structure

The number of naturally produced adults, $adults_{natural,j}$, and the number of hatchery origin adults, $adults_{hatch,j}$, were assigned ages that they returned to freshwater to spawn. In the Central Valley, fall-run Chinook salmon spend two, three, four or five years in the ocean before returning to their natal stream to spawn (Satterthwaite et al. 2017). The assignment of ages was modeled using a multinomial distribution:

[33] $x_{ocean,j,l} \sim multinomial\left(\left(adults_{natural,j} + adults_{hatch,j}\right), \boldsymbol{p}_{return}\right)$

$$\boldsymbol{p_{return}} = [0.2\ 0.4\ 0.3\ 0.1]$$

where $x_{ocean,j,l}$ was the number of ocean adults from watershed j in the ocean residence class l= 2, 3, 4, or 5 years and $\boldsymbol{p}_{return}$ was the associated probability vector for each class l.

Habitat data

Habitat data for these analyses were derived from a 1-D hydrologic model (Hammersmark 2014). This process involved evaluating the relationship between flow and depth at multiple cross sections of the riverbed at each 400m river reach. Within each of these cross sections, the amount of suitable spawning, fry, and parr habitat was calculated (Table 4.4). Spawning habitat was calculated using a global habitat suitability index derived from both depth and velocity suitability curves (Hammersmark 2014). Juvenile habitat included areas of the wetted stream channel with suitable depth within 1.5 m of the shoreline. This 1.5 m buffer was used to reflect juvenile salmon's preference for slower moving water (Beakes et al. 2014). In addition, juvenile habitat was divided into fry habitat (0-0.3 m deep) and parr habitat (0.3-0.9 m deep; (Hammersmark and Tu 2015). Spawning and juvenile habitat availability was also estimated using two different flows that were chosen reflect two common flow regimes in this system, a high and low flow scenario (Table 4.4). Multiple flows were included because habitat availability in the LAR was directly related to flow (Hammersmark and Tu 2015).

Survival Rates and Model Calibration

Many of the parameters required in the model lacked empirically derived estimates. For these instances, I derived calibrated estimates to ensure that the population model produced results that were characteristic of the dynamics of LAR fall Chinook Salmon. Specifically, I calibrated the parameters: s_{egg}, s_{fry}, s_{parr}, s_{frymig}, $s_{parrmig}$, $s_{smoltmig}$,

s_{hatch}, $qual_{fry}$ and $qual_{parr}$. The habitat quality parameters ($qual_{fry}$ and $qual_{parr}$) were required to ensure that all the outmigrant strategies (fry, parr, and smolt outmigrants) were represented while keeping the in-river survival rates biologically realistic. In the LAR, all three size classes are have been detected as outmigrants (Williams 2001, Silva and Bouton 2015). Specifically, I wanted to make sure the inequalities $s_{egg} < s_{fry} < s_{parr}$ and $s_{frymig} < s_{parrmig} < s_{smoltmig}$ were true. The calibrated values provided a starting point to begin to evaluate how they influenced the model and the decision making process. Evaluating the influence of an unknown parameter on the decision model outputs is a key component of the SDM process.

I used the genetic algorithm found in the R package *rgenoud* (Mebane and Sekhon 2011) to calibrate these 9 parameters simultaneously. A heuristic method such as a genetic algorithm is ideal for solving this kind of problem with a large, unknown state space that requires simultaneous fitting of several interdependent parameters. This genetic algorithm required a utility function and it produced a set of parameters that attempted to minimize that utility function. For this application, I let the model run for 5 years using observed escapement values from 2004-2009 in each of those years. The model was then allowed to run for another 5 years to allow each simulated ocean residence group to contribute to escapement. After each year, the absolute difference between the simulated escapement and the actual measured escapement was calculated. The sum of these annual values was used as the utility to minimize. I constrained the optimization to only consider values that fulfilled the survival inequalities mentioned above. These inequalities ensured that larger fish have higher survival, which resulted in more realistic survival estimates. This ensured that the resulting parameters would represent the dynamics of LAR Chinook salmon.

The remaining parameters were estimated using local expert judgement (Tables 4.2 and 4.3). Empirical data is always preferable when parameterizing a model; however data from expert elicitation can serve as a starting point when it comes to prioritizing data needs. The implementing agencies and their collaborators provides estimates for the remainder environmental covariates and survival rates.

Policy Optimization

Given the decision problem described above, I now have a means to simulate the population at each time-step *t*, a reward function or utility (naturally produced adult equivalents), as well as a list of possible actions. Taken together, these components form the basis of a Markov Decision Process (MDP). MDPs can be solved using stochastic dynamic programming (SDP) which is able to take advantage of Markovian processes, population dynamics of salmon in this instance, to solve decision problems. The goal of solving an MDP is to find a set of decisions or actions through time that maximize a utility function, while simultaneously accounting for various inherent sources of stochasticity. In addition, they are computationally more consistent and efficient than heuristic methods or grid search optimization routines.

These problems can be generally formalized in discrete time as:

[34] $$\max_{[\boldsymbol{d}(t)\in\boldsymbol{D}]} \sum_{t=t_0}^{t_f} \gamma^t \cdot F(\boldsymbol{x},\boldsymbol{d},\boldsymbol{z},t) + F_T\left[\boldsymbol{x}\left(t_f\right)\right]$$

subject to:

$$\boldsymbol{x}(t+1) = \boldsymbol{x}(t) + f(\boldsymbol{x},\boldsymbol{d},\boldsymbol{z},t)$$

[35] $\boldsymbol{x}(t_0) = \boldsymbol{x_0}$

$\boldsymbol{x}(t) \in \boldsymbol{X}$

where *F*() is a time specific utility function, F_T() assigns a terminal value to the system, $\boldsymbol{x}$ is a vector of system states, $\boldsymbol{d}$ is a vector of time-specific decisions or actions, $\boldsymbol{z}$ is a vector of random variables influencing dynamics but not under decision control, γ is a discount factor and *f*() describes system dynamics. In other words, we want to maximize the function *F*() over time steps t_i for $i = 0,1,\ldots, f$, given system dynamics in the function *f*(). As the constraints in equation 35 indicate, this is a Markov process, meaning that the value of $\boldsymbol{x}(t{+}1)$ is only dependent on the value of $\boldsymbol{x}(\mathrm{t})$ and the system dynamics, $f(\boldsymbol{x},\boldsymbol{d},\boldsymbol{z},t)$, at time *t*. Thus, we can invoke the principle of optimality (Bellman 1957) and use backwards induction to optimize our utility function. Consider the Hamilton-Jacobi-Bellman (HJB) equation:

[36] $$J^*[\boldsymbol{x}(t),t] = \max_{[\underline{d}(t)\in\underline{D}]}[F(\boldsymbol{x},\boldsymbol{d},t)\cdot\gamma^t + J^*(\boldsymbol{x}(t+1),t+1)]$$

Equation 36 states that a decision at time *t* (assuming time steps of 1) is only optimal if all the remaining decisions are also optimal. Under this framework, we can derive an entire set of optimal decisions by finding the optimal decision at the final time step, t_f, then working backwards to find the optimal decision at t_{f-1}. This process is repeated until an entire set of optimal decisions is found for the entire time series $[t_0,t_f]$. In the end, this process guarantees an optimal decision set when they are implemented forwards in time. If this process is repeated over a long enough time frame, the vector $\boldsymbol{d}(t,x)$ may converge to a set of a set of stationary, state-specific optimal decisions. This process of is known as policy iteration because it provides optimal decisions for each possible system state.

Given the unintuitive nature of inductive reasoning, the formal proof can be found in either Bellman's (1957) article or Bathers (2000) text.

To simplify solving equation 36 and deriving a time-specific set of optimal decisions, we can define the HJB equation as using transition probabilities to create a Markov chain of system dynamics. If we define the conditional probability of being in state $\boldsymbol{x}_{t+1}$ at time t+1 as:

[37] $\pi(\boldsymbol{x}_{t+1} | \boldsymbol{x}_t, \boldsymbol{d}_t)$

then the HJB equation can be rewritten as:

[38] $$J^*[\boldsymbol{x}(t), t] = \max_{[\underline{d}(t) \in \underline{D}]} \begin{bmatrix} \overline{F}(\boldsymbol{x}, \boldsymbol{d}, t) \cdot \gamma^t + \\ \sum_{x_{t+1}} \pi(\boldsymbol{x}_{t+1} | \boldsymbol{x}_t, \boldsymbol{d}_t) J^*(\boldsymbol{x}(t+1), t+1) \end{bmatrix}$$

where $\overline{F}(\boldsymbol{x}, \boldsymbol{d}, t)$ is the expected utility for the next immediate time step.

This approach allowed me to derive policies that were applicable to the entire river. The utility function ($F(\boldsymbol{x},\boldsymbol{d},t)$) for this problem was simply the number of wild origin adult equivalents at time step t. Next, I derived transition probability matrices ($\pi(\boldsymbol{x}_{t+1}|\boldsymbol{x}_t,\boldsymbol{d}_t)$) using the population dynamics model described earlier. I chose to define the system state as discrete combinations of fry rearing habitat, spawning habitat, and thermal suitability in an individual 400m stream reach (see section below). Using this definition of system states, I was able to generate optimal management alternatives for any given stream reach given its current system state.

System state definition

I used the MDP framework to derive a stationary, state specific policy for a generic 400 m reach of stream. The derived policy answers the question of "what would the optimal habitat restoration option be in this reach given the thermal suitability, the amount of observed spawners, and the amount of available habitat?" I used metrics to define the system state that could capture the ability of an individual reach to accommodate both spawners and rearing juveniles. Additionally, the system states needed to be observable and influenced by the each of the management alternatives. Keeping that in mind, I chose to define system states as a combination of three variables. The first variable was the amount of spawning habitat (m^2) per spawning female and the second was the amount of fry rearing habitat (m^2) per spawning female. The combination of these two habitat variables, along with the temperature profile was what defined the state-space (x_T) as a whole:

$$[39] \quad x_T = \left[\frac{Spawnhab_T}{Redd}, \frac{FryHab_T}{Redd}\right]$$

where *T* represented the thermal suitability strata of the reach. Thermal suitability in a specific reach was a function of how far it was from Folsom dam and it directly determined the rearing survival rates for juvenile fish (eq. 14). Thus, juvenile survival rates ultimately determined the effect of a habitat restoration project (e.g., bank excavation). For instance, it was more likely that an excavation project would be more beneficial (in terms of maximizing natural production) in an area where fry and parr survival was higher. To account for this, three separate temperature strata, *T*, were considered, one each for river strata that had low, medium, and high fry survival rates (Figure 4.3). These bins were determined based on the tertiles of the juvenile temperature suitability curve (eq. 14) of the reaches of the LAR that were under consideration (Figure 4.3). Thus, state metric (x_T) was made up of four pieces of information that were collected by the decision makers: stream temperature, spawning habitat availability, fry habitat availability, and the number of females (redds) in a specific reach. I chose these habitat metrics to define the state-space because they were influenced by the decision alternatives and because they had the greatest effect on natural production (See sensitivity analysis).

This definition of the system state required discretized values to implement the HJB equation presented above. I discretized both the habitat dimensions of the defined states into bins of 50 in the range of 0 to 1000+ (21^2 total habitat states). This range and binning was chosen so the effect of each decision (or no decision) would have an effect on future system states and it also reflected the potential range of state values possible in the Lower American River.

All three the decision alternatives (do nothing, gravel addition and bank excavation) were considered as decision alternatives while solving this MDP. The goal of this optimization was to derive a state-specific policy that will be applicable to the entire LAR; thus I choose to use the system-wide mean effect of each decision alternative. This was to ensure that the policy derived in the MDP wasn't site specific, and thus applicable to the entirety of the LAR.

Under these state definitions, I was able to calculate both transition matrices (π) and the reward function ($\overline{F}(\boldsymbol{x}, \boldsymbol{d}, t)$). To calculate the transition matrices, I simulated a single time step and determined how many reaches were in each of the in each system state initially. Then a decision was implemented and the number of reaches in each system state was determined again. This process was repeated 10,000 times for each decision alternative and allowed to me determine the probability that a reach in any system state will transition into a different system state given a management action. Simultaneously, I calculated the utility (total number of naturally produced adults) after implementing each decision. These values were averaged across the system states, x, to determine the expected state-specific reward for each decision $\overline{F}(\boldsymbol{x}, \boldsymbol{d}, t)$. I assumed the discount parameter, γ, was equal to 0.99. All analyses were programmed and run in the statistical program *R* (R Core Team 2018).

Sensitivity Analyses

To determine which model parameters were the most influential in the decision model, I ran several different kinds of sensitivity analyses. Each of these was aimed at identifying the model parameters that influenced either the model's utility function or the optimal decision in a single annual time step. The one and two-way response profiles were used to evaluate how influential specific parameters were to determining the optimal decision at a single time step. The decisions I considered for these sensitivity analyses were do nothing, a gravel addition for each reach k, and an excavation project for each river reach k for a total of 141 decision alternatives. These types of analyses were important for identifying key uncertainties in the model and learning how these uncertainties influenced decision-making.

One-way sensitivity analysis

The one-way sensitivity analysis was performed by varying each of the population model's parameters one at a time by +50% and -50% of their original mean value, while holding all the remaining model parameters at their expected values. During each parameter perturbation, I calculated the total number of naturally produced adult equivalents, $adults_{natural}$, after a single time step. This process isolated the influence that each individual parameter had on the utility and demonstrated how influential the parameters were relative to one another. A parameter was considered influential if the value of the utility changed substantially while the parameter was varied between +50% and -50% of its original value.

Two-way sensitivity analysis

A two-way sensitivity analysis is used to evaluate how two parameters interact with one another across a range of their values to affect the estimated utility. The two-way sensitivity analysis isolates a single pair of parameters so their interaction can be evaluated. It is similar to the one-way sensitivity analysis, except that two parameters are varied simultaneously. For every combination of model parameters, I varied each simultaneously between +50% and -50% of their mean values while holding all other parameters at their expected values. The total number of naturally produced adults was calculated after a single time step for every combination of parameters values.

Total habitat and outmigrant survival sensitivity

I also performed a sensitivity analysis to evaluate what combination of juvenile outmigrant survival and total habitat amount would be necessary to achieve the CVPIA doubling goals. This analysis is a two-way sensitivity analysis but instead of perturbing two individual parameters, I'm perturbing two groups of parameters. The first group is all the wild-origin outmigrant survival rates (s_{frymig}, $s_{parrmig}$, $s_{smoltmig}$). The second group of parameters were all the habitat inputs ($Spawnhab_k$, $Fryhab_k$, $Parrhab_k$) in each reach k. Both groups of parameters were perturbed from their current value to +900% of their current value. For each combination of parameter perturbations I determined the number of naturally produced adult equivalents after a single time step.

Response Profiles

A response profile sensitivity analysis evaluates how the identity of optimal decisions vary across a range of values of one or more parameters. A one-way response profile sensitivity analysis is similar to the one-way sensitivity analysis, in that a single parameter is perturbed at a time. However, instead of focusing how different parameters affect the utility, these analyses evaluate how the optimal decision alternative may change across a range of parameter values. In other words, it answers the question, "would your optimal decision be different if this individual parameter took a different value?" I varied the value of each parameter in the model by +50% and -50% of its mean value while all the other parameters were held at their expected values. For every value of the parameter being varied, all the decision alternatives were applied and the decision with the greatest utility value was reported. So for any given parameter, I can determine if the optimal decision changes across a range of its values and where (at what value) those changes occur in that range.

Two-way Response Profiles

I also performed a two-way response profile to explore how the optimal decision changed across the values of two model parameters simultaneously. The goal of this analysis is to determine how two components of the model interact to determine an optimal decision alternative. During this analysis, two model parameters were varied independently between -50% and +50% of their mean values, while any other model parameters were held constant at their expected values. For every combination of values of each of the parameters that are being perturbed, the optimal decision was determined for a single time step. This analysis was run for all combinations of the model parameters.

I also performed a two-way response profile analysis using the effect size of each decision alternative. This analysis answers the questions of how much more or less habitat would a project have to create before the optimal decision would change. The amount of habitat the gravel addition and the floodplain excavation decision alternatives could make were varied simultaneously by ±50% of their original values across every reach. For each combination of gravel addition effect size and floodplain excavation effect size I determined the optimal decision.

Forward Simulation

I used the policy derived from the MDP to evaluate how the optimal policy performed compared to taking no action over the course of 100 years. In each year, I used the current habitat conditions (amount of spawning and fry rearing habitats and the thermal suitability) and an estimate of the number of number of redds to determine the optimal decision for each reach using the appropriate policy. The number of redds present in particular reach, for a given year is not likely to be directly observable in time to implement a decision in the same year. Typically, the number of redds in watershed are estimated using carcass counts, aerial photography, or another escapement based estimation process after the spawning season (Williams 2001, Gallagher and Gallagher 2005). I calculated the mean redd count over the previous five years in each watershed to account for the lag in redd estimation and the variability in redds that occur between years. I then applied those optimal decisions to those river reaches one at a time. The action in the reach that maximized natural production was then chosen as the decision that would be implemented in that time step. This process was repeated for each year in the simulation. I then ran another simulation of 100 years with no actions being taken to compare how the MDP policies performed compared to taking no action.

Results

Population Model performance

Overall, the population model tracked the population dynamics and features of the Lower American River well. The model was able to reasonably replicate the variable levels of escapement seen in previous years (Figure 4.4). Letting the model run for a single year produced a mean escapement of 25,625, with a standard deviation of 11,161. The mean natural production after a single year was 9,658, with a standard deviation of 4,225. Additionally, the mean hatchery production was 72,321 with a standard deviation of 16,274. It should be noted, that this model was calibrated using data from a period of time when ocean conditions were generally poor (2010-2014).

The population model was able to accurately represent the diversity of out-migrant Chinook salmon life histories as well. A single year of simulation showed that the average proportion of Chinook leaving as fry, parr, and smolts produced 66%, 14%, and 20% of the adult equivalents produced respectively (Figure 4.5). This follows closely what was observed during 2015 when a screw trap was run at the confluence of the American River and the Sacramento River: 71% fry, 14% parr, and 15% smolts (Silva and Bouton 2015).

Policy optimization

The policy optimization identified three different state-dependent optimal decisions for all three water temperature strata. In each case, the policy iteration was able to reach policy convergence in less than 10 iterations. The effect of the thermal strata on the policy was marked, especially comparing the policy from the reaches where juvenile survival was lowest to the other two thermal strata (Figures 4.6-4.8). Unlike the policies from the strata with higher survival, in this policy there was a great range of optimal decisions across all the system values. The decision to implement a floodplain excavation was optimal at larger values of spawning habitat/redd compared to the other policies.

Sensitivity Analyses

One-way sensitivity analysis

The one-way sensitivity analysis showed only a few parameters had much influence on the adult equivalents produced in a single year (Figure 4.9). The parameters with the largest influence both were related to the hatchery production of the model. The size of the hatchery release, the number of smolts that were produced and released by the Nimbus fish hatchery, was the most influential and the out-migrant survival of those hatchery fish was the next closest parameter. Both these parameters caused the total number of adult equivalents to vary almost ±50% of its original, unperturbed value. The models sensitivity to the hatchery submodel wasn't surprising as currently hatchery fish make up the largest proportion of returning adults in the Lower American River (Palmer-Zwahlen and Kormos 2013, Palmer-Zwahlen and Kormos 2015). However, hatchery production and survival are not under the authority of the decision makers, so for the rest of sensitivity analyses I focus on the remaining model parameters.

Aside from the parameters associated with the hatchery, the next most influential parameters included: fry size, egg-to-fry survival, sex ratio, and fry outmigrant survival. With the exception of the sex ratio of spawning adults, all these parameters were focused on the early life history of these Chinook salmon. Also, a fish's decision to stay and rear or to migrate downstream was directly tied to the territory size of each individual as well as the available habitat. In the model, fry size was a proxy for the amount of available habitat in the model. This one-way sensitivity analysis shows that fry habitat availability, in-stream survival and out-migration survival were all the largest drivers of the production of adult equivalents.

I was surprised that both redd size and the age-specific fecundity rates were not influential parameters. I had assumed that redd size would have been an effective predictor of the number of adult equivalents produced because the number of redds dug directly determines the number of potential juveniles that are produced. The same was true for all the age-specific fecundity rates. Both these adult associated parameters were not as influential as other parameters associated with the juvenile life stages.

Two-way sensitivity analysis

Almost all the two-way sensitivity analyses where similar to the one-way sensitivity analyses, only a handful of the results indicated that two parameters interacted in a non-linear manner. One of the most interesting two-way sensitivity analysis was that between the fry habitat quality parameter and the parr habitat quality parameter (Figure 4.10). Varying these parameters simultaneously showed that generally at low levels of parr habitat quality, fry habitat quality no longer becomes influential. Conversely, at high levels of parr habitat quality, fry habitat quality becomes influential. Specifically, at high values of juvenile habitat quality as fry habitat quality decreases we see that overall production of adult equivalents increases.

The interaction between the mean size of juveniles and outmigrant survival also were influential in determining the production of adult-equivalents. When the size of fry are small (and the amount of habitat each individual occupies), the out-migration survival of fry begins to have little effect on the number of adult equivalents produced (Figure 4.11). This was likely because territory size is proportional to body size so that fry carrying capacity is greater than parr carrying capacity. As a result, more fry remain to rear to become parr and smolts. The total number of adult equivalents produced also increased as the size of fry decreased. When we consider how the size of parr interacted with juvenile out-migration survival rates (Figure 4.12), we see a similar pattern as in fry. Again when mean size of parr is decreased, outmigration survival becomes less influential because fewer and fewer juveniles migrate out of the watershed due to the higher densities they are able to sustain.

Total habitat and outmigrant survival sensitivity

The two-way sensitivity analysis between the total amount of habitat and all the outmigrant survival rates demonstrated that increasing both would result in the biggest gains in natural production (Figure 4.13). Attaining the CVPIA doubling goal would require huge increases in both the total amount of habitat and outmigrant survival. However, increasing one without the other would more than likely not result in reaching that goal.

Response profiles

The response profile identified five influential parameters that caused the optimal decision to change across their perturbed values (Table 4.5). Redd size caused the optimal decision to change twice under the values considered (Figure 4.14). It was interesting that red size had such a large influence on determining the optimal decision given it was relatively insensitive in the one-way sensitivity analysis. Adult freshwater survival was also an influential model component (Figure 4.15). Again, the optimal decision changed twice over the span of values this parameter took. The optimal decision was to make gravel additions except at very lowest values of adult survival. The other influential parameters identified by the response profile analysis were the sex ratio, commercial ocean harvest survival and recreational river harvest survival.

Two-way Response Profiles

Almost all the two-way response profile sensitivity analyses showed that the optimal decision was insensitive to most parameters. One combination of parameters did show some sensitivity, fry out-migration survival (s_{frymig}) and the size of fry (Figure 4.16). This only occurred while the value of the mean fry out-migration survival was decreased by 30% and simultaneously the value of the mean size of fry was decreased by 20%. Only in this small region of parameter values did the optimal decision change.

The optimal decision changed several time across a range of effect sizes for the two decision alternatives. The optimal decision was generally insensitive to the amount of habitat that the excavation projects were able to produce (Figure 4.17). Even a doubling in the amount of juvenile habitat that those projects did not change the optimal decision. The optimal decision was much more sensitive to the amount of habitat that the gravel projects create. However, the amount of habitat that the gravel projects would have to create would be almost nothing before the optimal decision becomes riverbank excavation. This definitively points to the advantages that creating spawning habitat has over creating juvenile rearing habitat in the LAR.

Forward Simulation

The forward simulation using the optimal policies showed that on a system wide scale it is almost always optimal to create gravel habitat (Figure 4.18). In the 100 years of the simulation, bank excavation was never identified as the system wide optimal decision. This is almost certainly because in the model spawning gravels (and thus spawning habitat) is decaying every year. The system begins deficient in spawning habitat and even with gravel additions, it remains spawning habitat deficient due to the gravel decay that occurs every year. Additionally, actions were only implemented in a total of 16 different reaches of the LAR. There also appeared to be a cyclic pattern to the where and when gravel additions took place (Figure 4.18).

The population level response to implementing the optimal decisions was noticeable, but unable to reverse the declining trend of natural production in the Lower American River (Figures 4.19 and 4.20). However, after 100 years of implementing the optimal policies there was a decrease in the rate of decline in both total escapement and total natural production. The decline in escapement was due to a decline in spawning habitat through the gravel decay that occurs each year. Hatchery production remained almost constant throughout the simulation.

Discussion

The optimal state-specific derived policy obtained from the MDP demonstrated that the amount of fry and spawning habitat within a specific reach ultimately determined what management alternative will be optimal. The policies indicated that stream restoration activities in the Lower American River were highly site specific. Unsurprisingly, there doesn’t appear to be a single management action that was appropriate for all stream reaches. Models that operated at larger spatial grains would likely miss this important result. The lower reaches of the river may become too warm during the time juvenile fall Chinook salmon rear (Williams 2001). It also may be more beneficial to have juveniles migrate out of the basin as fry rather than to stay and rear only to experience near lethal temperatures later in the summer.

The forward simulation showed that there were only a handful of sites on the LAR where implementing a restoration project would be optimal. After implementing the optimal policies for 100 years, there were only 16 reaches out of 70 where projects were implemented. This resulted in a pattern in which reaches would be repeatedly visited through time (Figure 4.17). Ideally, a strategy like this may allow decision makers to make targeted gravel supplements to the LAR through time. Also, in each instance the optimal decision was always to add spawning gravels. The LAR is thought to have limited spawning gravels available for Chinook salmon and these results seem to confirm this (Merz et al. 2012).

The result of the sensitivity analyses demonstrated that that the early life history stages of the Chinook salmon in the Lower American River are essential not only to population dynamics but they are also largely influential to the decision problem. It has been suspected that out-migrating fry and parr Chinook salmon contribute to the adult returns in Central Valley streams (Healey et al. 1991, Waples 1991). The simulated numbers of Chinook salmon leaving the LAR as fry, parr and smolts is seen in other Central Valley streams, where fry and parr make up the majority of outmigrants (Miller et al. 2010). The large number of simulated fry out-migrants explains why the parameters associated with the fry life stage (size of fry, fry in river survival, and fry out-migrant survival) had such a large effect optimal decision making. Small perturbations in almost any aspect of early life history survival can have large population level effects. It should be reiterated, that in this model, fry size directly influences the territory size of those animals. In fact, the state-specific optimal decisions point seem to be aimed at increasing the number of fry, and to a lesser extent parr, that migrate out the stream. This especially evident when we see that the optimal decisions in all the reaches (even the lowest reaches) was to create spawning habitat. This demonstrates how this model assumes fry use habitat and how that can ultimately affect optimal decision making. Although smolts tend to have better ocean survival, fish that remain in freshwater to rear also experience a lot of additional mortality. From the sensitivity analyses, it appears that management actions that increase the number of fish that can rear in may actually be detrimental to maximizing natural production. Although not directly incorporated in this model, I believe this may be especially true if stream temperatures continue to rise (Yoshiyama et al. 1998, Myrick and Cech Jr 2004). I believe that if we were able to incorporate in-stream temperatures we'd see that management actions that attempt to hold fish to rear to larger sizes (via habitat additions) would result in decreases in natural production.

All the sensitivity analyses suggested that resolving key uncertainties surrounding juvenile (fry and parr) survival and how they use in-stream habitats use should to be prioritized in future monitoring efforts. Minimizing these uncertainties would provide clearer insight into how effective the different management alternatives can be. In the decision model, I assumed that a juvenile's decision to migrate downstream was directly related to the amount of available habitat. This is a rather large assumption that needs to be evaluated empirically. There may be other environmental cues (e.g. time of year, flow, or temperature, genetics) not incorporated in this model that could explain the when and how juveniles decide to migrate. Alternative models of system dynamics can be evaluated in dynamic programming in a process known as adaptive optimization (Williams et al. 2002, Conroy and Peterson 2013). There are two forms of adaptive optimization: passive and active. In passive adaptive optimization the alternative models of system dynamics are used to produce separate sets of state transition matrices which are then averaged using weights identified *a priori* to derive an optimal policy. Active adaptive optimization treats the probability of one alternative model being correct over another as another system state known as the information state. The initial values of the information state are allowed to evolve through time and an optimal policy is derived for each information state. In both forms of adaptive optimization monitoring can be used to begin to resolve structural uncertainty while incorporating that uncertainty into decision making process. The SDM process started in this study would provide a very appropriate framework to test and resolve systemic uncertainties regarding different migration strategies that may occur in the Chinook salmon streams.

Defining the system states can be perhaps the most difficult parts of designing a MDP optimization. Simplification or discretization of the system state space is typically required to solve traditional MDPs due to the "curse of dimensionality" (Bellman and Dreyfus , Bellman 1957). I used just three metrics in a single reach to define the state space: fry habitat per red, spawning habitat per red and distance from the dam as a proxy for temperature. Although this approach provides an interpretable measure to represent the system state of a given reach, in reality there may exist several, continuous reach specific characteristics that may prove to be important to determining optimal decisions. MDPs that include multiple continuous state-spaces are known as general state-space MDPs, and require more advanced algorithms to accurately depict state-space transitions and rewards (Feng et al. 2004, Li and Littman 2005). I believe that such applications could be beneficial to stream restoration planning because they could allow for the effective computation of state specific optimal decisions while incorporating a complex state space.

Decision problems that operate at fine scales require data sources to match. Parameterizing fine scale decision problems can be difficult because of the high resolution data that is required. Although data can be aggregated to provide information for coarser resolutions, the opposite isn’t always true. For instance, information that is gathered at a coarser scale (e.g. watershed level) may not be appropriate to apply to a fine-scale, spatially explicit decision model. The SDM approach allows information gaps to be parameterized using expert opinion if empirical data is lacking. Expertly derived data can also be evaluated to determine if they influence how optimal decisions are made. The result allows decisions to be modeled and key uncertainties to be identified despite uncertainties that are the result of working at fine scales. Although fine scale decision problems can be data intensive, structured approaches to decision modeling can identify which data gaps are most critical to decision process which can inform future monitoring.

Structured decision modeling and dynamic programming provide a frame work and tools that can break a complex problem down to more manageable components which can inform future decision making. In this decision problem, there were a total of 141 decision alternatives (70 reaches, each with two decisions available plus the option to do nothing) that could be considered in a single time step. Solving a stochastic, sequential decision problem with that many decision alternatives would test the capabilities of even the most advanced heuristic optimization routines. Also, there is no guarantee that heuristic solution is an accurate approximation of the actual solution (Conroy and Peterson 2013, Alpaydin and Bach 2014). On the other hand, dynamic programming provides optimal polices that rely on just a handful of informative system states. The generality of the derived policies provides insight on which model parameters actually drive the decision making process. Identifying influential parameters is essential for natural resource managers as they plan future monitoring.

Risk is an inherent component of decision making and has to be considered in decision modeling. The discount factor (γ) used during the optimization is one way to represent risk because it represents the relative value of a reward across time steps. Mathematically γ needs to be < 1 in order for policy and value iteration methods to converge. Typically γ is set to either 0.95 or 0.99 to satisfy this condition. Smaller values of γ represent a decision maker that values rewards more immediately than over the long term. In this decision problem, keeping the discount factor close to 1 made sense because I assumed the decision maker was able to value salmon in the future at near the same rate as salmon in present. Decision makers may tolerate increased risk for more immediate returns in fish or wildlife populations that are self-sustaining and productive. The opposite would be true for populations that are imperiled or endangered because there is smaller margin for error. SDM and dynamic programming provides a frame work to quantitatively test these assumptions and determine how risk over a time horizon (as represented by γ) can alter optimal policies.

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Tables

Table 4.1 - The effect size of implementing either a gravel decision or a riverbank excavation on each type of habitat under two likely flow scenarios in each reach of the Lower American River, CA. The effect size was measured as the change in habitat (m^2) for each decision. The high and low flow scenarios correspond to inriver flows of 32.6 m^3/s and 56.6 m^3/s respectively.

		Action	Gravel Addition						Riverbank Excavation			
		Flow Scenario	Low			High			Low		High	
		Habitats Adjusted	Spawning	Fry	Parr	Spawning	Fry	Parr	Fry	Parr	Fry	Parr
Reach #	River km											
1	35.08		8412.3	-322.0	6070.2	-770.0	349.0	-648.0	3180.7	3180.7	3180.7	3180.7
2	34.67		-2401.1	-321.7	1590.1	-3199.1	2032.1	110.0	3692.6	3692.6	3692.6	3692.6
3	34.27		13649.4	-321.7	-7989.3	1305.0	-553.0	-3254.1	3281.3	3281.3	3281.3	3281.3
4	33.87		6956.2	-321.1	7266.2	7508.2	-189.0	139.0	3610.3	3610.3	3610.3	3610.3
5	33.48		9509.3	-321.8	-533.0	655.0	-1404.0	-3583.1	3857.1	3857.1	3857.1	3857.1
6	33.09		11759.4	-320.4	3716.1	9005.3	-465.0	-7242.2	3290.4	3290.4	3290.4	3290.4
7	32.69		13366.4	-316.2	12903.4	12121.4	-425.0	-4848.2	3948.5	3948.5	3948.5	3948.5
8	32.28		1119.0	-317.1	1370.0	2951.1	-1362.0	-866.0	3555.5	3555.5	3555.5	3555.5
9	31.86		2023.1	-321.9	719.0	3117.1	-1042.0	-1597.1	3628.6	3628.6	3628.6	3628.6
10	31.45		3534.1	-321.2	945.0	11586.4	-1149.0	-2300.1	3747.4	3747.4	3747.4	3747.4
11	31.05		522.0	-320.8	-1607.1	-3811.1	-2814.1	-8916.3	3528.0	3528.0	3528.0	3528.0
12	30.65		-9103.3	-318.4	-4200.1	-16798.5	-1322.0	-3995.1	3802.2	3802.2	3802.2	3802.2
13	30.25		5635.2	-321.8	5963.2	7775.3	-1628.1	1808.1	3637.7	3637.7	3637.7	3637.7
14	29.81		3609.1	-317.4	2065.1	2042.1	-1218.0	-213.0	4076.4	4076.4	4076.4	4076.4
15	29.32		3349.1	-318.4	3281.1	-220.0	-1485.0	-1645.1	4387.2	4387.2	4387.2	4387.2
16	28.87		7352.2	-320.5	5165.2	4396.1	-170.0	-972.0	2056.5	2056.5	2056.5	2056.5
17	28.35		13802.5	-322.5	1766.1	1133.0	766.0	-969.0	5100.1	5100.1	5100.1	5100.1

Table 4.1 - Continued

		Action	Gravel Addition						Riverbank Excavation			
		Flow Scenario	Low			High			Low		High	
		Habitats Adjusted	Spawning	Fry	Parr	Spawning	Fry	Parr	Fry	Parr	Fry	Parr
Reach #	River km											
18	27.90		7041.2	-322.8	-2458.1	559.0	-1529.1	-2356.1	2659.7	2659.7	2659.7	2659.7
19	27.41		4577.1	-321.6	-2531.1	-988.0	-1597.1	-2202.1	3683.4	3683.4	3683.4	3683.4
20	27.04		11006.4	-322.1	-36.0	6462.2	-1068.0	-2200.1	3390.9	3390.9	3390.9	3390.9
21	26.64		642.0	-322.1	11091.4	5868.2	-723.0	-2037.1	3464.1	3464.1	3464.1	3464.1
22	26.24		9040.3	-321.4	142.0	7366.2	-253.0	-7946.3	3281.3	3281.3	3281.3	3281.3
23	25.84		2551.1	-318.3	-3111.1	-5887.2	-930.0	-3064.1	3784.0	3784.0	3784.0	3784.0
24	25.44		-221.0	-320.7	-4598.2	2951.1	-1930.1	-6593.2	3116.7	3116.7	3116.7	3116.7
25	25.03		-2014.1	-317.7	-7322.2	-6067.2	-482.0	-2540.1	3582.9	3582.9	3582.9	3582.9
26	24.63		-390.0	-321.1	-8162.3	-3832.1	345.0	-3852.1	3473.2	3473.2	3473.2	3473.2
27	24.22		7968.3	-320.5	1587.1	-782.0	1589.1	-4827.2	3646.9	3646.9	3646.9	3646.9
28	23.82		11291.4	-319.3	4792.2	6171.2	-29.0	-3561.1	3354.4	3354.4	3354.4	3354.4
29	23.42		12251.4	-318.2	9738.3	-124.0	-377.0	-7726.3	3875.4	3875.4	3875.4	3875.4
30	23.01		13099.4	-317.8	3807.1	6040.2	338.0	-5611.2	3253.8	3253.8	3253.8	3253.8
31	22.61		10249.3	-321.1	9019.3	7424.2	386.0	-3486.1	3244.7	3244.7	3244.7	3244.7
32	22.21		8189.3	-321.4	-2937.1	2616.1	-1642.1	-3372.1	3354.4	3354.4	3354.4	3354.4
33	21.82		9220.3	-320.9	-1764.1	4088.1	-1140.0	-3600.1	2815.1	2815.1	2815.1	2815.1
34	21.41		23132.8	-321.3	7420.2	16344.5	-327.0	-3763.1	3875.4	3875.4	3875.4	3875.4
35	21.00		19197.6	-320.6	20515.7	12385.4	-777.0	334.0	3784.0	3784.0	3784.0	3784.0
36	20.57		188.0	-310.3	7832.3	-1604.1	7478.2	6147.2	2202.7	2202.7	2202.7	2202.7
37	20.16		10804.4	-325.4	12641.4	7043.2	-1305.0	4954.2	3299.5	3299.5	3299.5	3299.5
38	19.75		3706.1	-323.2	21726.7	414.0	-4598.2	5574.2	2751.1	2751.1	2751.1	2751.1
39	19.31		8421.3	-315.6	14040.5	516.0	-9763.3	19231.6	4588.3	4588.3	4588.3	4588.3

Table 4.1 - Continued

		Action	Gravel Addition						Riverbank Excavation			
		Flow Scenario	Low			High			Low		High	
		Habitats Adjusted	Spawning	Fry	Parr	Spawning	Fry	Parr	Fry	Parr	Fry	Parr
Reach #	River km											
40	18.86		7908.3	-327.8	1982.1	7541.2	3254.1	-1060.0	3537.2	3537.2	3537.2	3537.2
41	18.41		3614.1	-322.1	3221.1	1117.0	1751.1	-1077.0	3619.4	3619.4	3619.4	3619.4
42	17.99		12194.4	-321.1	807.0	11721.4	-111.0	-274.0	3811.4	3811.4	3811.4	3811.4
43	17.59		6922.2	-321.1	649.0	5249.2	-257.0	-1708.1	3518.9	3518.9	3518.9	3518.9
44	17.17		2802.1	-321.2	1945.1	5349.2	-690.0	-8881.3	3975.9	3975.9	3975.9	3975.9
45	16.76		2768.1	-318.6	623.0	3306.1	-201.0	-1612.1	3911.9	3911.9	3911.9	3911.9
46	16.34		7532.2	-321.1	4661.2	13023.4	-453.0	-8408.3	3774.8	3774.8	3774.8	3774.8
47	15.93		3718.1	-318.0	6204.2	2388.1	-952.0	-15070.5	3729.1	3729.1	3729.1	3729.1
48	15.53		6912.2	-314.7	13819.5	9261.3	1077.0	-11607.4	3729.1	3729.1	3729.1	3729.1
49	15.11		-8202.3	-315.6	-999.0	1858.1	422.0	-19667.6	4030.7	4030.7	4030.7	4030.7
50	14.71		-26256.9	-312.5	-5974.2	-7257.2	-390.0	-30267.0	3125.9	3125.9	3125.9	3125.9
51	14.31		4191.1	-310.2	-2004.1	5145.2	-1440.0	-13561.4	3464.1	3464.1	3464.1	3464.1
52	13.91		14.0	-316.3	-6482.2	-3148.1	-1693.1	-2735.1	3765.7	3765.7	3765.7	3765.7
53	13.51		-358.0	-322.0	-6468.2	-3107.1	-1642.1	-7222.2	3866.2	3866.2	3866.2	3866.2
54	13.11		409.0	-321.3	-361.0	264.0	-1456.0	-7474.2	3774.8	3774.8	3774.8	3774.8
55	12.73		2419.1	-321.1	3800.1	890.0	-1906.1	-9488.3	3582.9	3582.9	3582.9	3582.9
56	12.33		390.0	-319.8	4683.2	2252.1	-2158.1	-14386.5	3902.8	3902.8	3902.8	3902.8
57	11.92		-1707.1	-317.8	4414.1	414.0	-2254.1	-16556.5	3948.5	3948.5	3948.5	3948.5
58	11.52		-1866.1	-317.3	-2710.1	-4840.2	-2596.1	-22318.7	3674.3	3674.3	3674.3	3674.3
59	11.12		1572.1	-316.3	2812.1	-1704.1	-1946.1	-18450.6	4368.9	4368.9	4368.9	4368.9
60	10.70		7123.2	-316.9	10398.3	2644.1	-5325.2	-25462.8	4113.0	4113.0	4113.0	4113.0
61	10.28		15257.5	-305.1	22877.7	11243.4	-4951.2	-13796.5	3491.5	3491.5	3491.5	3491.5

Table 4.1 - Continued

		Action	Gravel Addition						Riverbank Excavation			
		Flow Scenario	Low			High			Low		High	
		Habitats Adjusted	Spawning	Fry	Parr	Spawning	Fry	Parr	Fry	Parr	Fry	Parr
Reach #	River km											
62	9.87		22779.7	-306.7	15065.5	14054.5	-5416.2	-26134.9	3665.1	3665.1	3665.1	3665.1
63	9.50		14723.5	-303.9	14638.5	6304.2	-4872.2	-17456.6	3098.5	3098.5	3098.5	3098.5
64	9.09		12505.4	-307.6	24643.8	8469.3	-3131.1	-3050.1	2239.3	2239.3	2239.3	2239.3
65	8.69		1298.0	-310.4	-23861.8	-14704.5	-63.0	-5054.2	2431.2	2431.2	2431.2	2431.2
66	8.24		13048.4	-319.6	15866.5	15172.5	-2962.1	-833.0	4670.5	4670.5	4670.5	4670.5
67	7.81		9501.3	-310.8	13306.4	2721.1	-2934.1	-860.0	3893.6	3893.6	3893.6	3893.6
68	7.37		62.0	-310.5	11686.4	-2087.1	-3082.1	-1009.0	3875.4	3875.4	3875.4	3875.4
69	6.97		-898.0	-310.6	7870.3	-4724.2	-2942.1	-1599.1	3528.0	3528.0	3528.0	3528.0
70	6.60		8894.3	-309.9	15411.5	9238.3	-2837.1	-581.0	3144.2	3144.2	3144.2	3144.2

Table 4.2 - Annual survival estimates for the fall-run Chinook salmon population dynamics model for the Lower American River, CA. These values were derived using from the calibration process. Calibrated parameters are indicated with *.

Parameter	Description	Mean	Stand. Dev.
$s_{comm,j}$	Ocean harvest survival	0.4000	0.1000
$s_{rec,j}$	Recreational in-stream survival	0.4500	0.2250
$s_{adult,j}$	Adult in-river survival	0.9963	0.0100
$s_{egg,j}$	egg-to-fry survival*	0.1527	0.0305
$s_{fry,j}$	fry-to-parr survival*	0.4223	0.0845
$s_{parr,j}$	parr-to-smolt survival*	0.5031	0.1006
$s_{frymig,j}$	fry outmigration survival*	0.0011	0.0002
$s_{parrmig,j}$	parr outmigration survival*	0.0185	0.0037
$s_{smolt,j}$	smolt outmigration survival*	0.0291	0.0058
$s_{hatch,j}$	hatchery survival adjustment*	0.0151	0.0030

Table 4.3 - Other parameter values for the fall-run Chinook Salmon population model in the Lower American River, CA. Parameters without a standard deviation are static. Calibrated parameters are indicated with *.

Parameter	Description	Mean	Stand. Dev.
$X_{ocean,\,1}$	Initial population size used to seed the model	77257	NA
$X_{ocean,2}$	Initial population size used to seed the model	77703	NA
$X_{ocean,3}$	Initial population size used to seed the model	77845	NA
$X_{ocean,4}$	Initial population size used to seed the model	79699	NA
$X_{ocean,5}$	Initial population size used to seed the model	80470	NA
sex	sex ratio	0.5	NA
$Reddsize_j$	Redd size (m2)	9.476	1.895
$Fecund_{2,j}$	fecundity for age 2 adults	4185	837
$Fecund_{3,j}$	fecundity for age 3 adults	5838	1167
$Fecund_{4,j}$	fecundity for age 4 adults	5994	1198
$Fecund_{5,j}$	fecundity for age 5 adults	7403	1480
L_{fry}	mean length (mm) of a fry sized fish	65	13
L_{parr}	mean length (mm) of a par sized fish	90	18
$qual_{fry}$	fry habitat quality parameter*	0.89	NA
$qual_{parr}$	parr habitat quality parameter*	0.25	NA

Table 4.4 - Habitat estimates (m^2) within each reach (~400m). Note that no habitat is available after river km 6.06 (reach # 70). The LAR stakeholders indicated the the temperatures in the lower reaches of the LAR are typically too warm for salmon spawning and rearing.

		Flow Scenairo	Low			High		
		m^3/s	32.6	93.4	93.4	56.6	141.6	141.6
		Habitat Type	Spawning	Fry	Parr	Spawning	Fry	Parr
Reach #	River km							
1	35.08		3337	2802	7128	3422	2256	6003
2	34.67		6888	4204	10831	6980	3250	8906
3	34.27		8735	4812	19280	15007	2419	12086
4	33.87		3073	7294	12938	4097	7265	14299
5	33.48		1257	3503	7799	1706	2578	7849
6	33.09		0	4933	9059	411	2308	9858
7	32.69		4639	4837	12610	3183	3233	10552
8	32.28		7073	4920	7997	2794	4870	10330
9	31.86		0	1240	4046	5	882	3105
10	31.45		4021	2869	9226	3951	2124	7281
11	31.05		1851	2641	7497	1689	3371	6720
12	30.65		13777	3419	11123	14491	4988	7177
13	30.25		5932	12987	11804	6347	6817	19243
14	29.81		3022	1487	4730	1819	1078	3088
15	29.32		5864	8780	21272	4133	8805	18537
16	28.87		833	6056	11131	936	6339	12579
17	28.35		3049	2277	7196	3840	2809	5792
18	27.90		6246	6733	22693	8842	5718	16502
19	27.41		970	2146	7238	1935	1627	4825
20	27.04		20	1741	3993	4	1590	3533
21	26.64		17588	3168	12033	13904	1815	7567
22	26.24		7616	2211	8549	6049	2333	5651
23	25.84		12898	4780	12126	11045	2598	9597
24	25.44		11617	1948	8805	6872	1338	4678
25	25.03		539	1523	6626	1913	970	3641
26	24.63		132	2784	6394	350	2524	6341
27	24.22		2508	5511	11478	3968	2962	12488
28	23.82		0	2376	5176	212	1085	4911
29	23.42		13731	6204	25169	18761	4658	18219
30	23.01		7535	5441	16304	9100	4767	14106
31	22.61		13170	5590	22366	14378	4578	12186
32	22.21		4527	2990	10382	4066	2429	7917

Table 4.4 - Continued

		Flow Scenairo	Low			High		
		m^3/s	32.6	93.4	93.4	56.6	141.6	141.6
		Habitat Type	Spawning	Fry	Parr	Spawning	Fry	Parr
Reach #	River km							
33	21.82		0	2082	5833	81	2050	5407
34	21.41		63	2625	9079	338	1465	8147
35	21.00		8085	13838	25823	9655	11952	24863
36	20.57		4810	28141	27751	9247	21844	41178
37	20.16		7121	16572	25275	4198	12398	28781
38	19.75		7376	25147	35985	8846	21012	48559
39	19.31		2937	4669	13853	4898	8045	11558
40	18.86		1393	2544	6700	1616	1968	5933
41	18.41		3505	5572	8046	3858	3402	9593
42	17.99		593	4561	9906	778	1462	9174
43	17.59		0	7408	25719	5	4877	26021
44	17.17		0	8829	18024	1	5441	17992
45	16.76		0	7944	19740	200	4761	16837
46	16.34		3234	5159	14387	2404	2596	12815
47	15.93		67	1537	5490	961	870	3776
48	15.53		6757	1889	5416	4278	1713	4065
49	15.11		20920	1708	10180	8239	1159	5854
50	14.71		13883	3029	11214	7231	2393	8883
51	14.31		5703	7043	25072	8029	6032	17035
52	13.91		1800	2158	12359	2599	1402	6531
53	13.51		0	2979	12735	0	2755	9383
54	13.11		0	7727	17531	0	5842	16669
55	12.73		0	3856	14892	0	2366	11854
56	12.33		963	3644	10239	804	864	9747
57	11.92		0	1606	4547	34	1008	3888
58	11.52		0	1335	5374	0	973	3941
59	11.12		0	757	2393	0	640	1854
60	10.70		0	691	1841	0	595	1607
61	10.28		13	1001	2897	256	812	2357
62	9.87		3120	5091	19704	8962	3801	16619
63	9.50		11934	3223	12127	8372	2206	8780
64	9.09		15811	5077	17115	15959	3434	10568

Table 4.4 - Continued

		Flow Scenairo	Low			High		
		m^3/s	32.6	93.4	93.4	56.6	141.6	141.6
		Habitat Type	Spawning	Fry	Parr	Spawning	Fry	Parr
Reach #	River km							
65	8.69		12243	3976	27042	11965	2798	7262
66	8.24		4694	2478	8577	4256	2688	4994
67	7.81		6884	2782	11449	8036	1384	4120
68	7.37		3166	1804	5090	3191	2633	3887
69	6.97		0	896	2470	0	1291	1379
70	6.60		0	670	1770	0	1764	2011
71	6.16		0	0	0	0	0	0
72	5.74		0	0	0	0	0	0
73	5.33		0	0	0	0	0	0
74	4.92		0	0	0	0	0	0
75	4.50		0	0	0	0	0	0
76	4.09		0	0	0	0	0	0
77	3.68		0	0	0	0	0	0
78	3.26		0	0	0	0	0	0
79	2.85		0	0	0	0	0	0
80	2.44		0	0	0	0	0	0
81	2.02		0	0	0	0	0	0
82	1.61		0	0	0	0	0	0
83	1.20		0	0	0	0	0	0
84	0.78		0	0	0	0	0	0
85	0.37		0	0	0	0	0	0

Table 4.5 - Results from the response profile analysis for the Lower American River decision model. The response profile analysis identified how many times the optimal decision would change across a range of values (±50% of the original mean value) for each parameter in the model. Only parameters where the opitmal decision changed more than once are reported.

Parameter	**Description**	**# Optimal Decisions**	**# Decision Changes**
sex	Adult sex ratio	2	1
reddsize	Redd size	2	1
s_{comm}	Commercial ocean harvest	2	1
s_{rec}	Recreational river Harvest	2	1
s_{adult}	Adult in-river Survival	2	1

Figures

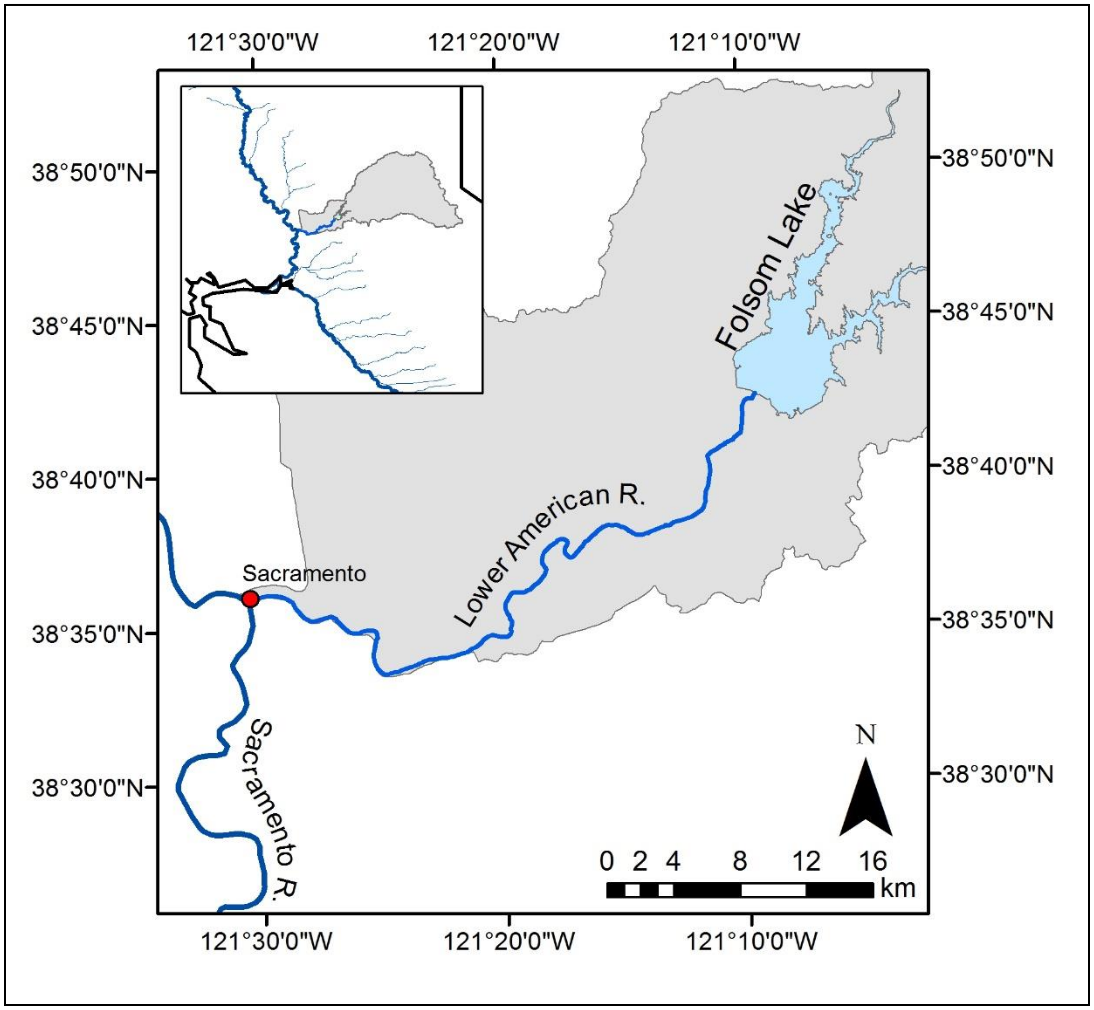

Figure 4.1 – A map of the American River watershed (grey) and the Lower American River.

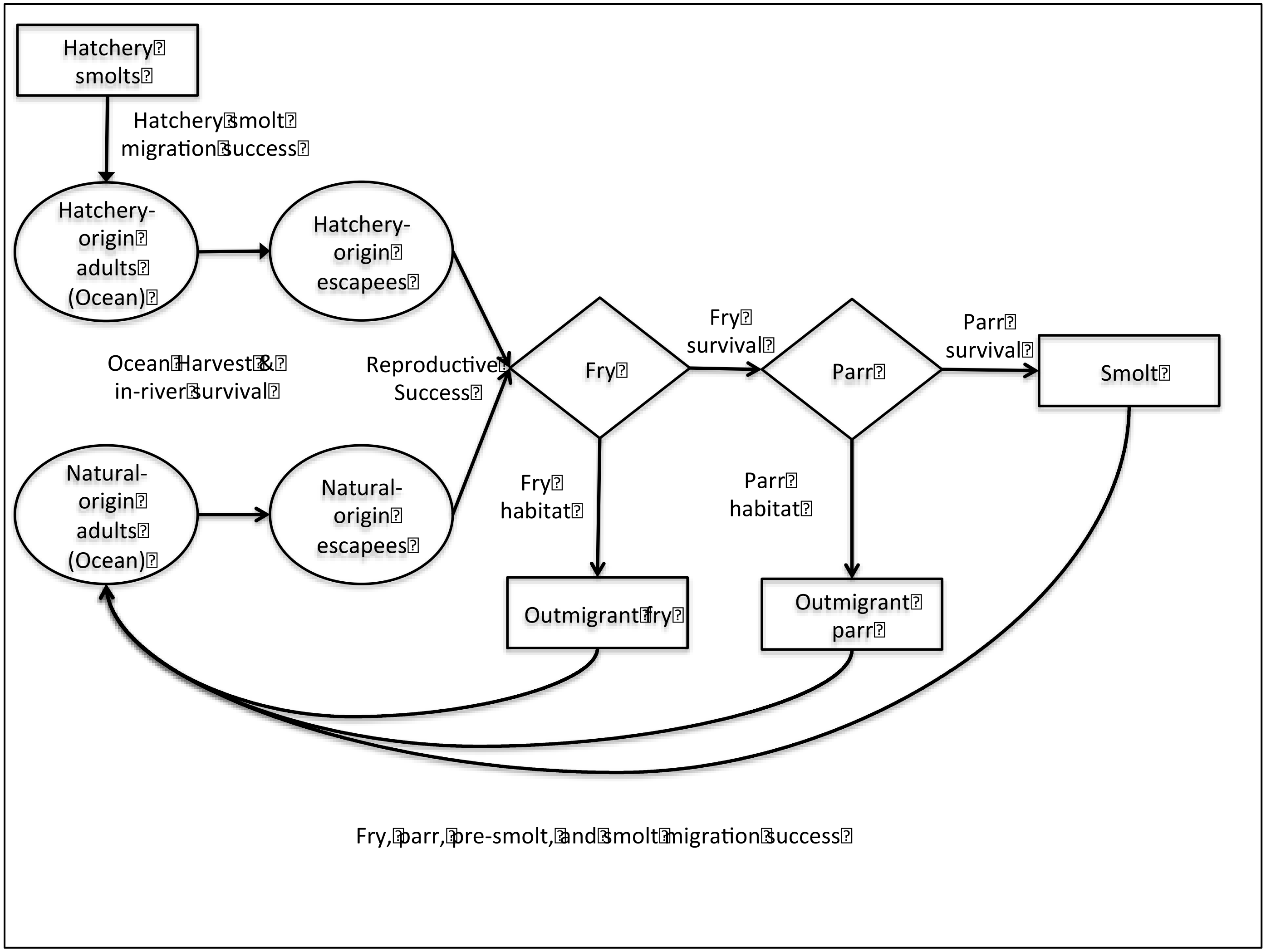

Figure 4.2 – A graphical representation of the life cycle of Chinook salmon. In this figure circles represent adults, diamonds represent rearing juveniles and boxes represent out-migrant juveniles.

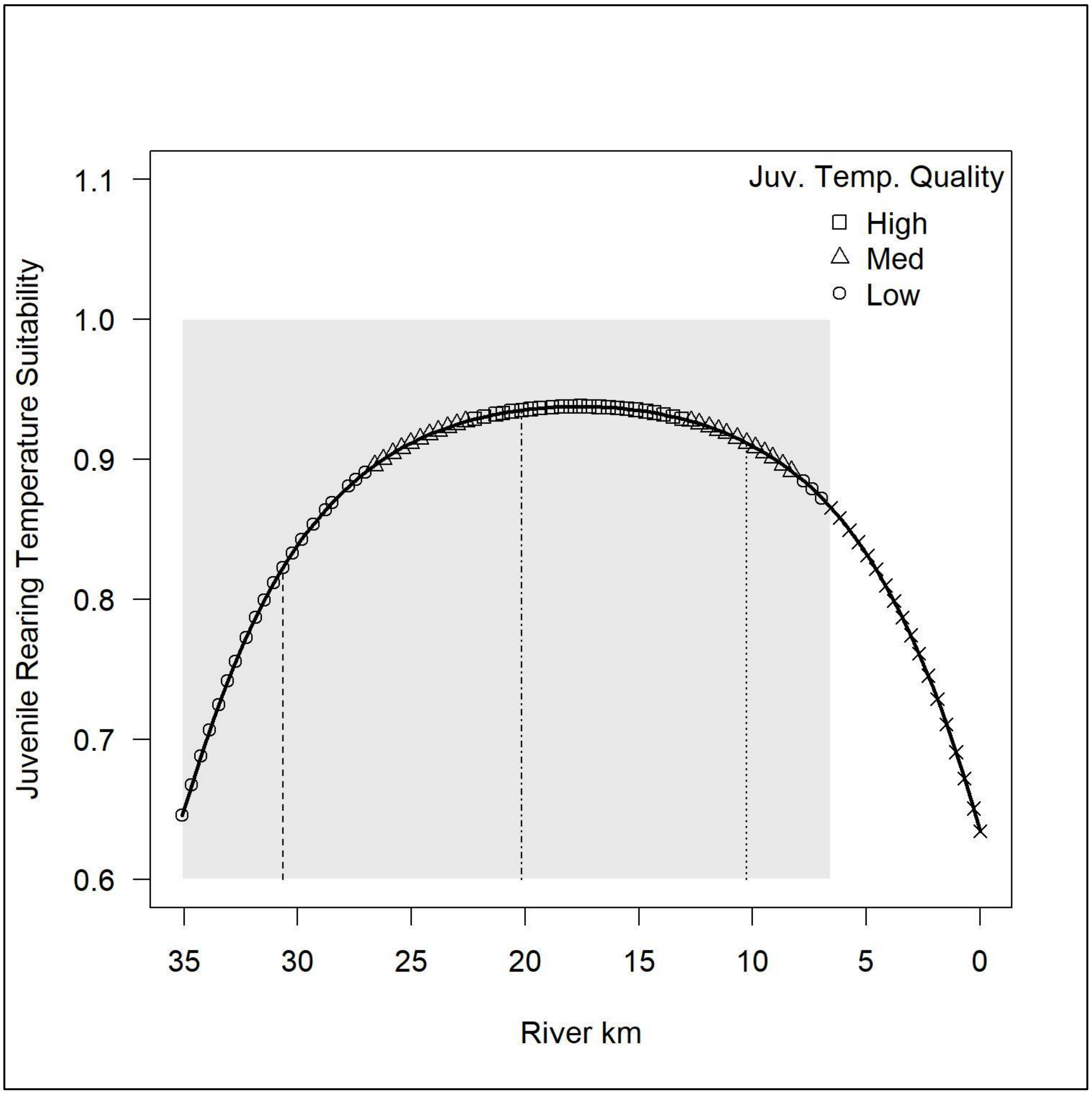

Figure 4.3 – The relationship between river kilometer and juvenile rearing thermal suitability (*temp*$_k$, eq. 14) for Chinook salmon in the Lower American River, CA. The shaded grey area represents the portions of the LAR that were considered for habitat restoration.

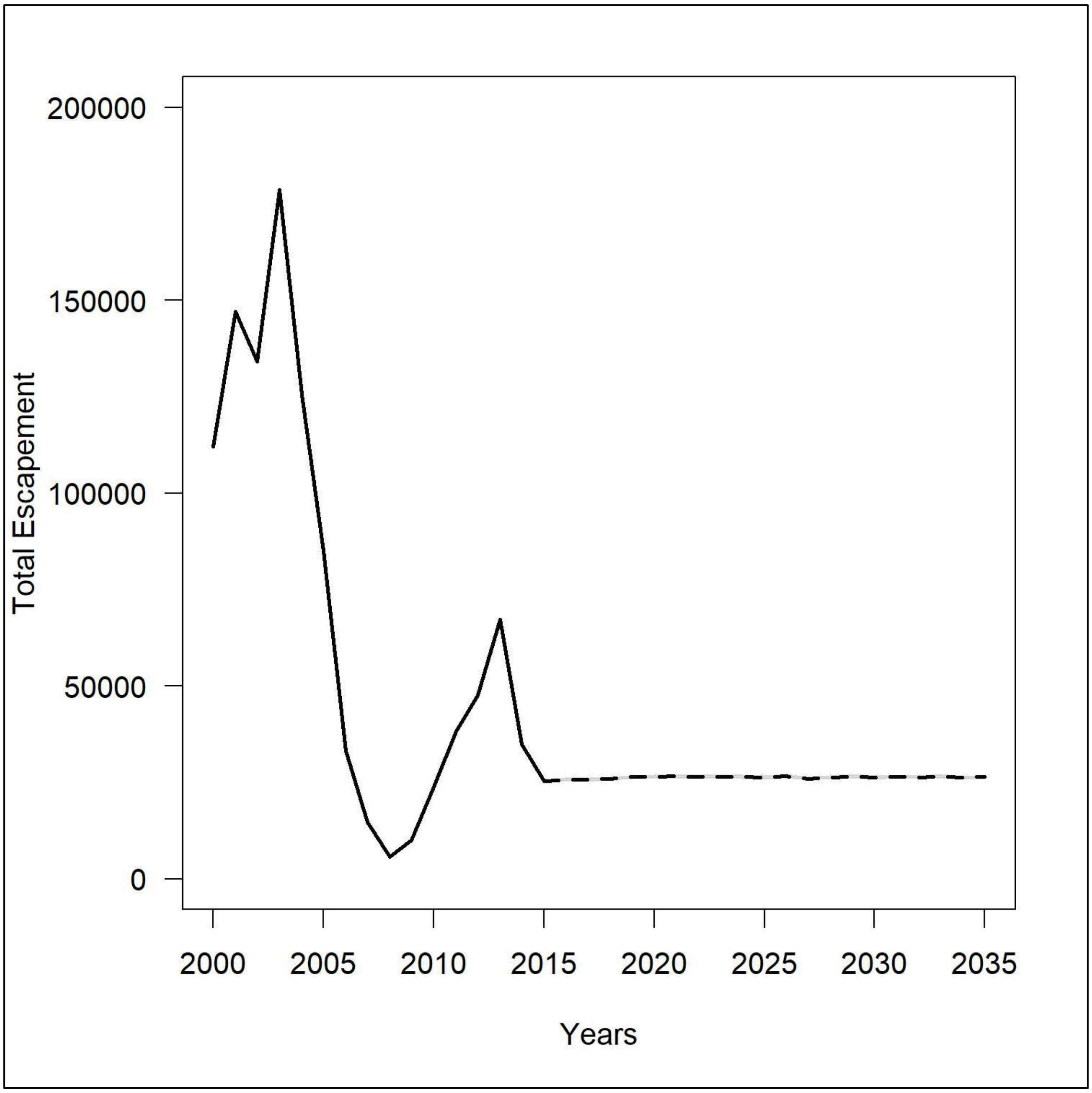

Figure 4.4 – Total escapement in the LAR from 2000 to 2015. The dashed line represents the mean simulated escapement from the population model for an additional 20 years.

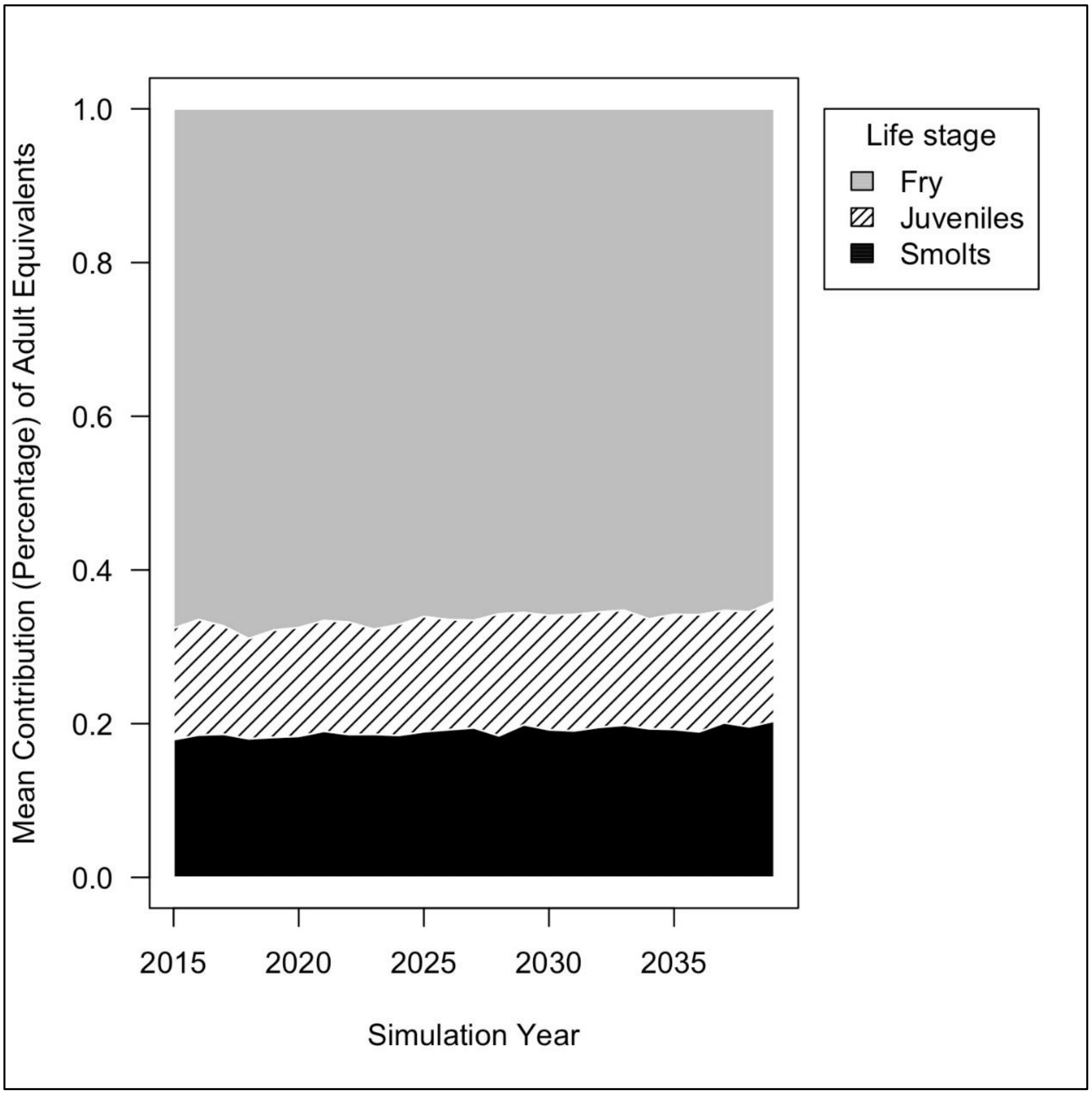

Figure 4.5 – The mean contribution of each out-migrant size class to the total number of adult equivalents produced each year.

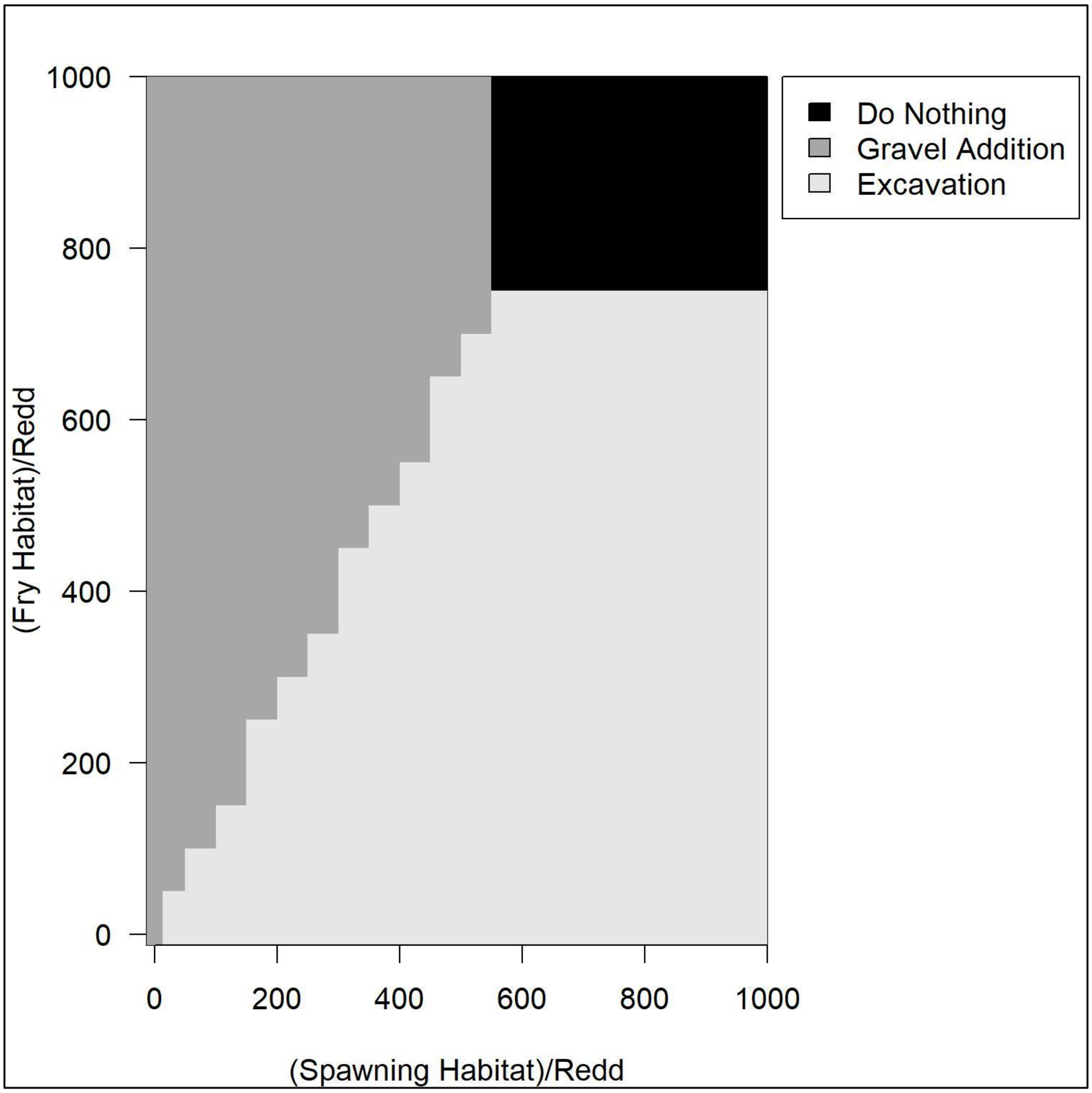

Figure 4.6 – Habitat restoration policy plot from river sections that experience "low" juvenile rearing temperature suitability. The different colors indicate which of the three management alternatives is optimal for that area of state-space.

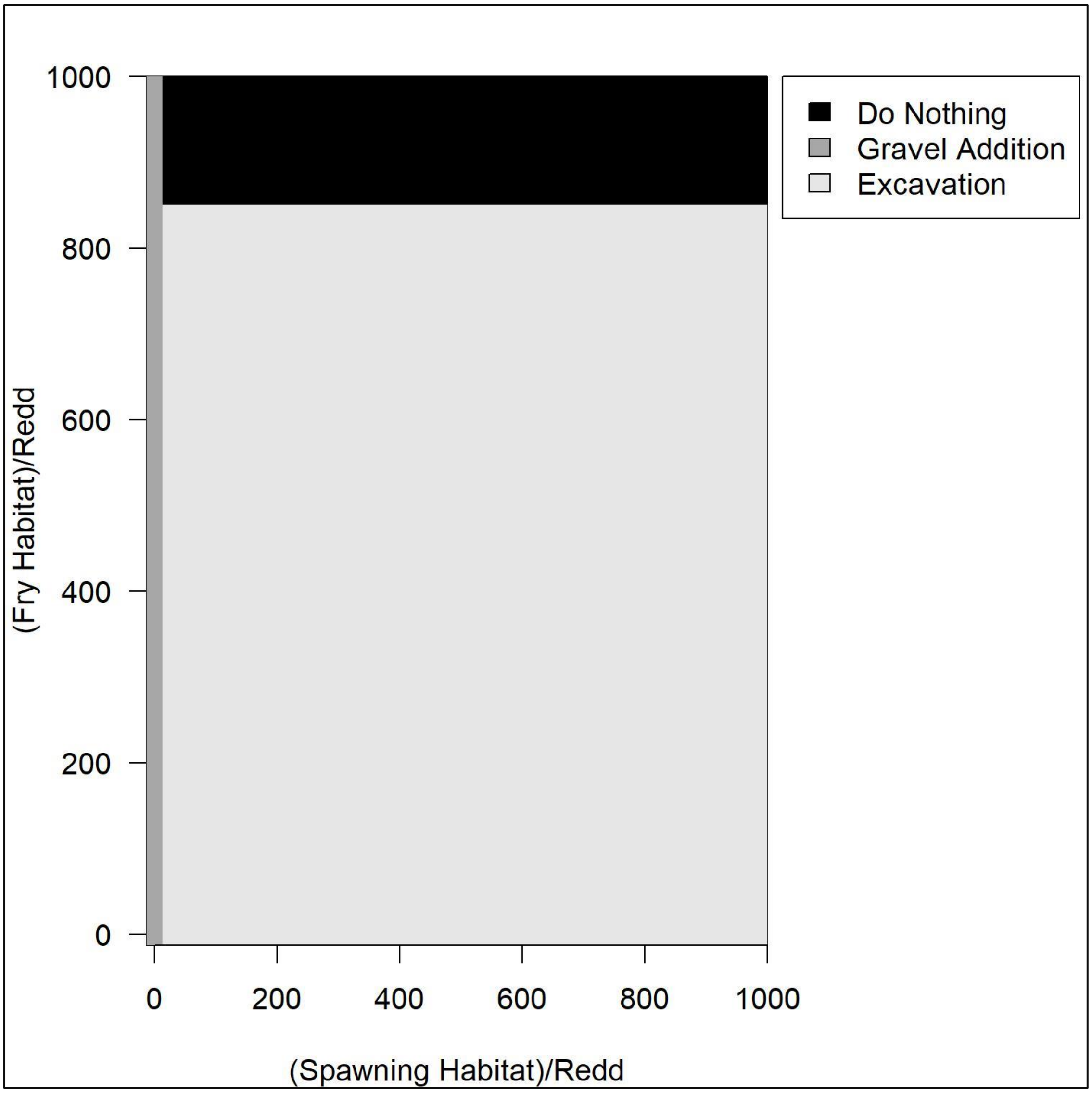

Figure 4.7 – Results from the SDP policy iteration from river sections that experience “medium” juvenile rearing temperature suitability. The different colors indicate which of the three management alternatives is optimal.

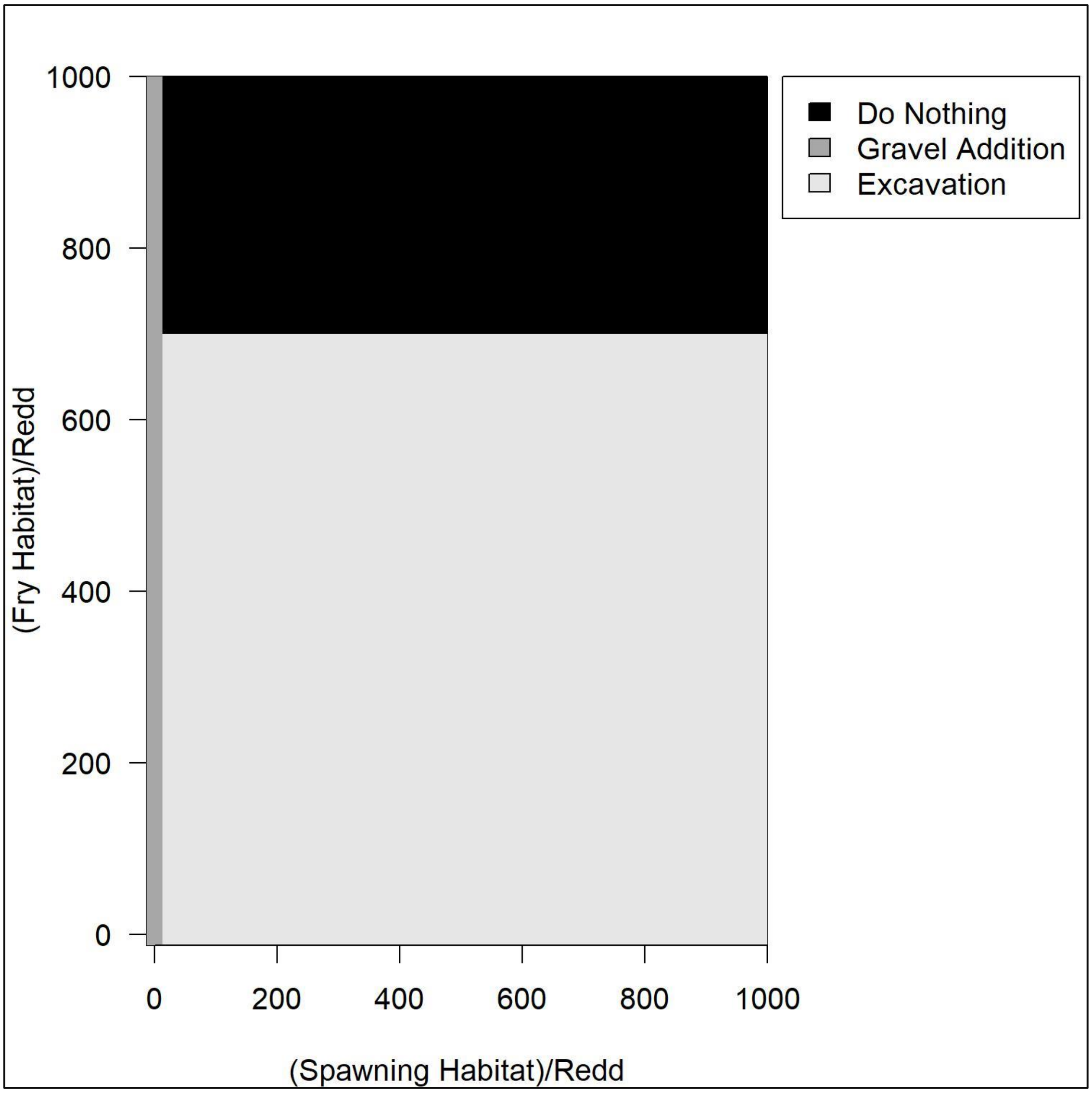

Figure 4.8 – Results from the SDP policy iteration from river sections that experience “high” juvenile rearing temperature suitability. The different colors indicate which of the three management alternatives is optimal.

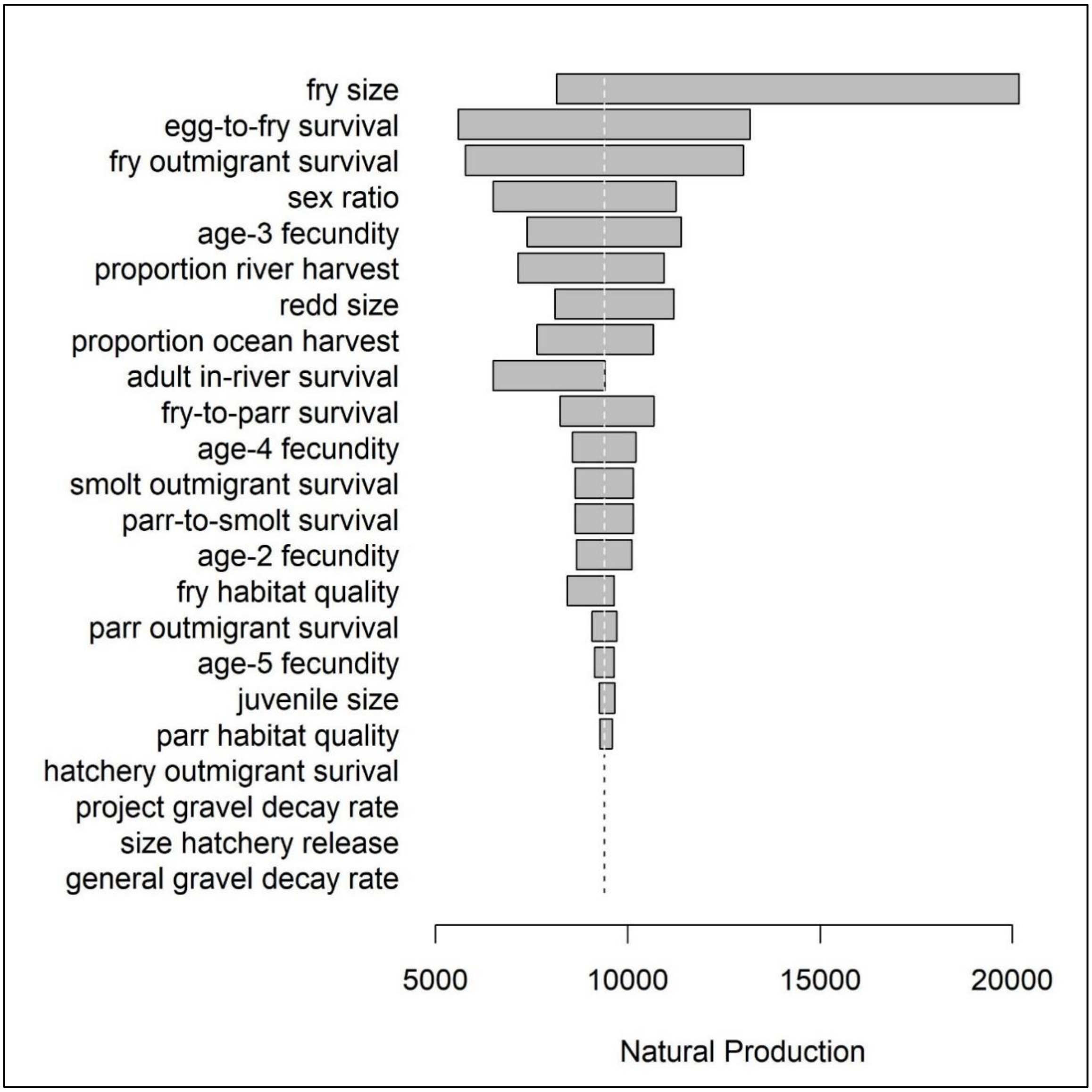

Figure 4.9 – Results of the one-way sensitivity analysis. The parameters are ordered from the most influential (top) to least influential (bottom).

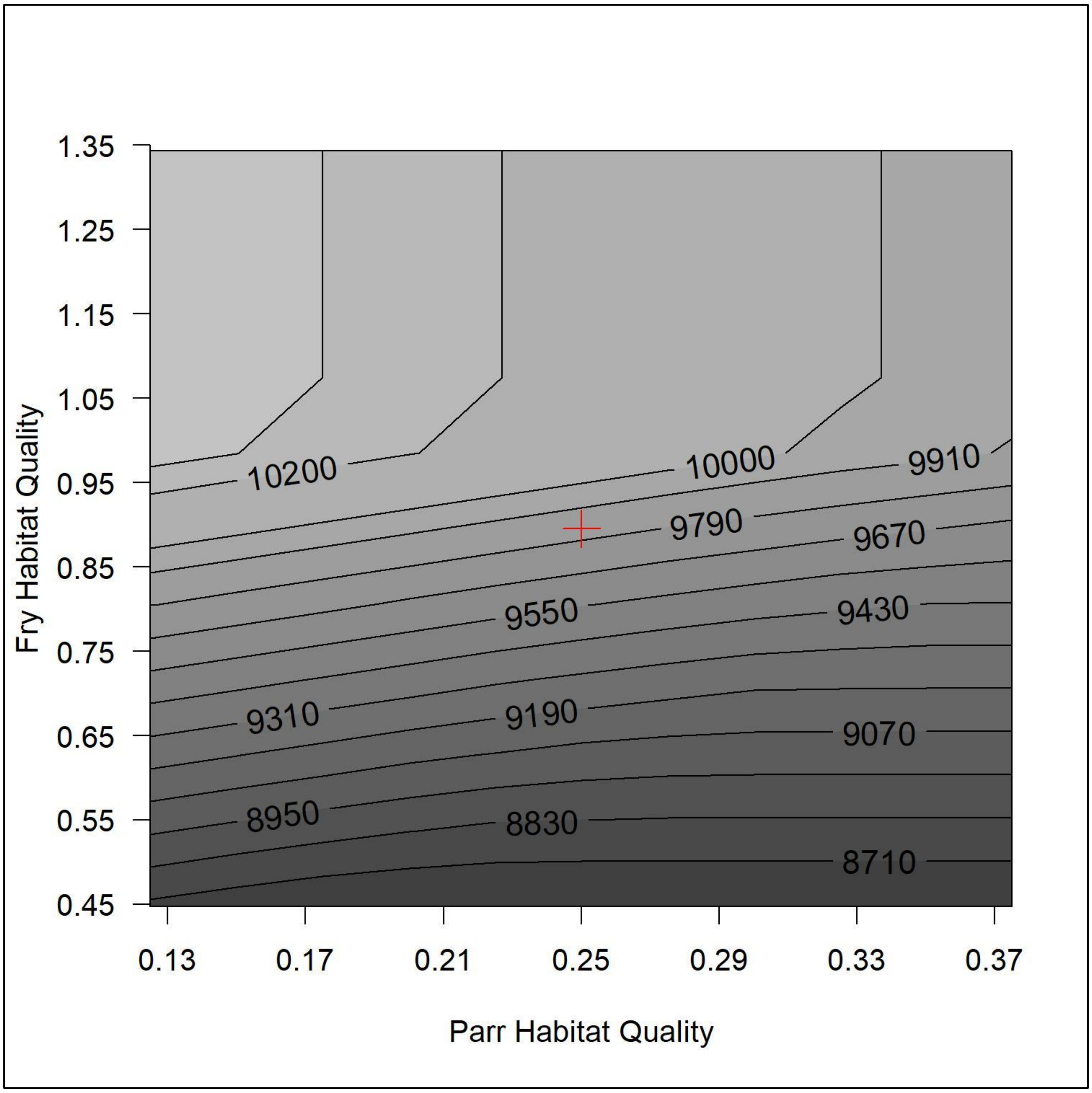

Figure 4.10 – A contour plot showing the results of the two-way sensitivity analysis of the fry habitat (y-axis) quality and parr habitat quality (x-axis). The contours represent the total number of naturally produced adult equivalents.

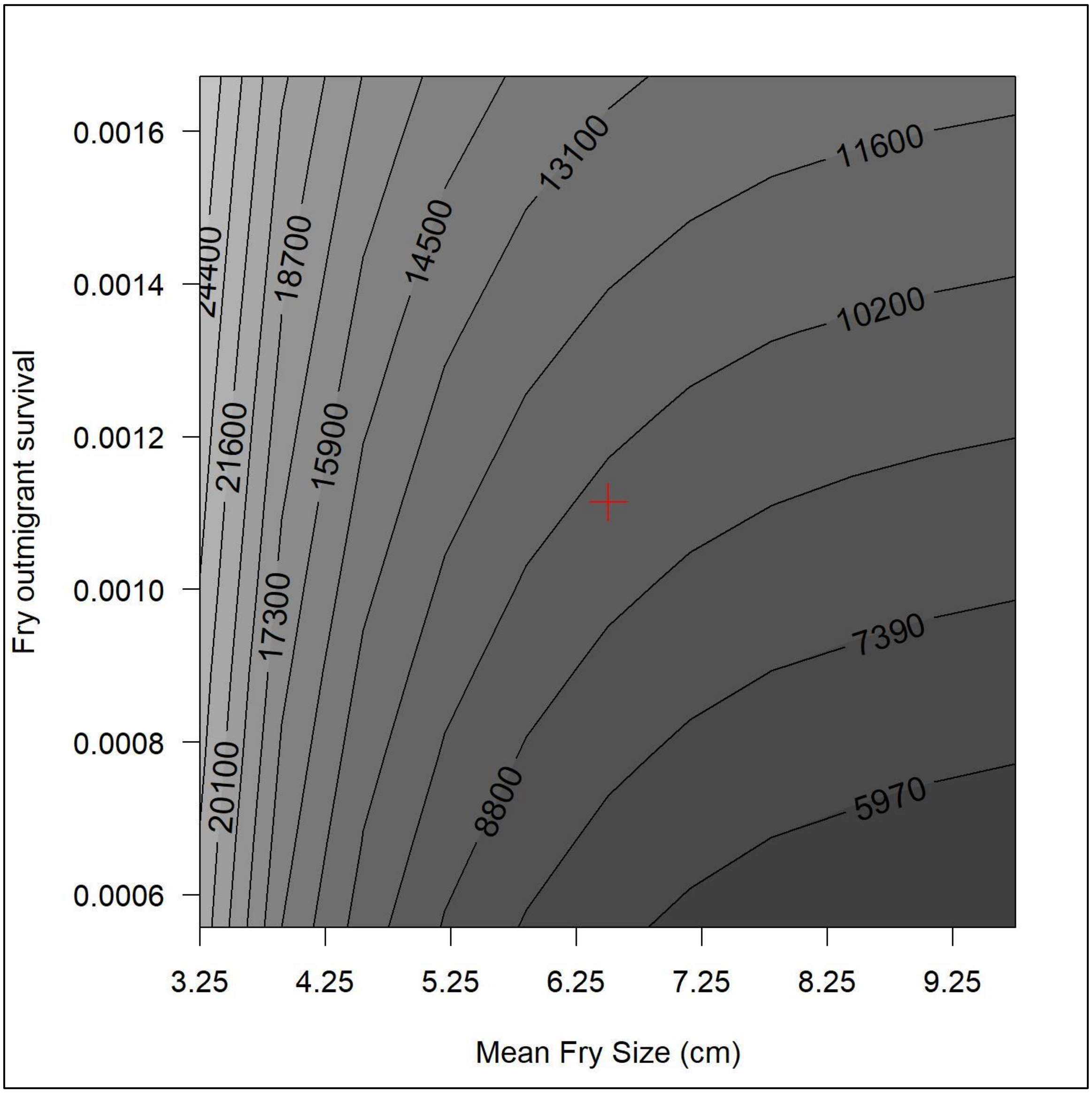

Figure 4.11 – Two-way sensitivity analysis depicting how the total number of naturally produced adult equivalents (contour lines) changes with different values of the size of fry (x-axis) and fry out-migrant survival (y-axis) in the LAR population model. The red cross represents the current mean values of both parameters used in population model.

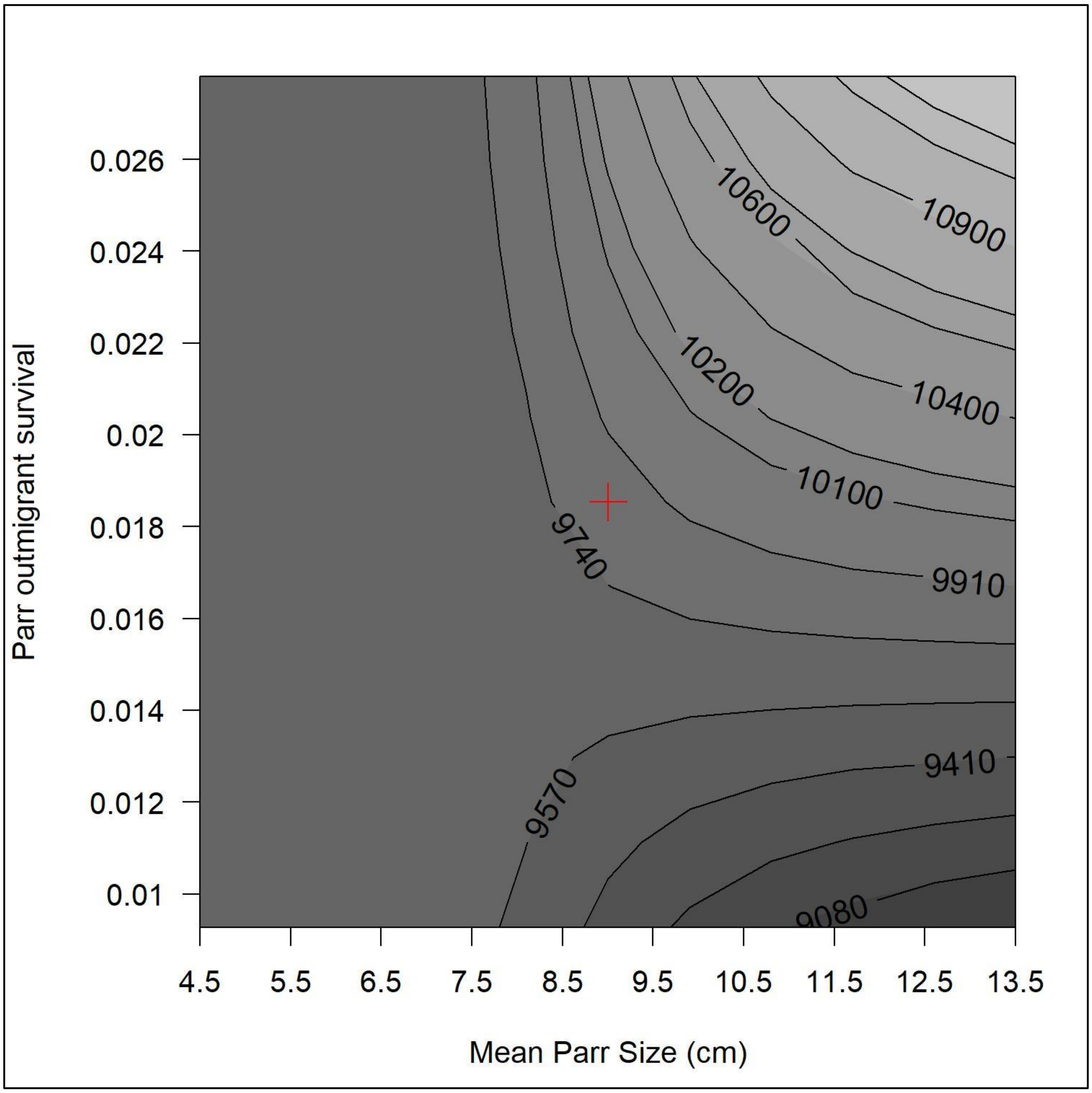

Figure 4.12 - Two-way sensitivity analysis depicting how total number of naturally produced adult equivalents (contour lines) changes with different values of the size of parr (x-axis) and parr out-migrant survival (y-axis) in the LAR population model. The red cross represents the current mean values of both parameters used in population model.

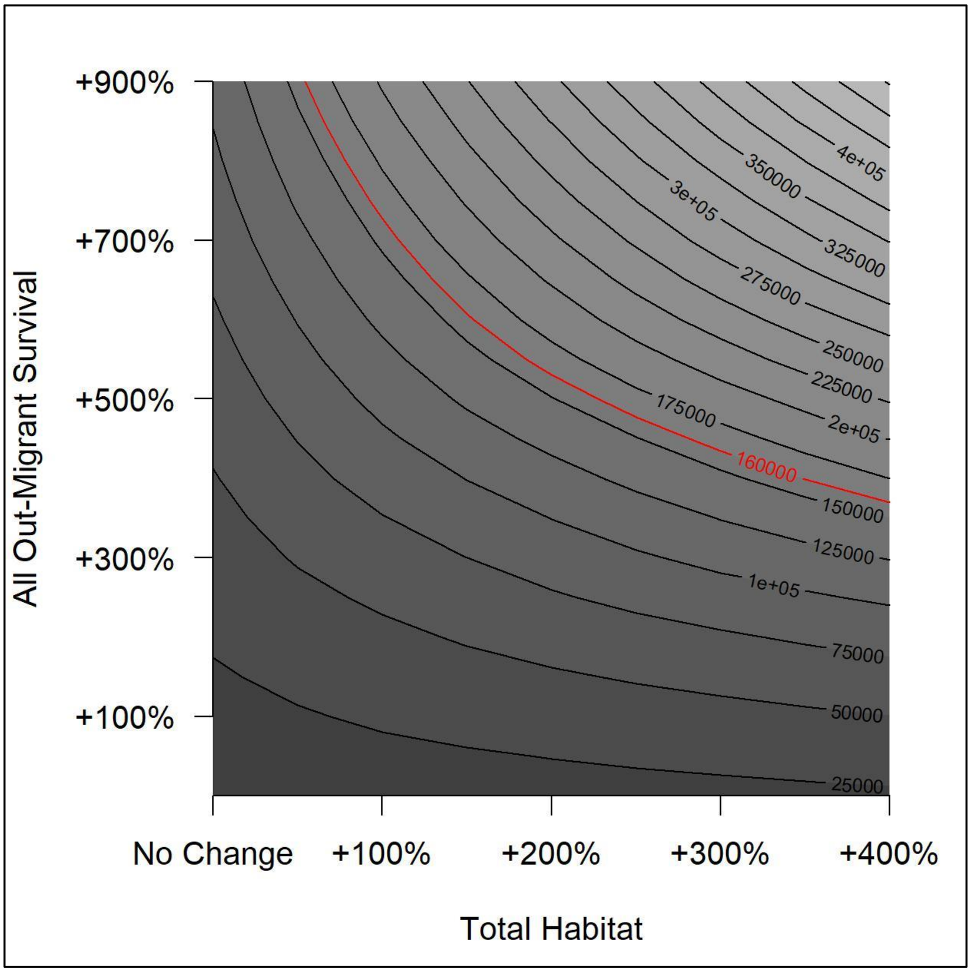

Figure 4.13 – The contours on this plot represent different levels of natural production of fall-run Chinook salmon in the Lower American River, CA. The axes represent different levels of juvenile out-migrant survival (for all size/age classes) and the total amount of all types of habitat. The red contour indicates the 160,000 doubling goal stipulated by the CVPIA. For instance, if the total amount of habitat (in its current relative configuration) was increased by 100% (e.g. doubled), all things being constant, juvenile out-migrant survival for all size/age classes would have to increase over 700% to meet the doubling goal.

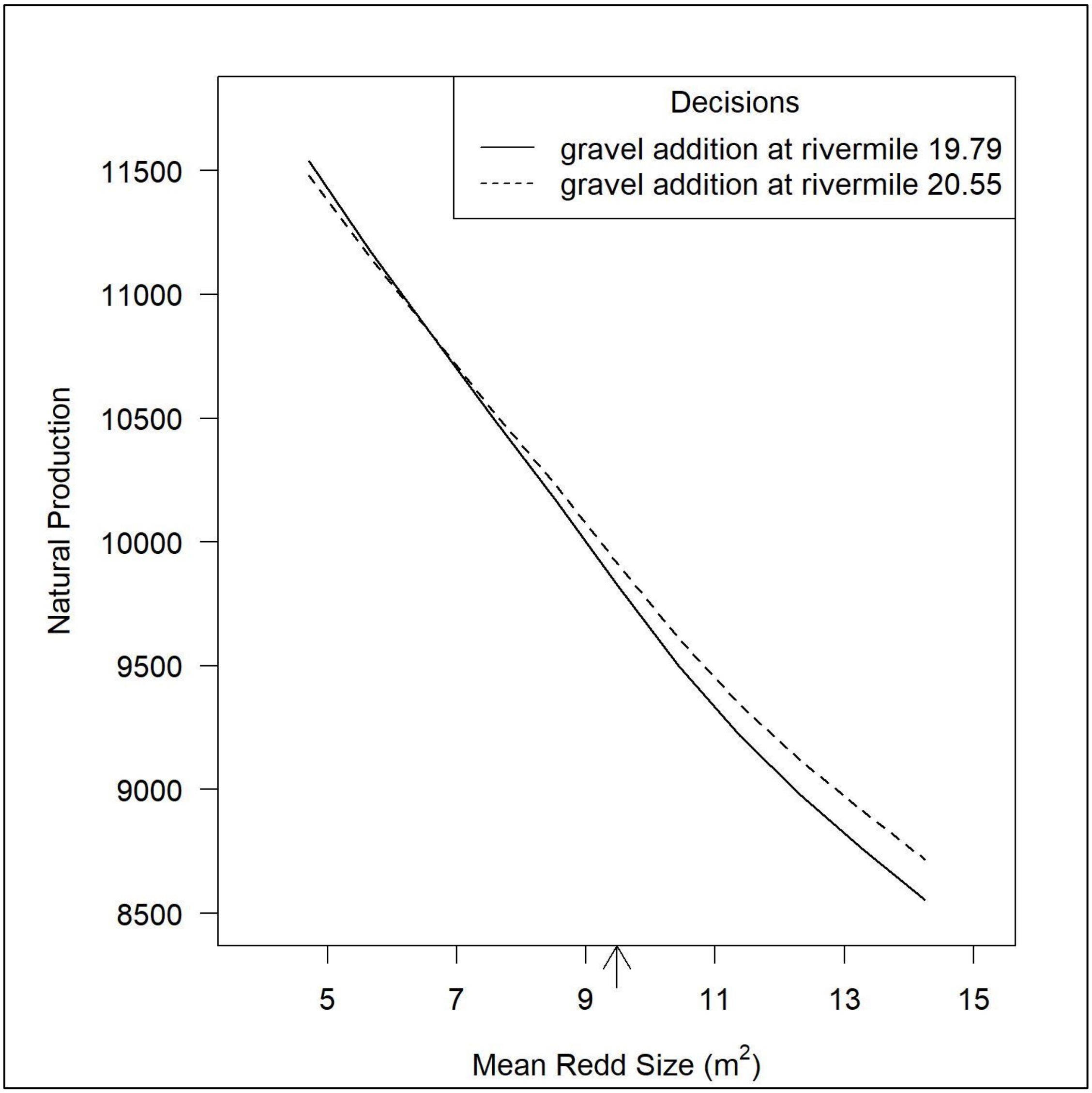

Figure 4.14 – One way response profile for the parameter for the *mean redd size* in the LAR decision model. The arrow on the x-axis indicates the current mean value used in the decision model.

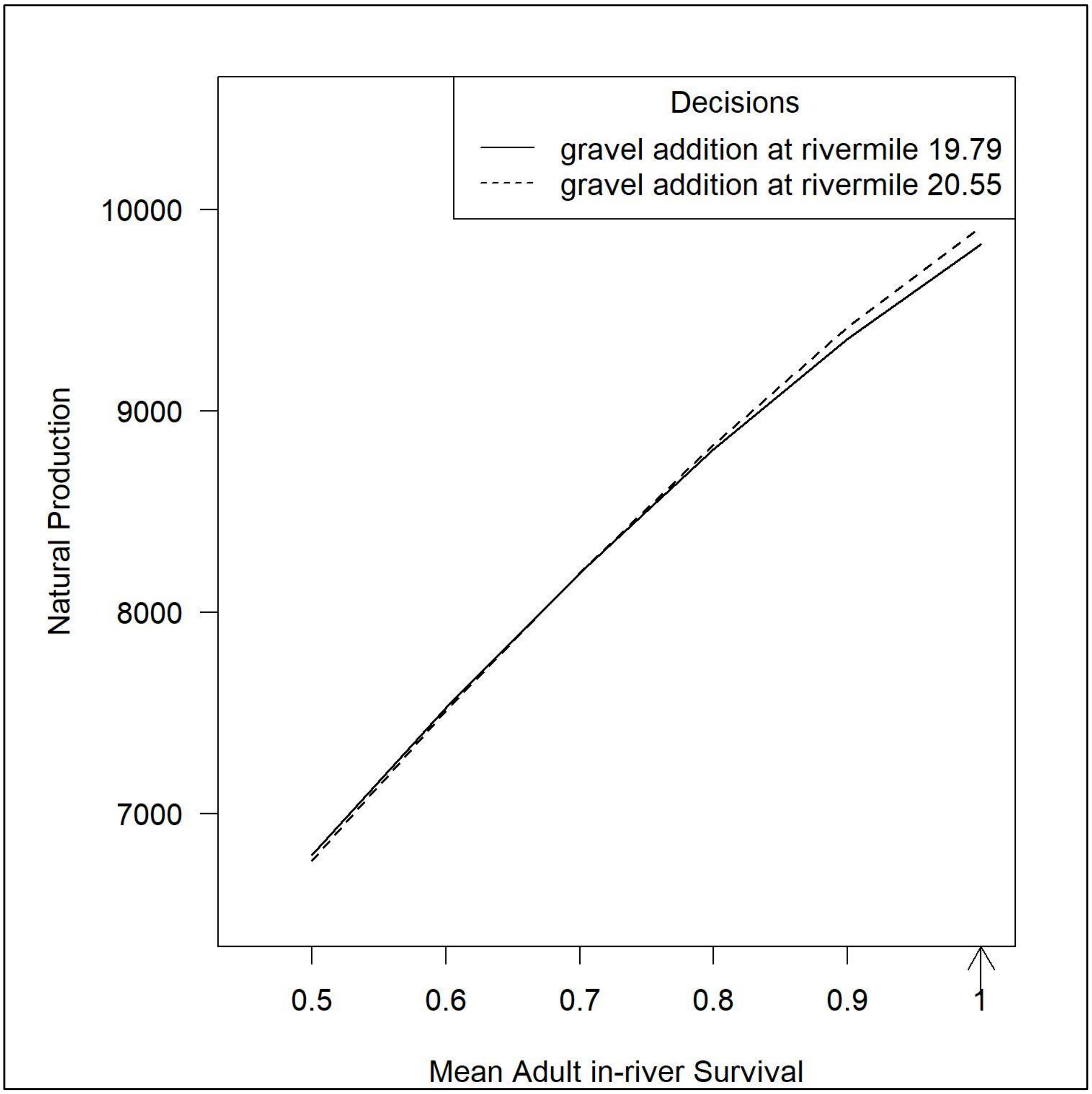

Figure 4.15 – One-way response profile for the parameter for the mean *s_adult_mean* in the LAR decision model. The arrow on the x-axis indicates the current mean value used in the decision model.

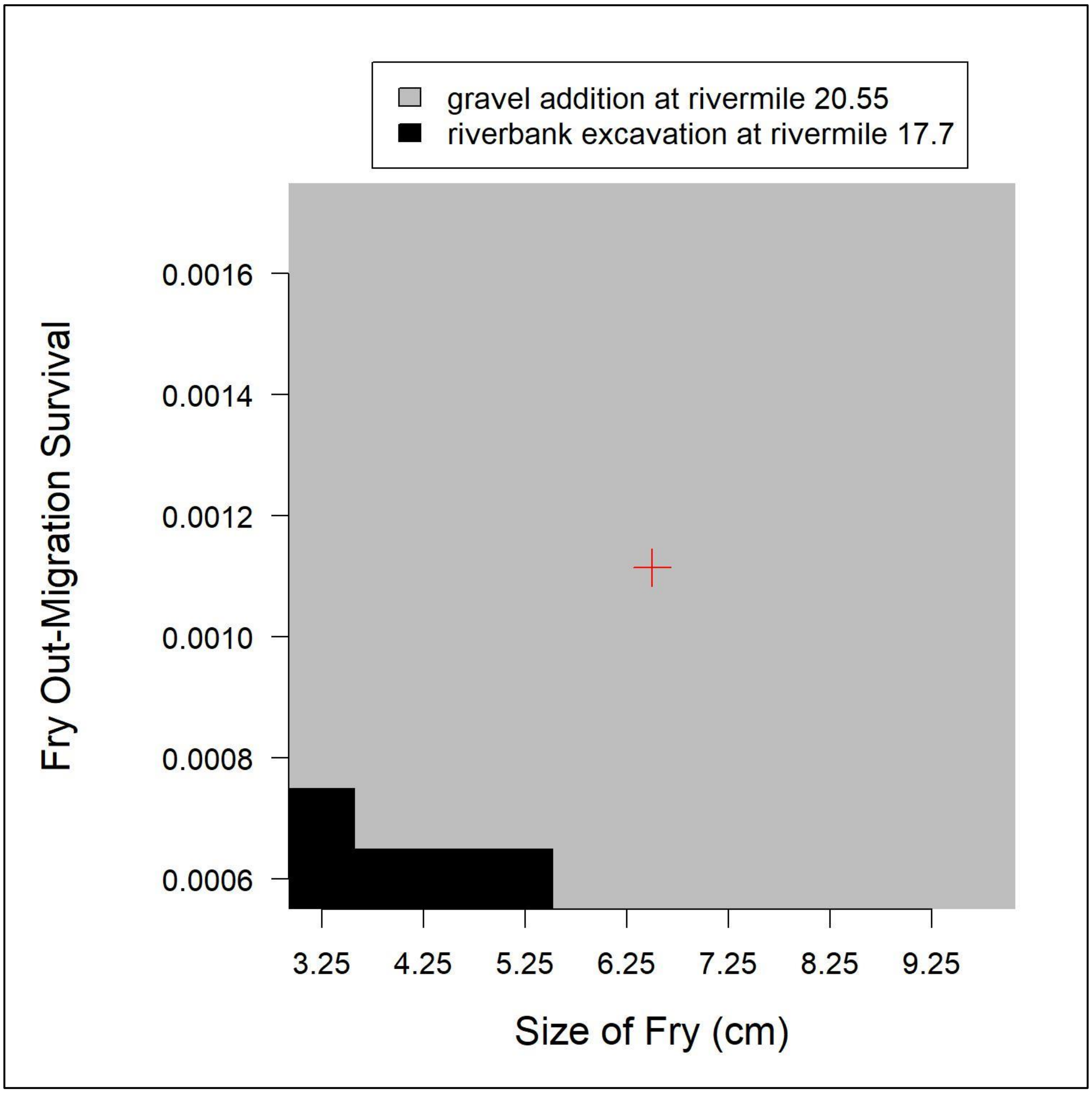

Figure 4.16 – Two-way response profile sensitivity plot depicting the optimal decisions across different values of both fry out-migrant survival and the size of fry. The red cross represents the current mean value of both parameters used in the population model.

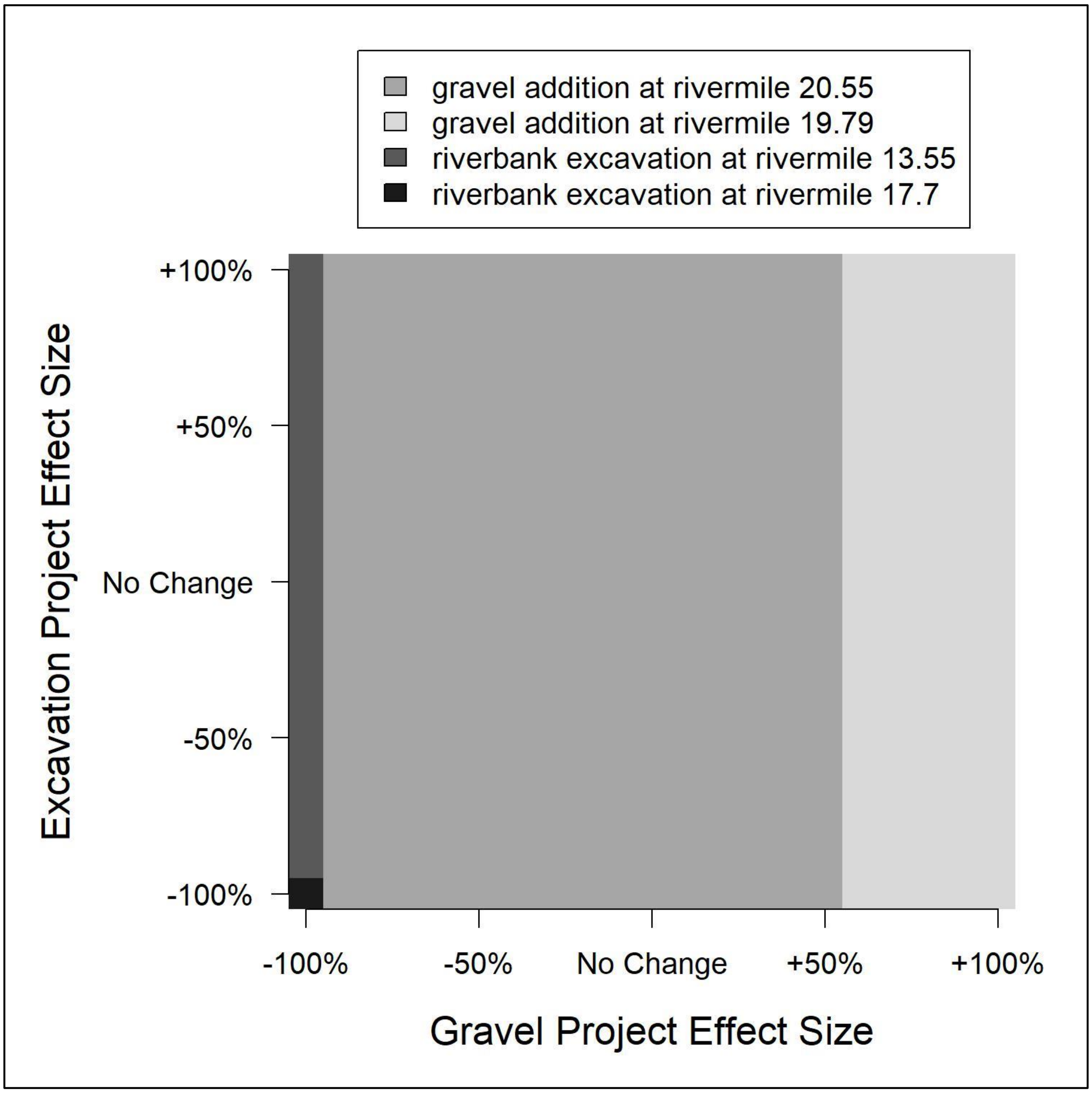

Figure 4.17 – Two-way response profile plot evaluating how changes to the effect sizes of the two types of restoration activities in the LAR can affect the optimal decision in a single time step.

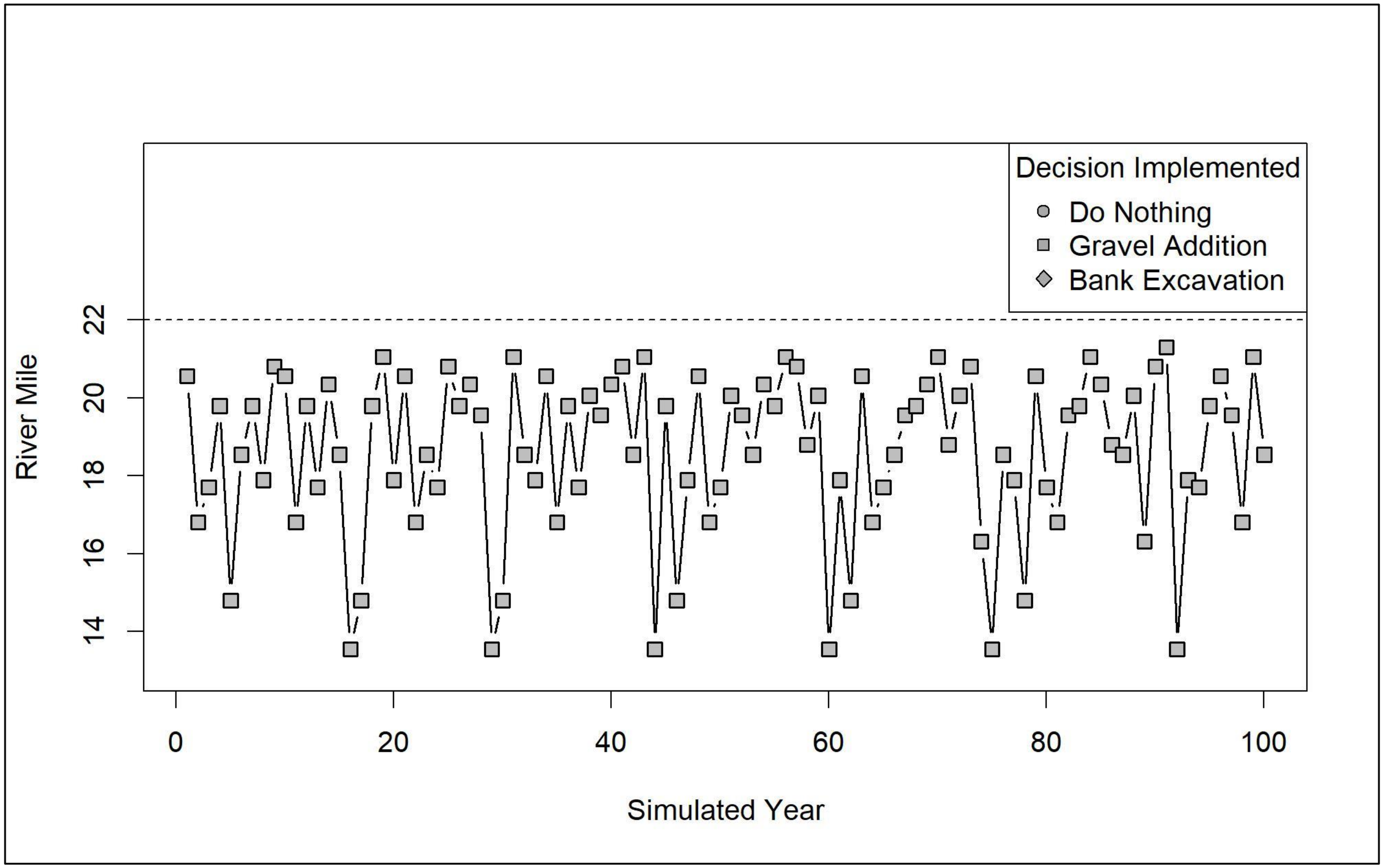

Figure 4.18 – Optimal decisions implemented from the forward simulation of the population of fall-run Chinook salmon in the Lower American River. The plot indicates the location in the river each decision was implemented at, which decision was implemented, and the simulated year it was implemented. The dashed line indicates the upper extent of the river (e.g. Folsom Dam).

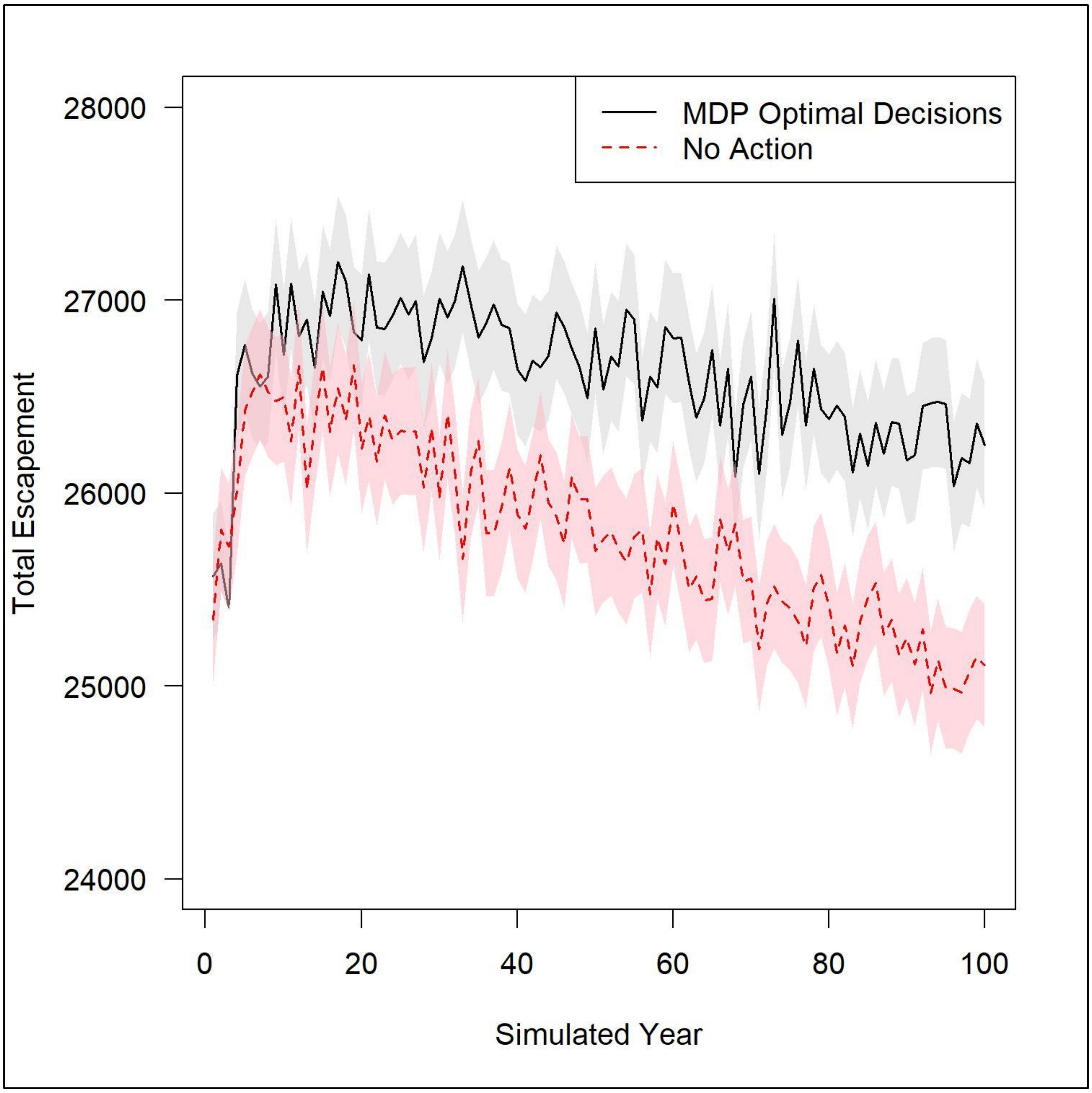

Figure 4.19 – Total escapement vs. simulation year the forward simulation of the optimal habitat restoration policies and no action alternative. The shaded areas represent ±2 SE.

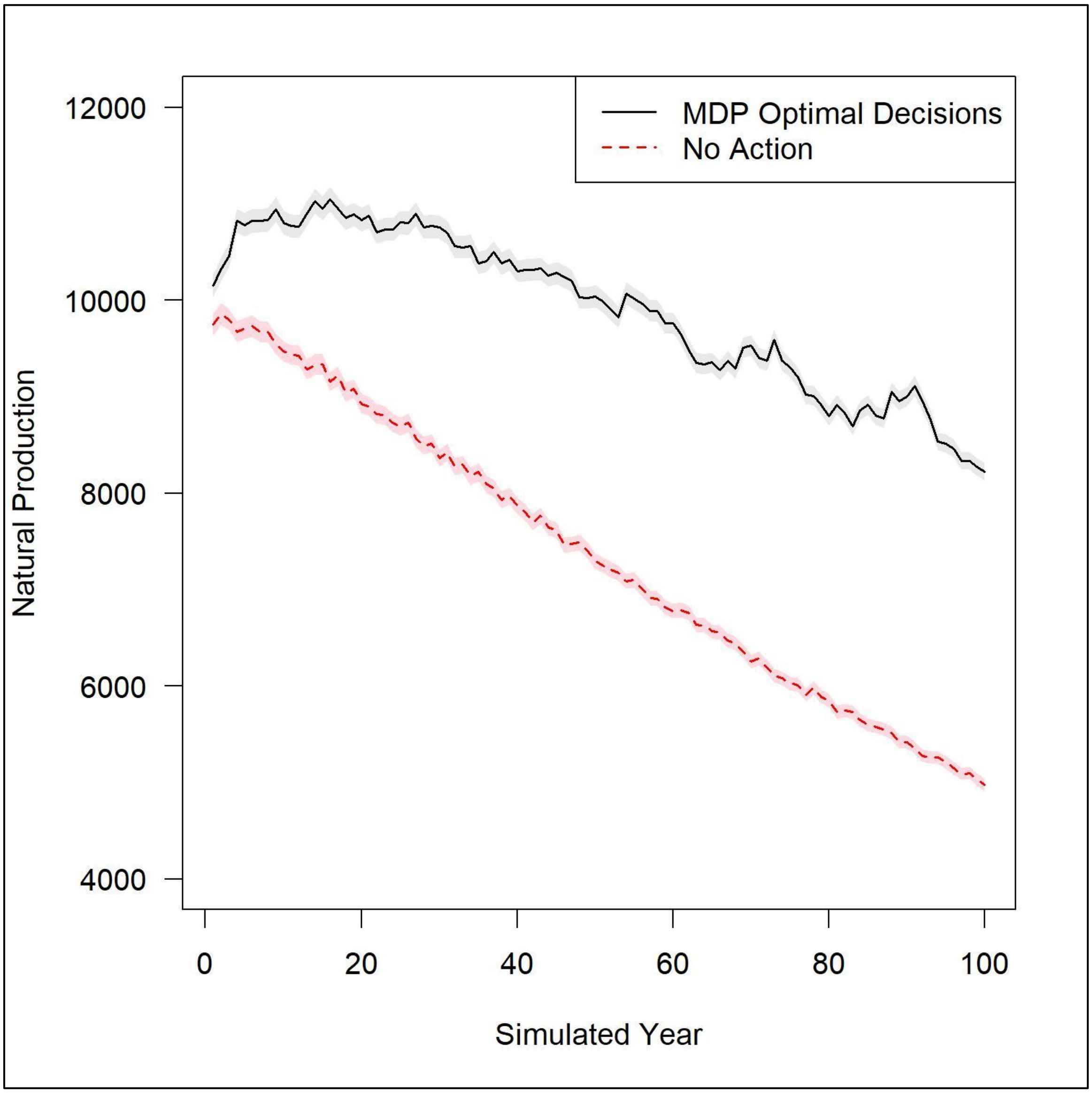

Figure 4.20 –Natural production vs. simulation year the forward simulation of the optimal habitat restoration policies and no action alternative. The shaded areas represent ±2 SE.

CHAPTER 5: APPLICATION OF A MULTITIME-SCALE MARKOV DECISION PROBLEM TO IDENTIFY OPTIMAL CHINOOK HABITAT RESTORATION STRATEGIES IN A HIERARCHICAL MANAGEMENT SYSTEM

Abstract

Uncertainty is a defining feature of the decision making process in natural resource management and can manifest in several ways: environmental variation, partial controllability, partial observability, or as structural uncertainty. Decision problems in natural resource management often involve several, interconnected decision makers, usually working at different temporal and spatial scales. Multitime-scale Markov decision processes (MMDPs) provide a framework to derive optimal decisions from hierarchically structured sequential decision making processes. I developed a MMDP approach to solve a stream habitat restoration problem with two tiers of decision makers working at different spatial scales. The objective of tiers of decision makers is to maximize the production of natural origin Chinook salmon. The decision problem was structured with an upper tier decision maker (large scale) allocating funds to lower tier decision makers (fine scale) who actually implement on the ground restoration projects. I was able to simultaneously derive state specific optimal policies for both tiers of decision makers. The upper tier optimal policy identified optimal resource allocation strategies given different funding states. The lower tier policies identified optimal habitat restoration projects for a given configuration of habitat in each watershed. Sensitivity analyses identify… The work in this study bridges the gap between large and small-scale decision models in natural resource management by applying a MMDP to a Chinook salmon management problem in CVPIA streams.

Introduction

Uncertainty is a defining feature of the decision making process in natural resource management. In the context of natural resource management, uncertainty can manifest itself as environmental variation, partial controllability, partial observability, or as structural uncertainty (Nichols et al. 2011, Williams 2011, Williams and Johnson 2013). How uncertainties interact and compound with one another is especially important when trying to determine what influences decision making in natural resource management. Ultimately, all sources of uncertainty contribute to how natural resource managers perceive the systems they are tasked to manage. Often, large amounts of uncertainty can lead to risk adverse decision-making. That is, the perceived risk of an unintentional negative outcome resulting from a management action is so great that managers may choose to pursue less optimal management actions (Thompson 2002, Cullen and Small 2004). Risk adverse decision strategies often sacrifice significant, long term gains for immediate, less optimal returns. Acknowledging and identifying types of uncertainty is the first step towards more efficient and effective natural resource management strategies.

Structured decision making (SDM) is a decision support framework that connects decision alternatives with objectives and allows a formal, quantitative evaluation of uncertainty for a decision problem that requires sequential actions (Clemen 1996, Conroy and Peterson 2013). The largest strength of the SDM process is identifying the uncertainties that can influence decision-making. Because the SDM approach can incorporate sequential decision making situations, it is possible to reduce uncertainties while implementing management actions that can lead to more effective management actions through time. Examples of decision modeling in natural resource management include animal harvest (Conroy et al. 2002, Peterson and Evans 2003), endangered or threatened species management (Rout et al. 2009, Runge 2011, Brignon et al. 2017), and freshwater management (Pearson et al. 2010, Peterson and Freeman 2016). Most decision problems consist of a single decision maker or a group acting as a single entity that implement management actions to achieve some objective in the face of environmental uncertainty. However, decision making in natural resource management often involves several, interconnected decision makers, usually working at different temporal and spatial scales. For instance, in any state level natural resource department regional fishery biologists coordinate with a statewide fishery manager before implementing new rules or regulations.

Uncertainty is compounded in systems where there is a hierarchy of interconnected or dependent decision makers tasked with making sequential decisions at different spatial and temporal scales. Structuring these types of decision problems as hierarchies of interdependent problems is a useful approach for decomposing complex systems into smaller, more manageable problems. Typically, these problems are modeled with multiple levels of decision makers, with fewer decision makers at higher levels and more decision makers at lower levels. The results, and any associated uncertainty, of actions taken by lower level decision makers are passed on to decision makers at higher levels (Figure 5.1). For a given decision problem, as the number of decision makers and/or the number of tiers in the hierarchy increase the system state-space also exponentially increases. State-space is defined as the set of all possible configurations of the components that define a system. The exponential expansion of state-space results in what is generally known as “the curse of dimensionality,” since the state-spaces can grow (in terms of the number of dimensions) to sizes that prohibit any real world application (Bellman and Dreyfus 1962). Solving hierarchical or multilevel sequential decision problems has been a subject of research in fields of machine learning and operations research for some time (Sutton 1995, Kristensen and Jørgensen 2000, Guestrin and Gordon 2002). Most of these applications are designed to model and optimize systems that involve multiple levels of decision makers that are organized in a pyramid-like structure, meaning there are fewer decision makers as you move towards the top of the hierarchy (e.g., such as manufacturing; McGovern et al. 1998, Chang et al. 2003). This means the decisions of the top tier affect how decisions are made at lower tiers (Figure 5.1). Typically, feedback is also included so that the decisions made at lower tiers also influence the higher tiers either indirectly or directly through a utility calculation (Wernz and Deshmukh 2010). A useful feature of these types of decision frameworks is that the actions at each level don’t necessarily have to occur at the same time scales (Sutton 1995, Sutton et al. 1999). For instance, a decision can be made once every five time steps (e.g., years) at the top of the pyramid, whereas a decision can be made at every time step at the bottom of the pyramid. All the structural, temporal and spatial features of modeling a multi-level decision problem require careful consideration when attempting to derive optimal management actions.

One approach to deriving optimal decisions from a multilevel decision problem is an extension of traditional Markov Decision Problems (MDPs) known as hierarchical Markov decision problems or multi-time scale Markov decision processes (MMDPs). These approaches provide the framework to derive optimal decisions from hierarchically structured sequential decision making processes (Chang et al. 2003, Wernz and Deshmukh 2012). MMDPs can be thought of as two or more MDPs that are layered on top of one another. Generally, in MMDPs high level decision makers can influence the decision sets available at lower levels. Additionally, the decision made by lower levels influence the utility (the metric to be optimized) of higher levels. This feedback process allows information to indirectly flow between decision makers at different levels, which can create situations where cooperation between the decision makers can yield more optimal results than if they were operating in isolation. Although MMDPs have been explored in context of systems operations and industrial engineering, it has not yet been applied to problems in natural resource management.

Decision problems in natural resource management are often structured as hierarchical sequential decision problems with several decision makers working together at different spatial and temporal scales. It remains unclear how interactions between decision makers can affect decision making at each hierarchical level when accompanied by ecological uncertainties. For instance, the anticipated effects of climate change may be interpreted differently by decision makers at different levels in the same decision hierarchy. How the interactions between decisions makers might change given their specific responses remains unclear. Similarly, if decision makers work at different temporal scales (e.g., an annual decision versus quinquennial decision) they likely face different sources of uncertainty and probably use different types of data to inform their decision making process. A better understanding of how uncertainties that work at different scales can influence a hierarchical decision problems would provide insights into how decision makers may cooperate to develop better natural resource management strategies.

Restoration of Chinook salmon (*Oncorhynchus tshawytscha*) populations in California's Central Valley is an ideal example of natural resource decision problem that has an explicit hierarchical structure. Chinook salmon stocks in California's Central Valley consist of four distinct seasonal runs: fall, late-fall, winter, and spring; each of which used to be distributed throughout the Sacramento and San Joaquin basins (Figure 5.2). These runs of Chinook salmon have been declining for the past 100 years primarily due to over harvest and habitat degradation. The passage of the Central Valley Plan (CVP) in 1931 exasperated exacerbated the habitat degradation issues through the construction of multiple flood control and irrigation projects throughout the Central Valley. The installation of dams and irrigation canals left salmon unable to access their historic spawning and rearing habitats and of those habitats remaining, most were severely degraded (Nehlsen et al. 1991, Lichatowich 1999). The combination of habitat degradation and over harvest ultimately lead to a sharp decline in the salmon stocks, which ultimately resulted in the passage of the Central Valley Plan Improvement Act (CVPIA) in 1992. The goal of the CVPIA was to rehabilitate many of the populations of anadromous species adversely affected by the CVP, particularly Chinook salmon. Perhaps of the most iconic goal of the CVPIA is to double natural salmon production from the 1991 levels in each CVPIA administered stream (31 populations of Chinook salmon). The term "natural production" refers to fish that are not of hatchery origin. So under this definition, the offspring of two hatchery fish spawning would be considered naturally produced. Despite efforts since the passage of the CVPIA the natural production doubling goal has yet to be attained.

The spatial scale, goals, and federal oversight of the CVPIA determined how this program was structured and ultimately implemented. The U.S. Fish and Wildlife Service and the U.S. Bureau of Reclamation jointly oversee CVPIA actions. These entities act as the primary decision makers regarding salmon management and habitat restoration actions in the Central Valley. Together they ultimately decide which actions are funded across all the CVPIA watersheds but at broad scales. That is, these two implementing agencies choose the combinations of the types of restoration actions and the streams that are best for achieving program objectives. To implement restorations, the implementing agencies cooperate with other entities (e.g., California Department of Fish and Game and local watershed councils) and local stakeholders the actually propose and implement specific management actions at specific locations within each stream. This is the general hierarchy of decision making process. The primary decision makers decide to fund some habitat restoration process, however it's up to the local decision makers to determine how, where, and when to implement those projects. The result is a set of decision makers operating at two different spatial and temporal scales. Thus, a multilevel decision making framework may provide an ideal approach for dealing with the hierarchical structure of Chinook salmon restoration and management in CVPIA streams.

In this chapter, I bridge the gap between large and small-scale decision models in natural resource management by applying a MMDP to a Chinook salmon management problem in CVPIA streams. In the previous chapters, I showed how to identify optimal salmon restoration and management decisions at large spatial scales (chapter 2) as well as at small spatial scales (chapter 3) in CVPIA streams. This hierarchical structure can be exploited using hierarchical or multilevel Markovian decision processes, which can be solved to find optimal decisions or policies for both sets of decision makers simultaneously (Wernz and Deshmukh 2010, 2012). The objectives for this chapter are to 1.) Develop a multiscale habitat restoration decision problem with two tiers of decision makers, 2.) Solve the multiscale decision problem as a MMDP using dynamic programming and 3.) Identify which uncertainties in the decision models were influential to the decision were making process.

Methods

I developed and implemented a MMDP to solve a two-tiered hierarchical stream habitat restoration decision problem based on CVPIA Chinook salmon management. In this section, I first provide an overview of the decision problem and describe the models that I used to parameterize the decision problem. Next, I describe the general MMDP framework and the optimality equations used to derive optimal policies. Finally, I describe several sensitivity analyses I performed to evaluate how uncertainties influence decision making.

Study Site

California's Central Valley is a large watershed, stretching 720 km north to south, 70 km east to west and covering > 70,000 km^2. The Sacramento River and the San Joaquin River are the primary tributaries that make up the two main branches of the Central Valley. The Sacramento River is the longest river in California and begins in the

Northern Sierra Nevada mountain range. From there it flows 719 kilometers south until it meets the confluence of the San Joaquin. The San Joaquin River begins in the southern Sierra Nevada and flows north. The confluence of these rivers creates the large and complex Sacramento-San Joaquin delta. The delta eventually makes it way out the Pacific through the San Francisco Bay. A total of 25 populations of fall-run Chinook salmon are included under CVPIA management. Most the populations (19) are distributed throughout the Sacramento basin, with the remaining populations located in the San Joaquin basin (Figure 5.1). The watersheds vary in size from 18,000 – 3.5M ha (median 106,000 ha) with between 33 and 209 river kilometers open to anadromous species. These watersheds were chosen for this analysis because they are actively managed as part of the CVPIA fisheries program.

Although 25 populations of fall-run Chinook salmon are administered by the CVPIA, I choose to develop this problem with three distinct watersheds where each is representative of a common "type" of CVPIA watershed (Figure 5.1). I identified three basic types of watersheds administered by the CVPIA: upper Sacramento tributaries, lower Sacramento tributaries and San Joaquin tributaries. Each of these types of tributary represent a typical combination of instream conditions and habitat configuration. Upper Sacramento (USAC) tributaries have historically been some of the most productive for Chinook salmon. These tributaries all lack hatchery inputs and rely on natural production and straying fish to sustain their populations (Palmer-Zwahlen and Kormos 2015). The land use surrounding USAC tributaries is primarily public forest service land or agricultural. Lower Sacramento tributaries (LSAC) all originate in the Sierra Nevada mountain range, and flow west into the Sacramento. These watersheds are closer to the delta or connect directly into the delta, which means juveniles have a shorter route during their outmigration. Also, many LSAC tributaries (Lower American, Feather, and Mokelumne rivers) have hatcheries that supplement their populations. The land use in LSAC tributaries is highly developed with most lands being urbanized or in agricultural production. The last type of watershed are tributaries in the San Joaquin (SJ). These watersheds tend to not be as productive as Sacramento tributaries and also lack hatchery support. The land use surrounding the portions of SJ tributaries open to anadromous fish are dominated by agriculture. High summertime water temperatures are major concern for cold waters species in SJ tributaries. In the decision model, the differences between the watersheds were realized as differences in in-river and outmigration survival rates (Table 5.1).

Decision Problem

In this analysis, I developed a two-tiered decision problem for fall-fun Chinook salmon habitat management in California's Central Valley. The decision problem was framed to reflect the current decision making structure of the CVPIA and its local management partners. The upper tier was comprised of the CVPIA implementing agencies: the U.S. Bureau of Reclamation and the U.S. Fish and Wildlife Service. For the sake of this analysis, I considered these partners a single decision making entity. The upper tier decision maker decided how to allocate CVPIA resources among the CVPIA administered watersheds. The second tier was made up of local watershed managers from different watersheds that decide how to implement funds awarded to their respective watersheds. Each watershed represented a common "type" (USAC, LSAC, and SJ) of tributary found in the Central Valley. The local watershed managers decided what kind of habitat restoration action would be most beneficial to their watershed. The fundamental objective for each tier was to maximize production of natural origin adult equivalents fall-run Chinook salmon within their respective spatial extents. The term "Adult equivalents" was defined as wild-origin adults (non-hatchery fish) expected to be produced from an annual cohort of juvenile salmon that migrate to the ocean.

Decision Problem - Lower Tier

Each watershed in the lower tier operated at the same spatial and temporal scale. It should also be made clear that the lower tier decision makers acted independently of one another as did the populations of fall-run Chinook salmon that they manage. The spatial extent for each watershed in the lower tier was the entirety of the river that was open to anadromy and the spatial grain was 400 m (~0.25 mile) reaches within that spatial extent. The size of the spatial grain was determined by the types of projects that have implemented in previous habitat restoration work in CVPIA streams. Temporally, the lower tier works on an annual time step. During each time step, a single management action could be implemented in each lower tier watershed.

Decision Problem – Lower Tier Objectives

Each decision maker in the lower tier shared a single fundamental objective, which was to maximize the number of naturally produced fall-run adult Chinook salmon in their respective watersheds. The number of naturally produced adult equivalent Chinook salmon served as the utility (the metric that will be used in the optimization) in each watershed. I identified two means objectives that would help accomplish the fundamental objective of maximizing the number of naturally produced fall-run Chinook salmon. Both were based on my previous work (Chapters 2 and 3) modeling salmon populations and decision processes in the CVPIA streams. The first means objective was to increase the amount of spawning habitat available to returning adult salmon. The second means objective was to increase the amount of rearing habitat available to juvenile Chinook salmon. Although there may be other means of increasing the number of naturally produced Chinook salmon (e.g., decreasing in-stream temperatures or pulsing stream flows at critical times), I chose to limit the analysis to habitat restoration work, because habitat restoration projects are currently the most common types of projects implemented in CVPIA streams.

Decision Problem – Lower Tier Management Alternatives

The available alternative management actions were identical across all three watersheds and were aimed at influencing the means objectives identified above. The two management alternatives were spawning gravel additions and floodplain excavations. The management alternatives are assumed to be cost equivalent in each watershed. During a gravel addition, approximately 9000 m^3 (12,000 $yard^3$) of gravel are added into a single 400m (~0.25 mile) reach of river. Gravel is trucked into to the site and then placed into the stream channel using heavy machinery. Ideally, the gravel is able to settle into the contours of the stream channel and provide additional spawning habitats. I used the results from a 1-D hydrologic model that simulated gravel additions in the Lower American River to get an estimate of the average effect size of an individual gravel addition (Hammersmark 2014, Hammersmark and Tu 2015). For this application, I assumed that the average effect size was the same across all three lower tier watersheds. The second decision alternative was to excavate a stream bank to create additional floodplain, juvenile rearing habitat. This is done to create juvenile rearing habitat by providing access to slower moving waters with more cover. These are the types of habitats that juvenile Chinook salmon require to avoid predation as well as to feed (Sommer et al. 2001). These projects require heavy machinery to manually excavate a volume of earth to lower the effective floodplain to provide shallow off-channel habitat. The mean effect size of a gravel excavation was assumed to be equal across all three watersheds (Table 5.2). These two management alternatives were scaled so they were considered cost equivalent in their implementation.

Decision Problem – Top Tier Overview

The upper tier decision maker represents both the U.S. Bureau of Reclamation and U.S. Fish and Wildlife Service. Scale is the primary difference between the decision makers in the lower tier and the decision maker in the upper tier. The spatial extent of the upper tier decision problem is the sum of the extents in the lower tier and the spatial grain in the top tier is each individual watershed in the lower tier. The difference in scale between the two sets of decisions means the lower tier decision maker works on a more spatially explicit scale and the upper tier decision maker works on a spatially implicit scale. I structured the top tier decision problem as a resource allocation problem to answer the question, “Which watershed should I provide funds to increase total salmon production?” At the upper tier, the decision making process occurs at a slower time scale compared to the decision process in the second tier. Decisions in the upper tier occur once every three years compared to on an annual basis in the lower tier. The top tier decision maker only allocates funds to the lower tier watersheds once every three years. This difference in time scales to reflect how funding cycles are often structured in the CVPIA and other natural resource management decision situations.

Decision Problem – Top Tier Objectives

The fundamental objective of upper tier decision maker is to maximize the total number of naturally produced Chinook salmon in the entire system given a limited amount of resources. I identified three means objectives that can serve this fundamental objective. Each means objective is simply funding a habitat restoration project in a different lower tier watershed. Unlike the decision makers in the lower tier, this decision make does not identify specific projects to implement, just which watershed(s) receive funding to implement projects.

Top Tier – Management Alternatives

The upper tier decision maker can only influence the levels of natural production for fall-run Chinook salmon through allocating funds to lower tier watersheds. The watersheds then use those funds to implement habitat restoration projects. In this decision set, only a single management alternative could be implemented in each lower tier time step, which results in a maximum of three projects occurring in a single upper tier time step. There is no restriction that limits how many projects can occur in a single watershed over the course of an upper tier time step. Thus, the management alternatives available to the upper tier decision maker are simply all the permutations of how up to three total projects can be allocated between the three watersheds.

Decision Models

In this section, I describe the simulation models that were used to parameterize all the components of the MMDP. In the lower tier, the decision model simulates how different lower tier management alternatives effect a single reach in each type of watershed under different configurations of habitats. The lower tier decision model was used to derive a policy that identifies the type of management alternatives (gravel addition or floodplain excavation) that is optimal for different configurations of spawning and rearing habitat. The upper tier decision model determines the system wide expected number of adult salmon that would be produced through different funding alternatives. The upper decision model was then used to derive a policy that would determine the optimal allocation of funds between all three lower watersheds given different combinations of total funding and delta migration survival.

Lower Tier Decision Model

I used the fine scale, life cycle model introduced in chapter 3 as the basis for each lower tier watershed's decision model. This model is used to simulate the dynamics of a fall-run Chinook salmon population in a Central Valley stream. A key feature of this model is that it allowed me to simulate the dynamics of fall-run Chinook salmon populations and also evaluate how populations respond to alternative restoration actions. The primary inputs for the model are initial adult escapement, current habitat availability, adult spawning success rates, juvenile survival rates and juvenile-to-adult outmigration and survival rates. In turn, the primary outputs of the model are the number of naturally produced adult equivalents for a given cohort.

The population dynamics model consisted of six sub-models: *escapement, reproductive success, fry rearing and habitat, parr rearing and habitat, hatchery migration success,* and *fry, parr and smolt migration success* (Figure 5.3) and operated on an annual time step. I define a fry as a juvenile salmon <65mm in total length (TL), a parr juvenile salmon between >65mm and <90mm TL, and a smolt as a juvenile salmon >90mm TL. The *escapement* sub-model simulated adult Chinook salmon in the ocean that migrated from the ocean into each their natal watershed. These migrating individuals experienced mortality from ocean harvest and recreational angler harvest. After entering freshwater, adult salmon fish were distributed throughout the spawning sections of each watershed. The escapees then create redds and produce fry in the *reproductive success* sub-model. The *fry rearing and habitat* and *parr rearing and habitat* sub-models simulated the juvenile rearing process. For each of these sub-models, individuals either found habitat, grew, and survived or they migrated out of the watershed as fry or parr. If habitat was not available in the stream section where a fish resided, that fish can moved downstream in an attempt to find rearing habitat. Fish that survived both rearing processes ultimately become smolts, after which they migrate to the ocean. Also, in each section of the river the temperature suitability was determined by how far a specific watershed was from the river's confluence with the Sacramento or San Joaquin. The river sections that were further upstream were considered better (colder) with respect to temperature suitability. Temperature suitability influence the habitat quality for each life stage, with colder water representing better quality habitat. Hatchery contributions were only considered in the LSAC watershed. The hatchery component is simulated in the *hatchery migration success* sub-model where hatchery origin smolts are released from the hatchery. Lastly, the *fry, parr, and smolt migration success* sub-model applied a juvenile-to-adult survival rate. This rate depended on a juvenile migrant fish's life history stage when it left the watershed. A complete description of this model can be found in *Methods* section of chapter 2.

Upper Tier Decision Model

The upper tier decision model simulated the how the upper tier decision maker received and dispersed funds among the watersheds. During this process, the upper tier decision maker allocated funds to the lower tier decision makers that they in turn use to implement habitat restoration activities within the watershed they administer. The output for this model was the total number of naturally produced adult equivalent Chinook salmon from all lower tier watersheds. Optimal decisions in the upper tier were determined by estimating natural production at different funding levels, of a specific funding strategy. The inputs for the upper tier decision model were the annual funding level and the watershed specific cost of implementing a habitat restoration action. The output was the total number of naturally produced Chinook salmon from the second tier decision model.

The upper tier decision maker only considered their current level of funds and the relative costs of implementing each management alternative in each watershed. The amount of money that the upper tier decision maker had at time *T* depended on the amount of money they had at the end of the previous time step (T-1). This was represented by

[1] $X_T = X_{T-1} + F_T - C_{A(T)}$

where X_T was the amount of money decision maker has at time step T, F_T was the amount of funding that upper tier decision maker received at time step T and $C_{A(T)}$ was the costs of implementing action A at time step T. The cost of implementing a specific action was determined through the relationship:

[2] $C_{A(T)} = \sum_k a_{T,k} \cdot c_k$

where $a_{T,k}$ was the number of actions that are implemented in lower tier watershed k at time step T, and c_k was the cost associated with implementing a single action in watershed k. In this model, project costs were randomly sampled from a normal distribution with a mean equal to 5, 2.5, and 2.5 for the LSAC, USAC, and SJ watersheds respectively. I assumed each distribution had a coefficient of variation of 0.2, which resulted in standard deviations of 1.5, 0.75, and 0.75 for watershed k. Similarly, F_T was also a random draw from a normal distribution with mean 6 and standard deviation 1.04. I parameterized the funding and cost estimates to reflect the geographical differences in costs that typically occur within a multilevel natural resource decision problem. The costs associated of implementing a project in each of the watersheds were determined using cost estimates from previous habitat projects in the Central Valley. I decided to make all cost estimates relative to one another rather than use exact dollar estimates to make the project cost differences between the watersheds more clear.

The total number of naturally produced adult equivalent Chinook salmon in the lower tier was determined as:

$$[3] \quad R_T = \begin{cases} \sum_k \sum_{t=(T\cdot 3)-2}^{(T\cdot 3)} g_k\big(A(T) \epsilon\, a_{T,k}, t\big), & X_T \geq 0 \\ 0, & otherwise \end{cases}$$

where g_k was the function that predicts the number of naturally produced Chinook salmon in the lower tier population model from watershed k, t represents the relatively faster time step of the second tier (annual). In other words, the output for tier one was simply the sum of the amount of salmon that were produced across each all the lower tier watersheds. In the event that a management action was implemented and the costs of that management plan exceeded the current level of funding, the decision maker lost those funds and no projects were implemented. This penalty ensured that only actions that were fully funded were implemented and it made expensive projects potentially riskier endeavors. It should be noted that the number of fish produced was only tied to the top tier by how the top tier decision maker decided to allocate funds. Once, the top tier decision maker allocated funds, it was up to the lower tier decision makers to decide how to implement those funds (e.g., gravel project vs excavation project).

System State Definitions

To implement the MMDP framework, I also needed to define the system states for both decision making tiers. The decision models described above were used to determine the transition probabilities for each set of system states. The system states were assumed to be fully observable for each decision maker.

Lower Tier System state definition

I chose to define the state space (x) with two habitat dimensions: the amounts of spawning habitat (m^2) per redd and rearing habitat (m^2) per redd in an individual 400m stream reach:

$$x = \left[\frac{Spawnhab}{Redd}, \frac{FryHab}{Redd}\right]$$

This metric was made up of three pieces of information that are already collected by the decision makers in each watershed: spawning habitat, fry habitat, and an estimate of the number of females (redds) on a specific river section. The system state definition in the lower tiers will answer the question of “what would the optimal habitat restoration option be in this given the current amount of observed spawners and habitat?” The number of redds present in particular reach, for a given year is not likely to be directly observable in time to implement a decision in the same year. Typically, the number of redds in watershed are estimated using carcass counts, aerial photography, or another escapement based estimation process after the spawning season (Williams 2001, Gallagher and Gallagher 2005). Instead, I defined the number of redds in the system state (x) as the mean redd count over the previous five years in each 400m reach to account for the lag in redd estimation and the variability in redds that occur between years. The current amount of habitat in x is assumed to be known and observable. This is the exact same habitat definitions I used in Chapter 3, when deriving optimal policies in the Lower American River.

This definition of the system state required that system state values are discretized, rather than continuous, to implement the optimization approach described below. I discretized both dimensions of the defined state-space into bins of 50 in the range of 0 to 1000+ for a total of 21^2 states. This range and bin size was chosen so that the effect of each decision (or no decision) on the current system state would be reflected in the state transition probabilities and it also reflected the potential range of state-space values possible in the CVPIA watersheds.

Under this definition of the states, I was able to calculate both transition probabilities (P^l) and the reward function (R^l) in each watershed in the lower tier. To calculate the transition matrices, I simulated a single time step and determined how many reaches were in each initial state. Then a decision was implemented and the number of reaches in each new state was determined. This process was repeated 10,000 times for each decision alternative and allowed to me determine the probability that a reach in any system state will transition into a different system state given a management action.

Upper Tier System state definition

I defined the upper tier states as the amount of funding available to the upper tier decision maker. The amount of funding available depended primarily on two pieces of information, the costs of implementing a specific management alternative and the funding level. The upper tier state was discretized into three states: low (0-3), medium (4-6) and high (7-9). This range and number of states was chosen to represent a full range of funding scenarios. The state transition probabilities (P^u) for the upper tier were calculated through simulation using equations 1 - 2. In each iteration, I simulated a management alternative and associated costs, which were subtracted from the initial funding state. This was done 10,000 times for each decision alternative (lower tier funding combinations), during which the initial and ending states were recorded to determine the overall transitions probability of each decision alternative.

Outmigration survival system state

Average outmigration survival was the final system state that was included in the MMDP analysis. In these models, outmigration survival represented the probability that an outmigrant juvenile (fry, parr, or smolt) returned to their natal watershed as a spawning adult. Outmigration survival represented the product of two survival processes: 1.) Migration through the migratory corridor, 2.) juvenile-to-adult survival in the ocean. The migratory corridor consists of the lower portions of the Sacramento and San Joaquin rivers and the delta. These areas are known to be survival bottlenecks for outmigrant juvenile Chinook salmon (Buchanan et al. 2018). These survival rates were highly influential to decision making at both a large and small scale habitat restoration (Chapters 2 and 3). I wanted to know if different migratory corridor conditions that favored outmigrants at different times of the year could influence optimal policies at both tiers of this decision problem. I considered three different migratory corridor conditions, each favored different outmigrants at different times. The timing of outmigration corresponded with different sizes of outmigrants: fry, parr, and smolt. Fry outmigrants left the natal watersheds earliest and smolts migrated last. When the migratory corridor favored a specific outmigrant size/timing class, I assumed it provided a 3-fold increase in the mean outmigration survival for that size/timing class in each lower tier watershed. This resulted in three sets of policies for each decision maker, one for each migratory corridor survival condition.

The MMDP Framework

The best way to envision a MMDP is as sets of traditional MDPs stacked on top of one another with upper tier reward (utility) dependent on the optimal policies in the lower tier. The MMDP structure I present here was largely an generalization of the work done by Chang *et al*. (2003). The primary difference was that I allowed lower tiers to have more than one decision maker. I present a framework that operated with two tiers of decision makers. The upper tier consisted of a single decision maker and the lower tier included several decision makers. For this problem, each decision maker in the second tier was treated as an independent MDP. The optimal policies from lower tier MDPs were used to determine the expected utility of implementing the optimal policy in each watershed. The cumulative expected utility values from the optimal policies in the lower tier were used as the reward for the upper tier (Figure 5.4). This allowed the top tier to then be solved as a normal MDP, with the caveat that the policy derived was contingent on the lower tier decision makers also acting optimally.

Like a traditional MDP, a MMDPs can be solved using a stochastic dynamic programming. The primary difference is the sequential manner in which the MDPs are solved (lowest to highest tier). The upper MDP had a finite state space I and a finite action space Λ. In this model time, n, was discrete with $n \epsilon \{0,1,2,\ldots,\}$ for the upper level. At each time step, the upper level began at state $i_n \epsilon$ I, and an action $\lambda_n \epsilon \Lambda$ was taken and i_n transitioned into i_{n+1} with probability $P^u(i_{n+1}|i_n, \lambda_n)$. The current state and action at the upper level determined the actions that were available to the decision makers in the lower level. Time on the lower tier moved in increments $t \epsilon \{t_0, t_1, t_2, \ldots\}$ and $\mathrm{t}_{\mathrm{nT}} = n$ (Figure 5.5). Thus, T acted as the scale factor between the two tiers and was equal to three for this decision model because decisions on the lower tier were made three times more often than on the upper tier. The action λ_n then caused a reward, R^U, to be accrued for the upper tier decision maker at each time step n. R^U was function that is dependent on the actions and dynamics in the lower tier. I provide a full definition for R^U after describing the dynamics of the lower tier below.

The lower tier MDPs were structured almost identically to the upper level but on the shorter time-scale and with a dependency upper level actions. For each decision maker k, at each time step t, an action $a_{k,t} \epsilon A$ occurred that caused the current state $x_{k,t} \epsilon X$ to transition to the next state $x_{k,t+1}$. This transition occurred according to the probability $P^l{}_k(x_{k,t+1}|x_{k,t}, a_{k,t}, i_n, \lambda_n)$ which resulted in a reward calculated according to $R^l{}_k(x_{k,t}, a_{k,t}, i_n, \lambda_n)$. Thus, both the state transition probabilities, and reward functions for the lower tier k watersheds were dependent on the upper tier's current state i_n and action λ_n. A policy in the lower tier was defined as $d^l{}_k = \{\pi^l{}_{k,n}\}$, where $\pi^l{}_{k,n}$ was a sequence of actions available to watershed k given the state space X_k, I, and action space Λ. This translated to a sequence of decisions being made at the lower tier across a single time step on the upper tier which was defined as $\pi^l{}_{k,n} = \left\{\phi_{k,t_{nT}}, \ldots, \phi_{k,t_{(n+1)T-1}}\right\}$. Where $\phi_{k,t_{nT}}$ was simply an action in watershed k that belonged to the policy $\pi^l{}_{k,n}$.

The discounted reward function for the upper tier was defined as,

$$[4] \quad R^u(x_{1:k}, i_n, \lambda_n, \pi_n^l) = E_{i_n,\lambda_n}^{x_{1:k}}\left[\sum_k \sum_{t=t_{nT}}^{t_{(n+1)T-1}} \alpha^{\sigma(t)} R_k^l\big(x_{k,t}, \phi_{k,t}(x_{k,t}, i_n, \lambda_n), i_n, \lambda_n\big)\right]$$

where $0 < \alpha < 1$ and $\sigma(t_{nT+r}) = \mathrm{r}$ for all n with $r = 0,1,\ldots,T\text{-}1$. Equation 4 describes a summation of the rewards calculated in each watershed in the lower tier given the watershed specific policy. The goal of the MMDP was to obtain a policy for the upper tier, $d^u \epsilon D^u$, in addition to the lower level policy d^l.

Optimal Policy Derivation

I defined the infinite horizon discounted value function as:

$$[5] \quad V^*(x_k, i) = \max_{d^u \epsilon D^u} \max_{d_k^l \epsilon D_k^l} E^{x_k, i}\left[\sum_{n=0}^{\infty} \gamma^n R^u\left(x_{1:k}, i_n, d^u\left(x_{k,t_{nT}}, i_n\right), \pi_n^l\right)\right]$$

which can be expanded using the definition of R^u to:

$$[6] \quad V^*(x_k, i) = \max_{d^u \epsilon D^u} \max_{d_k^l \epsilon D_k^l} E^{x_k, i}\left[\sum_{n=0}^{\infty} \gamma^n E_{i_n, \lambda_n}^{x_{1:k}}\left[\sum_{k=1}^{3} \sum_{t=t_{nT}}^{t_{(n+1)T-1}} \alpha^{\sigma(t)} \cdot\right.\right.$$

$$\left.\left. R_k^l\left(x_{k,t}, \phi_{k,t}\left(x_{k,t}, i_n, d^u\left(x_{k,t_{nT}}, i_n\right)\right), i_n, d^u\left(x_{k,t_{nT}}, i_n\right)\right)\right]\right]$$

The definition of V^* makes clear how the rewards at the upper tier are dependent on those at the lower tiers.

Optimal policies (d^u and $d^l{}_k$) were derived in the same way as a traditional, single level MDP. The upper level dynamics were essentially an MDP where the reward function was calculated from the lower tier MDPs. To solve the MMDP, I defined the optimality equation as:

$$[7] \quad V^*(x_k, i) = \max_{\lambda \epsilon \Lambda}\left(\max_{\pi^l[i,\lambda] \epsilon \Pi^l[i,\lambda]}\left(\begin{array}{c} R^u\left(x_{1:k}, i_n, \lambda_n, \pi_{1:k,n}^l\right) + \\ \gamma \sum_k \sum_{y \epsilon X} \sum_{j \epsilon I} P_{xy}^T(\pi^l[i, \lambda]) P^U(j|i, \lambda) V^*(y_k, j) \end{array}\right)\right),$$

where $P_{xy}^T(\pi^l[i, \lambda])$ was the probability that state y was reached by T-steps while starting in state x by following policy $\pi^l[i, \lambda]$. Equation 6 is a generalization of a Hamiltonian-Jacobi-Bellman equation (Bellman 1957). Equation 7 describes how a decision on the upper tier (λ) at time n was only optimal if all the remaining decisions on the upper tier were also optimal. Additionally, equation 7 indicates that a decision on the lower tier ($\pi_k^l[i, \lambda]$) was only optimal if all the remaining decisions in each of watershed on the lower tier were also optimal. Under this framework, I derived an entire set of optimal decisions at both tiers by finding the optimal decision at the final time step, n_f, then working backwards to find the optimal decision at n_{f-1}. This process was repeated until an entire set of optimal decisions was found for the entire time series $[n_0,n_f]$. If this process is repeated over a long enough time frame, both d^u and d^l may converge to a set of a set of stationary, state-specific optimal decisions. This process of is known as policy iteration and provides optimal decision alternatives for each possible system state for each decision maker (Chang et al. 2003).

Policy Iteration

I used stochastic linear programming and the MMDP equations to obtain optimal policies for each decision maker through policy iteration. I assumed a discount reward of 0.99 for both upper tier discount factor, α, as well as the lower tier discount factor, γ, due to the infinite horizon that policy iteration requires. I considered the policy to be stable after five iterations that produced the identical state-specific solutions. All analyses were programmed in R (R Core Team 2018).

Sensitivity Analyses

One-way sensitivity Analysis

I performed a one-way sensitivity analysis to determine how different model inputs ultimately influence the expected utility of the upper tier decision maker. During the one-way sensitivity analysis, each model input was perturbed by ±50% of its original mean value while all other input parameters were held constant at their mean value. I then derived optimal policies for both tiers of decision makers using the perturbed parameter value. Lastly, I calculated the expected reward value of the upper tier decision maker using the new optimal policy. The expected number of total adult equivalents produced was estimated by calculating the expected reward when implementing the optimal policies d^u and d_k^l at every state *i* and x_k, respectively.

[8] $U = E^{x_k,i}[V^*(x_k, i)]$

The larger the difference between the values *U* takes when a parameter was perturbed the more influential the parameter. By perturbing each parameter individually and by the same relative amount (±50%), I identified the parameters were most influential in determining optimal polices and the total number of fish produced in the entire system.

Fund Allocation Response Profile

Response profile analyses provided a method to determine how policies change over the range of a parameter. In this decision model, each upper tier policy can be best described by the expected amount of funds that the policy allocated to each lower tier watershed. I choose to evaluate how smolt outmigration survival values influenced the optimal policy. For this analysis, I perturbed the mean smolt outmigration survival value in each lower tier watershed simultaneously. Values of smolt outmigration survival were perturbed across a range of ±100% of their original values while all other inputs were held constant. The analysis was repeated for each of migratory corridor states. Influential parameters would cause the relative amount of resources allocated between watersheds to change across the range of values considered.

Relative Cost Policy Plot

The last sensitivity analysis I performed was a two-way sensitivity analysis to evaluate how the relative costs of projects influenced the upper tier policy. I wanted to understand the role project costs played in determining optimal fund allocation between the watersheds. I chose to evaluate the expected ratio of funds allocated between the LSAC and USAC across a range of different combinations of mean project costs (Eq. 3 – 4). A high (>1) ratio indicated that more resources were allocated to the LSAC and a lower ratio (<1) indicated the more resources were allocated to USAC. Similar to the other sensitivity analyses, this analysis was done for each migratory corridor condition.

Results

Lower Tier Policies

The lower tier policies were similar across each delta condition and in stream temperature suitability. The policies were almost identical between watersheds when the migratory corridor conditions favored parr or smolt outmigrants (Figure 5.6 & 5.7). These policies were generally dominated by the decision to do a floodplain excavation in stream reaches under high (Figure 5.6.a, 5.6.d, 5.6.g, 5.7.a, 5.7.d, 5.7.g) and medium (Figure 5.6.b, 5.6.e, 5.6.h, 5.7.b, 7.e, 5.7.h) stream temperature suitability. Gravel projects were optimal at the lowest values of spawning habitat per redd states. However, when the stream temperature suitability in a reach was low, gravel projects become optimal under a greater range of conditions (Figure 5.6.c, 5.6.f, 5.6.i, 5.7.c, 5.7.f, 5.7.i). Policies differed when the migratory corridor favored fry outmigrants (Figure 5.8). There was no clear pattern across all the watersheds and rearing temperature suitability and gravel projects were only optimal in the LSAC watershed under these conditions. In every policy plot, there was a threshold in the state combinations where the optimal decision became no action (Figure 5.6 – 5.8). In these regions, there were enough juvenile habitat per redd that any action would not yield additional production. The actual threshold values varied with migratory corridor conditions and rearing temperature suitability.

The migratory corridor conditions was the most influential factor in determining optimal policies within the lower tier watersheds. This is evident from how similar all the policies between watersheds were for each migratory corridor state. When the delta was favorable to parr or smolts the policies were similar across the watersheds and in each temperature suitability (Figure 5.6 – 5.8). The optimal policies within each watershed varied when the delta conditions favored fry outmigrants.

The expected reward of lower tier optimal policies followed a similar pattern for all three delta conditions (Figure 5.9 – 5.11). In all three types of watersheds, the greatest expected utility occurred when delta conditions favored smolt outmigrants, followed by conditions that favor fry outmigrants and lastly by delta conditions that favor parr outmigrants. Regardless of the delta conditions, the policies from the hatchery supplemented stream in the lower Sacramento (LSAC) had the highest expected rewards and the policies from stream in the San Joaquin basin (SJ) resulted in the lowest expected rewards. Migratory corridor conditions that favored smolt outmigrants resulted in the highest expected reward value in every watershed across the range of rearing temperature suitability.

The optimal policies indicated that lower tier decision makers had similar optimal policies despite the differences in survival rates (rearing and migration) between watersheds. Instead, the primary differences between these policies was the expected reward in each watershed. The reward function was the number of adult equivalents produced, which depended on the watershed specific survival rates. The expected reward values were passed to the upper tier decision maker and were influential in determining the optimal resource allocation at that coarser scale.

Upper Tier Policies

The optimal policy at the upper tier was focused on providing resources to the watersheds in the Sacramento basin (USAC and LSAC) across all combinations of system states (Figure 5.12). The policy never allocated resources to the watershed located in the San Joaquin basin (SJ) under any conditions, despite that the mean project costs in USAC and SJ watersheds were equal. This outcome was due to the low rearing and survival rates that occur in SJ that resulted lower production across lower tier management actions (Figure 5.13). Most resources were allocated to the LSAC watershed under most conditions except for medium funding with a delta condition that favored fry. Under these combinations of system states, all resources were allocated to USAC watershed. Here, the production of adult equivalents was similar between the LSAC and USAC watersheds that it was much more cost efficient to provide funds to USAC watershed. Under low funding, the optimal decision was to allocate all the funds to the LSAC watershed, regardless of the delta condition. The number of projects that were implemented within a watershed depended on the mean cost of a project in a watershed. Under the optimal policy, resources would be allocated in more than one watershed when funding was high and the delta favored fry migrants, and when funding was medium and delta favored smolt or parr outmigrants.

The expected reward of implementing the optimal upper tier policy varied across both delta conditions and funding levels (Figure 5.14). Regardless of delta condition, the total expected reward increased as the funding increased. This was due to the greater number of projects that can be implemented at higher funding levels. The expected reward also was lowest when the delta conditions favored parr across all funding levels.

Sensitivity Analyses

One-way Sensitivity Analyses

Three parameters were the most influential based on the one-way sensitivity analyses (Figure 5.15 – 5.17). The most important parameter for every migratory corridor state was the cost of a project in the Lower Sacramento watershed. The next two most important metrics were the mean level of funding and mean fry in-river rearing survival. Smolt outmigration survival in the Lower Sacramento stream was the most influential parameter across all three delta conditions regardless of the delta state. Lastly, the survival rates specific to the LSAC watershed were more influential than any of the watershed specific survival rates in the USAC or SJ watershed. Almost all the parameters related to the San Joaquin watershed were inconsequential to the estimate of adult equivalents produced regardless of the migratory corridor state.

Fund Allocation Response Profile

Response profile plots of the mean smolt outmigration survival parameters indicated that small changes in smolt outmigration survival influenced the optimal policy in the fry migratory corridor condition (Figure 5.18). A decrease in smolt outmigration survival resulted in more resources going to USAC watershed and an increase resulted in more resources going to the LSAC watershed. This effect was dampened under in the parr delta state (Figure 5.19). Smolt delta survival decrease of at least 10% caused a change in resources allocation. Under the smolt delta state, the policy became static across all smolt survival rates (Figure 5.20).

Relative Cost Policy Plot

The relative cost policy plots evaluated how the costs of projects in the LSAC and USAC watersheds interacted to determine how the upper tier decision maker would allocated limited resources. The relative costs of projects in these two watersheds was highly influential in determining how the optimal policy would allocate funds (Figure 5.21 – 5.23). The same general pattern was seen regardless of the delta condition: if the cost of a Lower Sacramento project decreased or the cost of a project in Upper Sacramento watershed increased the upper tier policy would allocate all the resources to the Lower Sacramento watershed (Figure 5.21 – 5.23). Small changes to the mean cost of a project in these watersheds could result in very different upper tier policies.

Discussion

In this study the optimal policies produced a strategy that focused almost all of the upper tier resources on the LSAC watershed. The optimal policy rarely prioritized restoration work in the USAC and SJ watersheds, which experienced lower rearing and corridor migration survival rates compared to the Lower Sacramento watersheds. The optimal policy never allocated resources to the San Joaquin watershed. Watersheds in the San Joaquin basin tend to experience warmer summer time temperatures than their Sacramento basin counterparts, which presumably results in higher mortality rates of rearing juvenile salmon (Williams 2006, Isaak et al. 2016). High temperatures, lethal to juvenile salmonids, (> 20°C) in the San Joaquin mainstem are more common than in the Sacramento (Marine and Cech Jr 2004, Myrick and Cech Jr 2004). Additionally, survival through the delta of San Joaquin origin smolts has been estimated to be less than 2% on average (Buchanan et al. 2018). For these reasons, the optimal strategy focused restoration efforts on the watersheds in the Sacramento (LSAC and USAC).

The MMDP policy for the decision problem I presented suggests it is almost always optimal to focus on a single, highly productive stream, even if it is more costly to do so. Almost all restoration activities are constrained by limited funds, which creates tradeoffs between which lower tier decision makers received resources. Focusing resources on a few streams can occur at the expense of doing many smaller projects in several streams. Clear Creek and Butte Creek are two tributaries of the Sacramento River where long term, intensive restoration efforts have yielded substantial increases in Chinook production (Kondolf et al. 2008). In Clear Creek, habitat restoration efforts began in 1996 and include spawning gravel augmentation, floodplain reconstruction, flow alteration, and dam removal. These efforts resulted in almost a three-fold increase in the escapement of wild fall-run Chinook salmon (Earley et al. 2013). A similar, comprehensive strategy was implemented in Butte Creek to benefit the spring-run Chinook population. After several dam removals and over 40 river kilometers of habitat restoration, spring-run escapement jumped from about 500 adults in 1987-1992 to over 20,000 in 1998 (Pejchar and Warner 2001).

Migratory species pose unique challenges to natural resource decision problems. Often local managers only have influence on a portion of the migratory species life cycle. However, processes that occur outside spatial extent that managers administer can still be highly influential to management goals. In this decision problem, the local watershed managers could only influence habitats within their own watershed. However, ocean and migratory corridor survival rates were among the most important factors in determining natural production and optimal habitat restoration policies. MMDPs are a tool that can transparently connect processes that occur at different scales to decision making. The benefits of monitoring and resolving uncertainties can be shared indirectly across scales and decision making hierarchy.

In this study, I've demonstrated how local processes, such as juvenile survival, can influence not only local decision making, but also regional decision making. This is an example of indirect feedback between decision tiers in a MMDP. Techniques that deconstruct complex decision problems into a smaller set of problems, such as MMDPs and other hierarchical approaches, make intuitive sense for problems that span multiple spatial scales (Parr and Russell 1998, Lane and Kaelbling 2001). MMDPs are essentially just generalized versions of a single level MDP, however they allow problems to be framed in a more logical and relatable fashion. The biggest appeal of a hierarchical approach is how it creates individualized policies for every decision maker at each level. It would be possible to frame a MMDP as an equivalent traditional single level MDP, however that would require the single state space to increase exponentially in size because it would cover the state space of each decision maker in the problem. The resulting state-space would be almost uninterpretable and any decision rule or policy that was derived from it would not be uniquely applicable to individual levels and associated decision makers.

The MMDP approach is a logical tool for hierarchical natural resource management decision problems, however some multi-agent, natural resource decision problems do not have built in hierarchies. Decentralized control problems are sequential decision problems with multiple, dependent decision makers working towards a common goal without a hierarchy (Bernstein et al. 2002). Decentralized control problems are applicable to habitat restoration problems with two or more managers working in a connected system where their actions are not independent. Large river systems, with multiple managers and migratory species are especially good candidates for such approaches. Decentralized control problems identify policies where the decision makers cooperate in order to reach their common objective. Although methods exist to derive optimal policies for decentralized control problems, they are limited to simple problems with few decision makers. As the number decision makers (*n*) in the problem increase, the number of dimensions of the state space grows *n*-exponentially. Habitat restoration rarely only involves a single manager. Identifying additional tools and approaches that can provide decision support to multiple managers simultaneously can help identify more optimal strategies.

One of the most important steps in the SDM process is identifying the objectives of the decision makers. In decision problems with multiple decision makers, objectives may be conflicting or competing. If multiple objectives exist in a traditional MDPs they have to be pooled into a single utility value using relative weights or another function. In this study, I assumed that the every decision maker had the same fundamental objective (maximize natural production), however this is not a requirement of hierarchical decision models. The MMDP approach breaks the complete decision problem into smaller, discrete problems so it is possible to have different or competing objectives at each decision making tier. The objectives from lower tiers directly determine lower tier policies which then influence how optimal policies at higher tiers are formed.

Large scale challenges, such as climate change, make methods that are able to quantitatively link large scale decision problems to small scale decision problems important tools in natural resource management. Global climate change is predicted to shift precipitation patterns, ocean conditions, and air temperatures across North America, which will have ramifications on ecological processes regardless of the scale (Lynch et al. 2016, Poesch et al. 2016). The sheer scale that climate change occurs at and the ecological processes it alters requires natural resource managers to consider how spatial and temporal scale influences their management actions. Species that require several types of habitat to complete their life cycle (such as salmon) will be uniquely vulnerable to climate changes (Crozier et al. 2008). Effective management of these kinds of species will require the cooperation of lots of different managers, working at many different spatial scales. MMDPs and other hierarchical decision tools provide managers working at different levels the means to determine how uncertainties can influence optimal decision making at different scales of a decision problem.

Dynamic programming can provide analytic solutions to decision problems as long as the number of dimensions of the state space is kept relatively small. I limited this problem to two tiers of decision makers with only four decision makers in total. My formulation of a resource allocation decision problem was limited in the number of lower tier decision makers it can accommodate while utilizing dynamic programming. The size of the decision set for the upper tier decision maker was directly determined by the number of decision makers in the lower tier. Solving larger, more complex decision problems may not be possible, or at least practical, with dynamic programming due to the computational requirement of calculating the objective function for every combination of the discretized state-space. However, reinforcement learning and other heuristic methods provide tools to approximate solutions to MDPs or MMDPs with high dimensionality (Barto and Mahadevan 2003, Sutton and Barto 2018).

To my knowledge, this is the first example of a hierarchically structured decision approach to a fisheries resource problem. The next logical step for future research would be to incorporate partial observability and/or partial controllability into a hierarchical natural resource decision problem. Partial observability refers to the uncertainty of knowing exactly what your current state is and partial controllability refers to the uncertainty that an action has its intended effect. These concepts are important, influential sources of uncertainty in other natural resource problems. It’s unknown how those sources of uncertainty may or may not drive optimal decision making with multiple decision makers working across different time and spatial scales.

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Tables

Table 5.1 - Mean juvenile outmigration survival rates for the three lower tier watersheds. The lifestage specific migration survival rates represent the probability an outmigrant juvnile returns to its natal stream as a spawning adult. All these parameters were assumed to have a corresponding standard deviation with a coefficient of variation of 0.2.

Watershed	Fry Rearing	Parr Rearing	Fry Migration	Parr Migration	Smolt Migration
Upper Sacramento	0.3	0.4	0.000013	0.00022	0.00046
Lower Sacramento	0.422	0.503	0.00002	0.0003	0.00059
San Joaquin	0.15	0.3	0.000004	0.00008	0.00019

Table 5.2 - Effect sizes for the two habitat restortaion projects available for lower tier decision makers. Values refect the changes in the amount of each type of habitat (m^2) in an individual 400m reach.

	Action Type	
	Gravel Addtion	Flood Plain Excavation
Spawning Habitat	4535	-
Fry Habitat	-748	3573
Parr Habitat	-690	3573

Figures

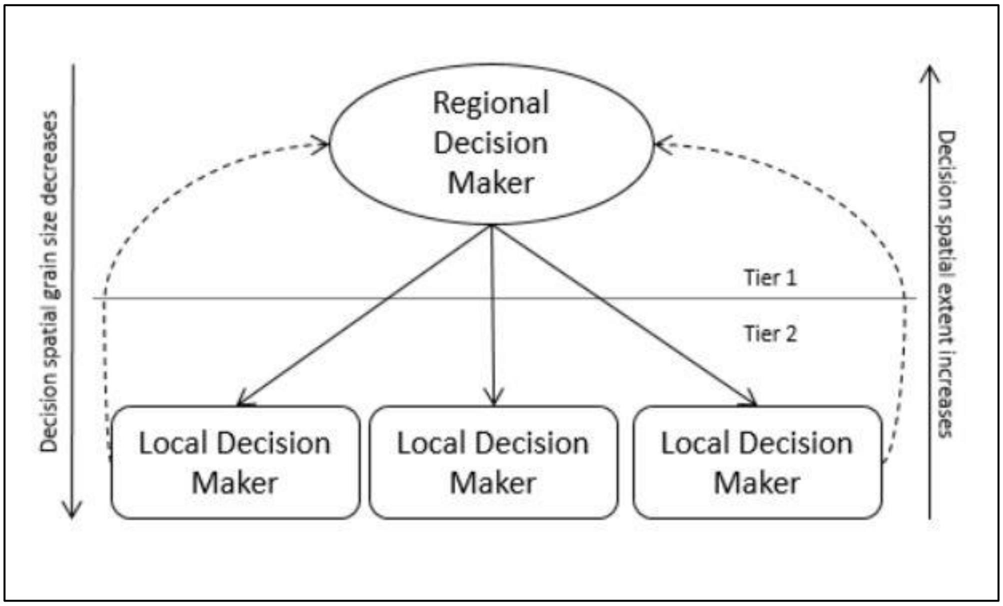

Figure 5.1 – The conceptual design of a multi-tiered decision making process. Solid arrows represent the actions of the regional decision maker. Dashed arrows reflect indirect feedback from Tier 2 back to the Tier 1 decision maker.

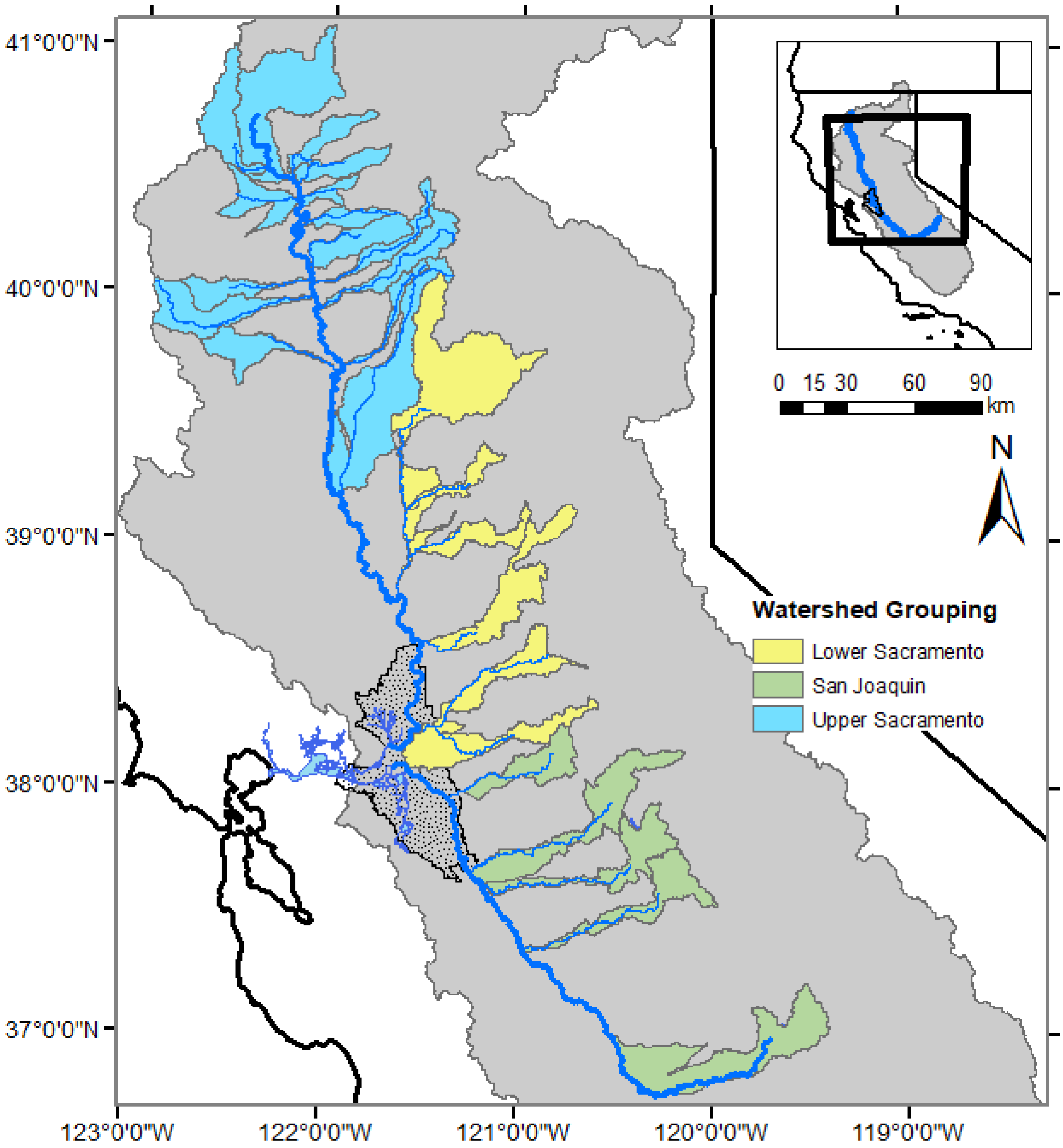

Figure 5.2 – Map of the Central Valley, CA watershed and the major tributaries the Sacramento River and the San Joaquin River. Both these river system begin in the Sierra-Nevada Range and empty into the Sacramento – San Joaquin Delta system before exiting to the Pacific Ocean through the San Francisco Bay. The watersheds administered by the CVPIA are shown.

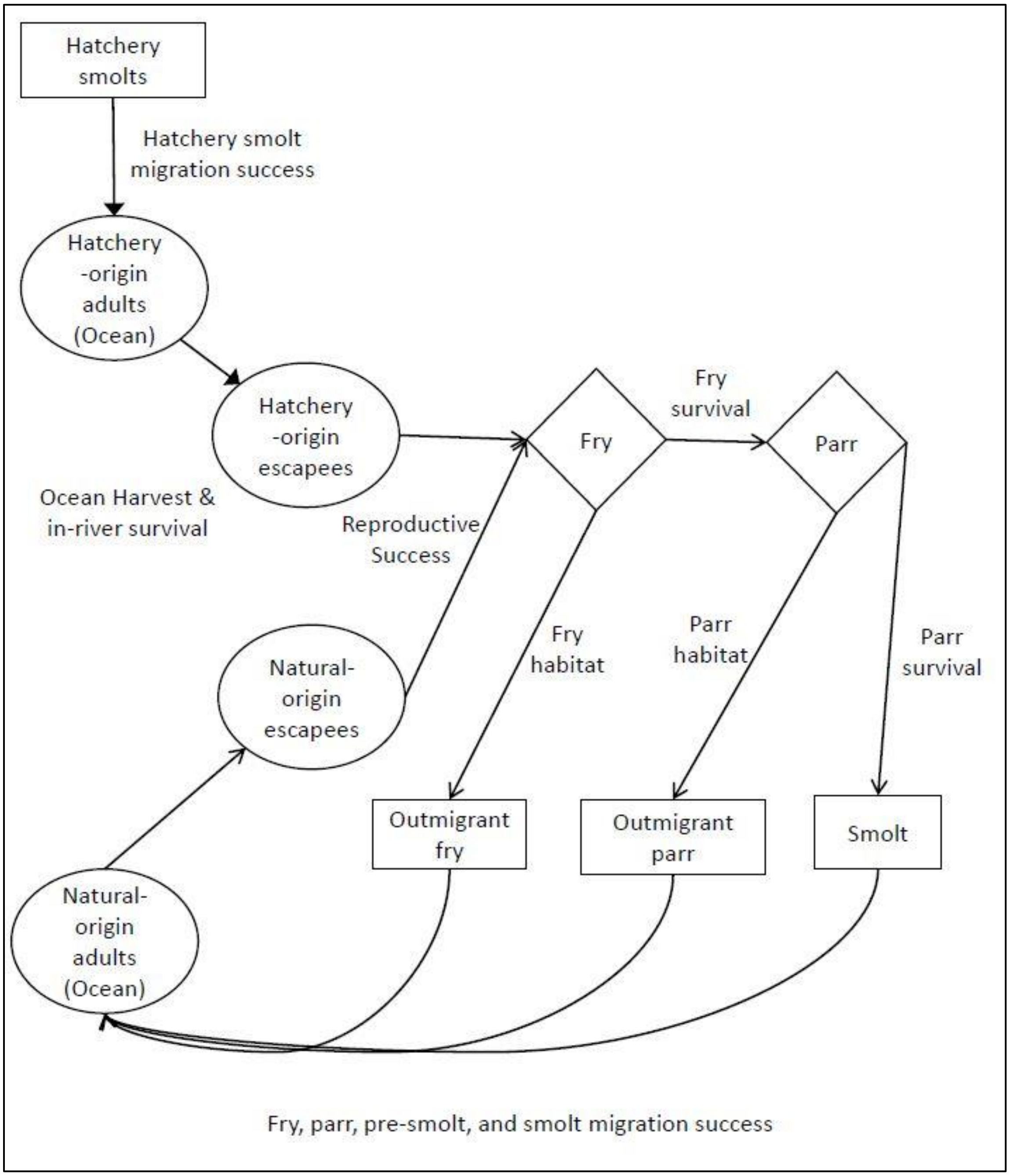

Figure 5.3 – A conceptual diagram of the life history population model used to evaluate management alternatives on populations of fall-run Chinook salmon for the lower tier watersheds. This process is identical to the model described in chapter 2. Circles represent adult stages, diamonds represent freshwater juvenile rearing stages, and boxes represent outmigrant juvenile stages. Arrows are the processes that transition an individual from one stage to the next.

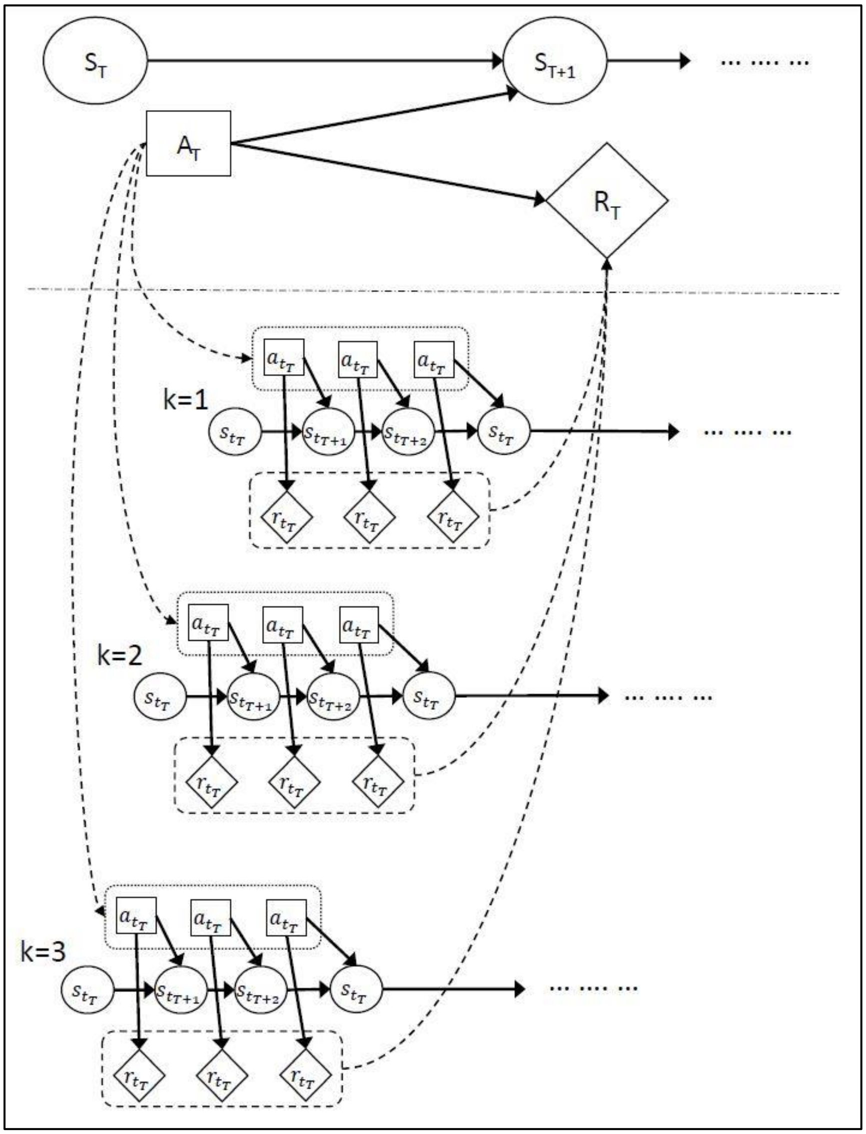

Figure 5.4 – The MMDP structure with a single upper tier decision maker and three lower tier decision makers (*k*). This diagram shows how the MMDP can be decomposed into a hierarchy of regular MDPs. In a regular MDP an action is taken at each time step that causes the system state to transition into a new state. During this process a reward is calculated. The circles represent the states, boxes represent actions, and diamonds represent rewards. In a single upper tier time step an action is taken that determines the actions space for the lower tiers. The lower tier MDPs then determines the rewards which are used to determine the upper tier reward.

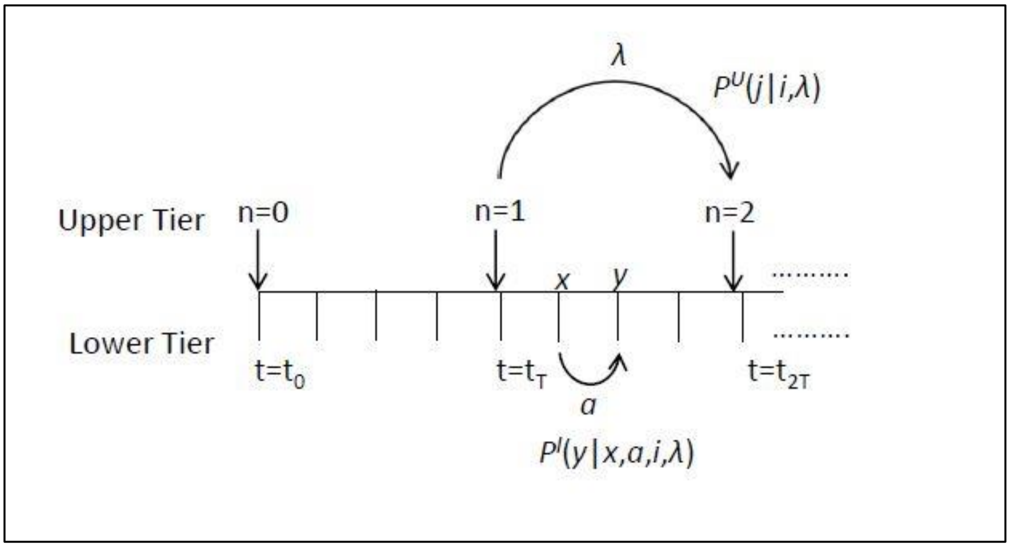

Figure 5.5 – A conceptual diagram of a MMDP that shows how the time scale between the upper tier (slow) and lower tier (fast) decision makers can differ. The upper tier decision maker makes a decision every time step *n* where action λ is implemented causing state *i* to transition to state *j* with probability $P^U(j|i, \lambda)$. Meanwhile, a similar process occurs at the lower tier, where decisions are made more often in between time step *n*. In this process, the lower tier decision maker implements action *a* which causes lower tier state *x* transition to state *y* with probability $P^l(y|x,a,i,\lambda)$. The actions available to the lower tier in between time steps *n* are determined by the upper tier action λ.

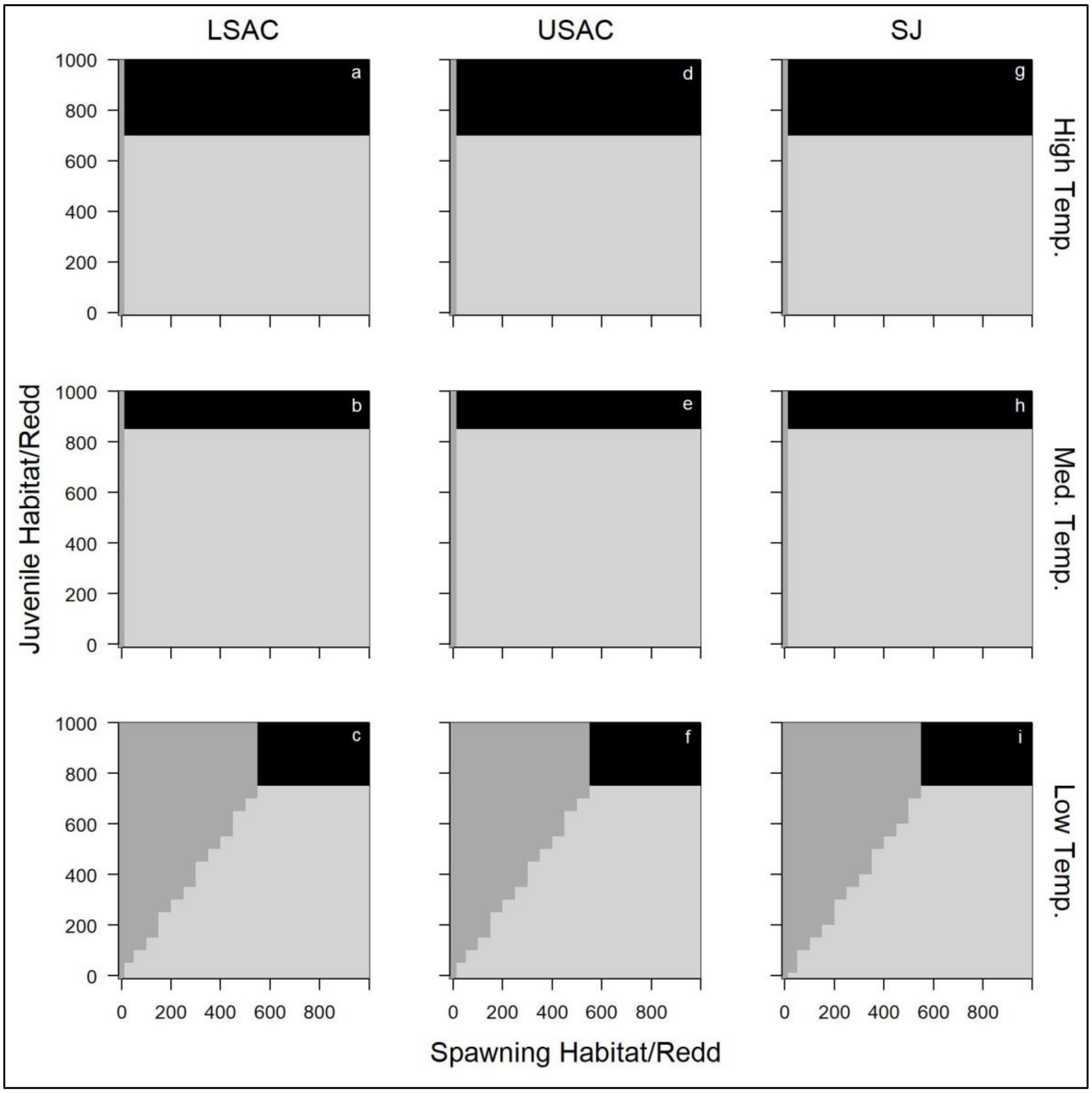

Figure 5.6 – Derived policies from the lower tier watersheds while in the parr migratory corridor state. Each plot shows the optimal management action for fall-run Chinook salmon in California's Central Valley across a range of habitat configurations. On the x-axis is the amount of spawning habitat (m^2) per redd and on the y-axis is the amount of juvenile rearing habitat (m^2) per redd. The colors represent what management action would be optimal for that habitat configuration: Dark grey = gravel project, light grey = excavation project, black = do nothing. Each column represents a different watershed and each row represents a different reach temperature suitability.

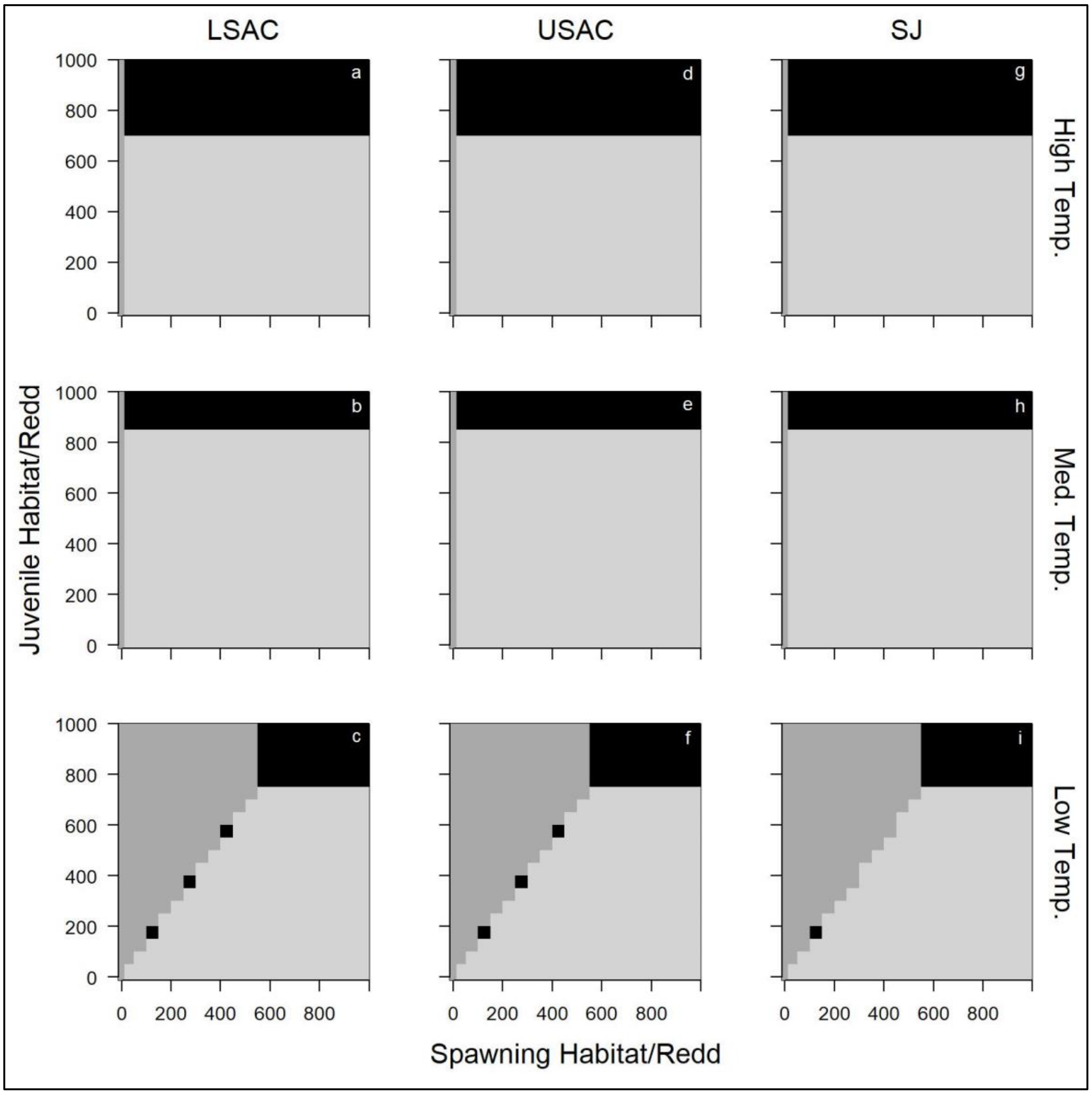

Figure 5.7 – Derived policies from the lower tier watersheds while in the smolt migratory corridor state. Each plot shows the optimal management action for fall-run Chinook salmon in California's Central Valley across a range of habitat configurations. On the x-axis is the amount of spawning habitat (m^2) per redd and on the y-axis is the amount of juvenile rearing habitat (m^2) per redd. The colors represent what management action would be optimal for that habitat configuration: Dark grey = gravel project, light grey = excavation project, black = do nothing. Each column represents a different watershed and each row represents a different reach temperature suitability.

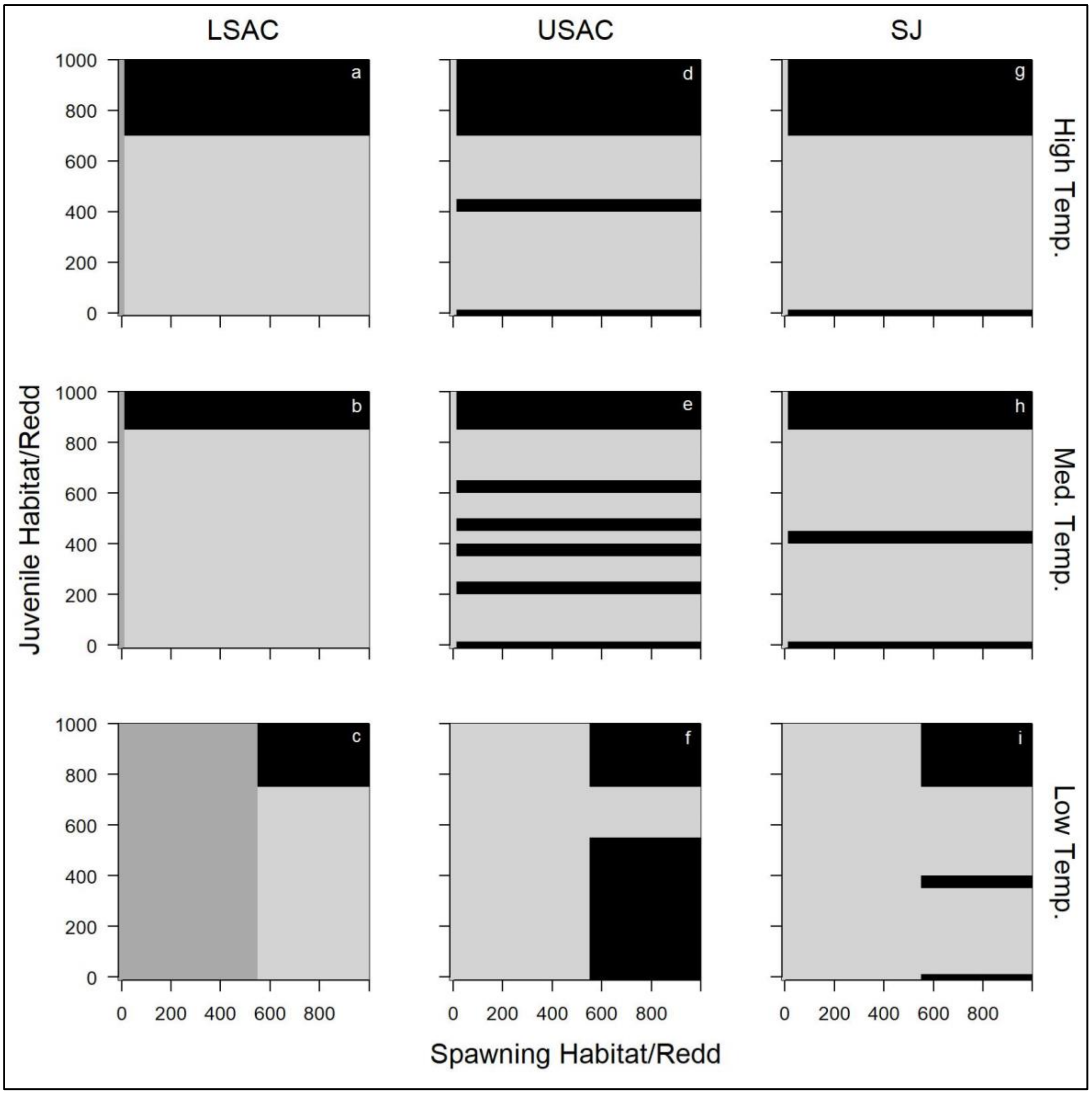

Figure 5.8 – Derived policies from the lower tier watersheds while in the migratory corridor state. Each plot shows the optimal management action for fall-run Chinook salmon in California's Central Valley across a range of habitat configurations. On the x-axis is the amount of spawning habitat (m^2) per redd and on the y-axis is the amount of juvenile rearing habitat (m^2) per redd. The colors represent what management action would be optimal for that habitat configuration: Dark grey = gravel project, light grey = excavation project, black = do nothing. Each column represents a different watershed and each row represents a different reach temperature suitability.

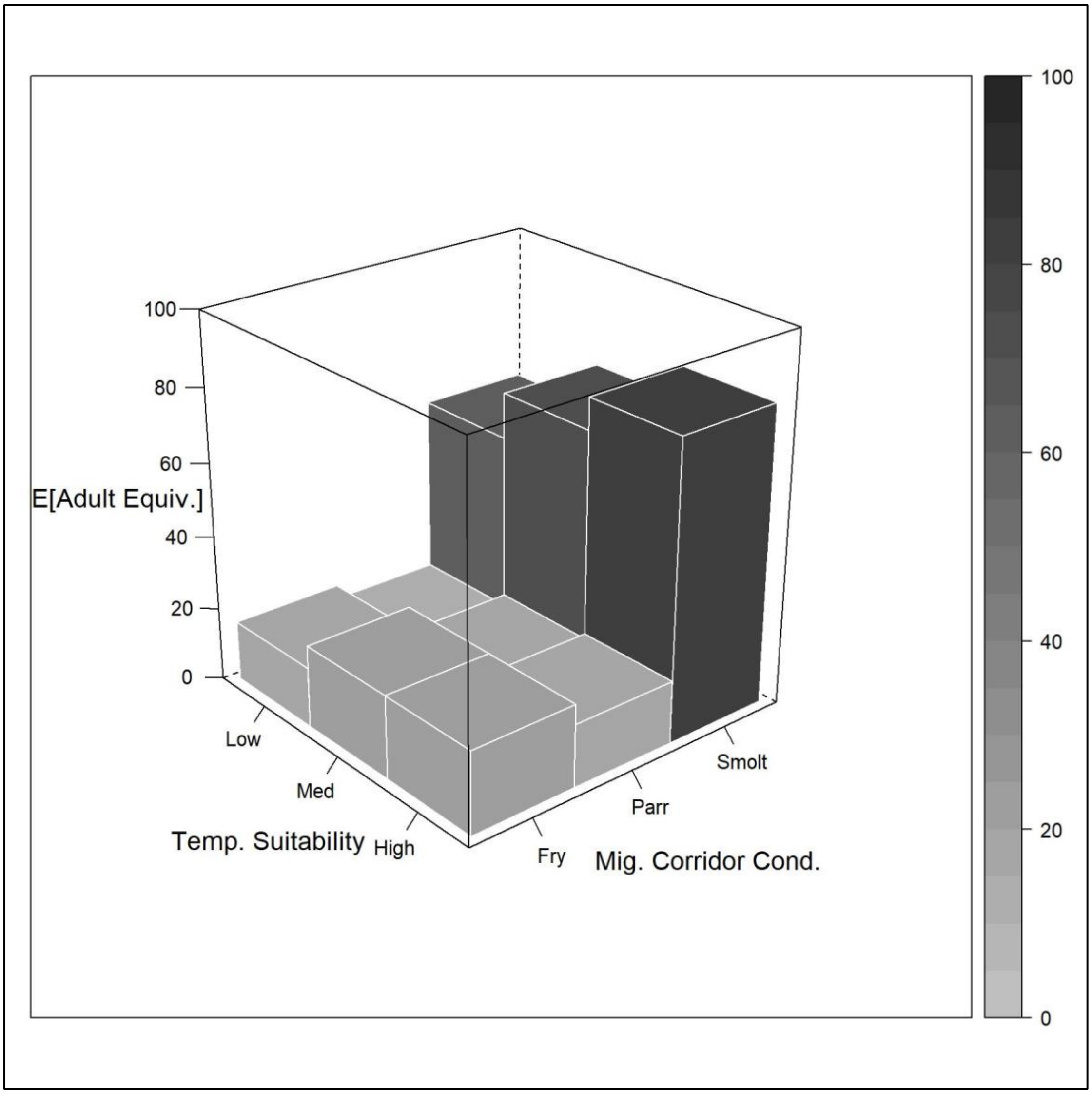

Figure 5.9 – The expected reward values for the lower tier policy derived for the LSAC in a single lower tier time step. The expected reward is the expected number of adult equivalents produced for at a given delta condition and temperature suitability.

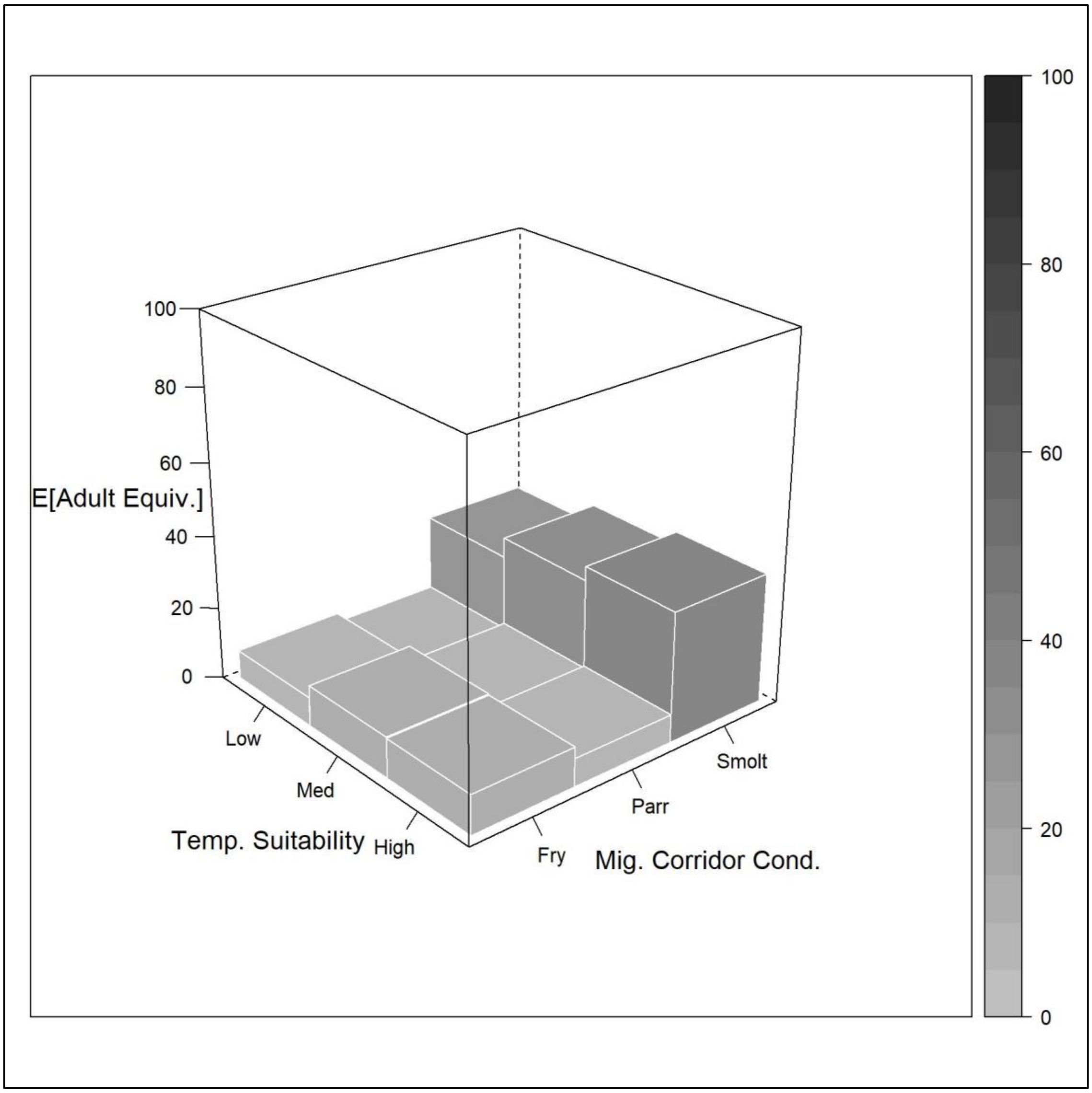

Figure 5.10 – The expected reward values for the lower tier policy derived for USAC in a single lower tier time step. The expected reward is the expected number of adult equivalents produced for at a given delta condition and temperature suitability.

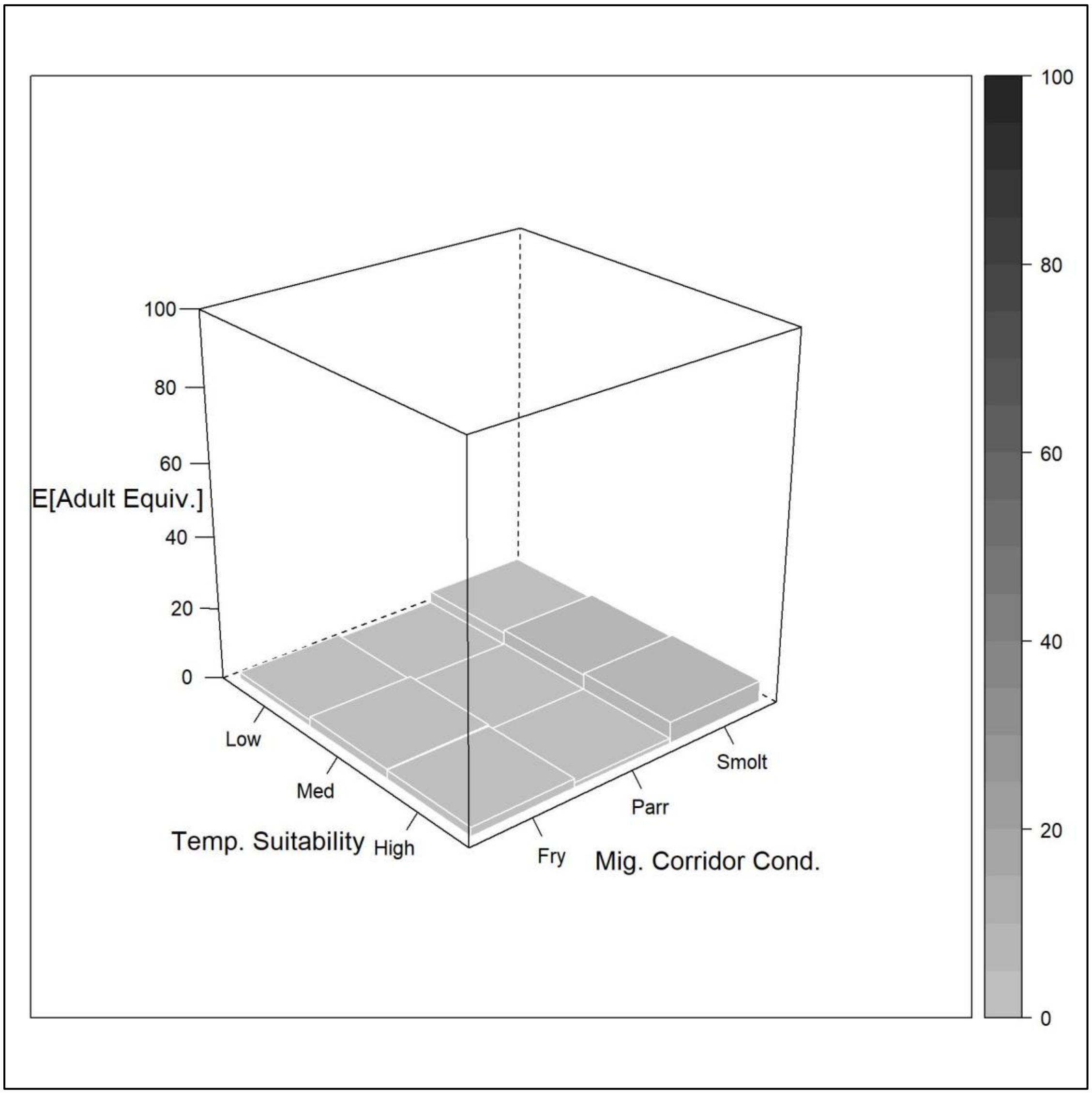

Figure 5.11 – The expected reward values for the lower tier policy derived for SJ in a single lower tier time step. The expected reward is the expected number of adult equivalents produced for at a given delta condition and temperature suitability.

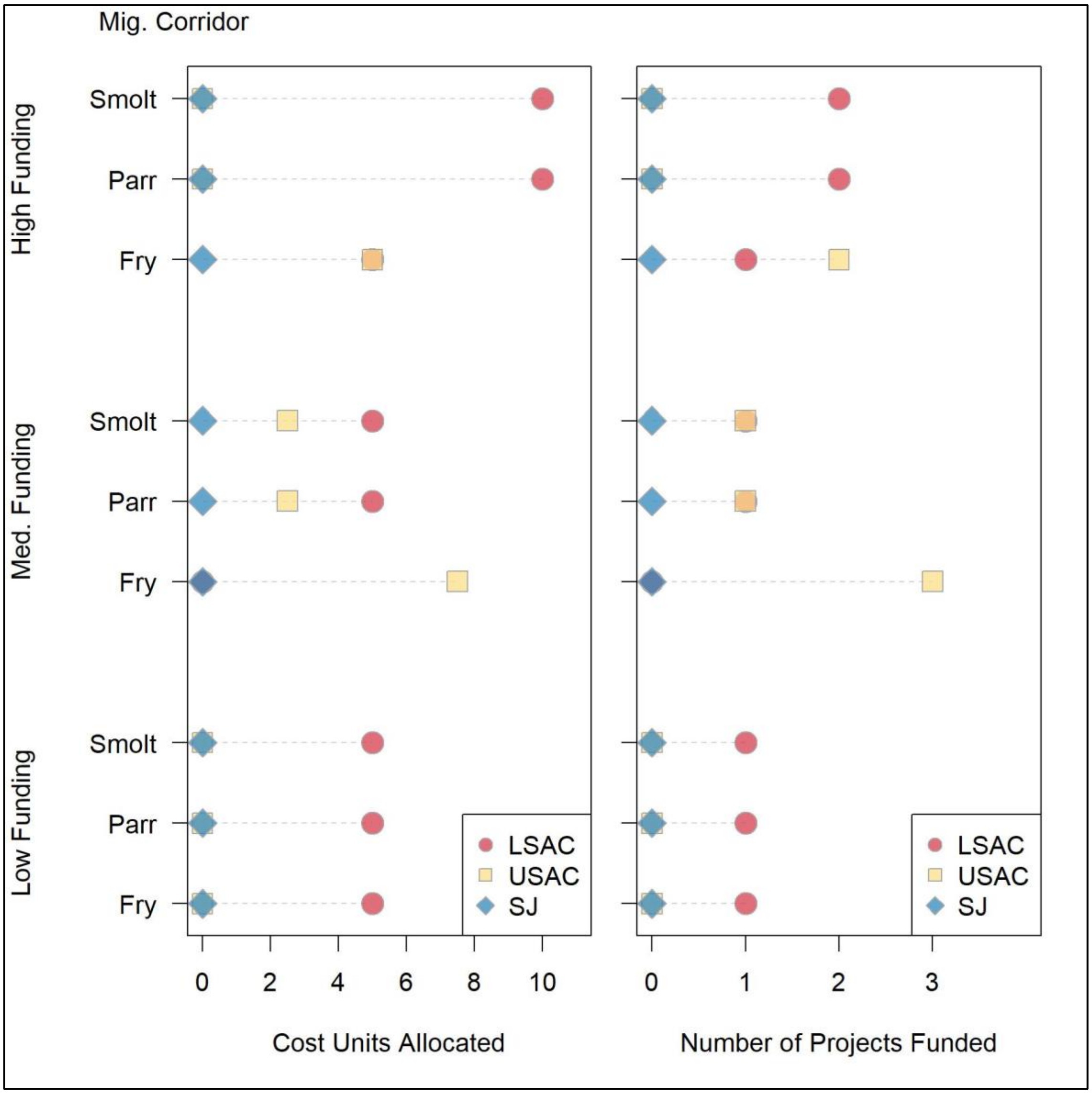

Figure 5.12 – A dot plot that shows the upper tier policy for fall-run Chinook salmon in the CVPIA administered streams. The y-axis shows all the different combinations of the two dimensions of state space: funding level and delta condition. The left panel shows how many cost units are allocated to each watershed in each state. The right panel shows the number of projects that would be implemented given the resources allocation in the left panel.

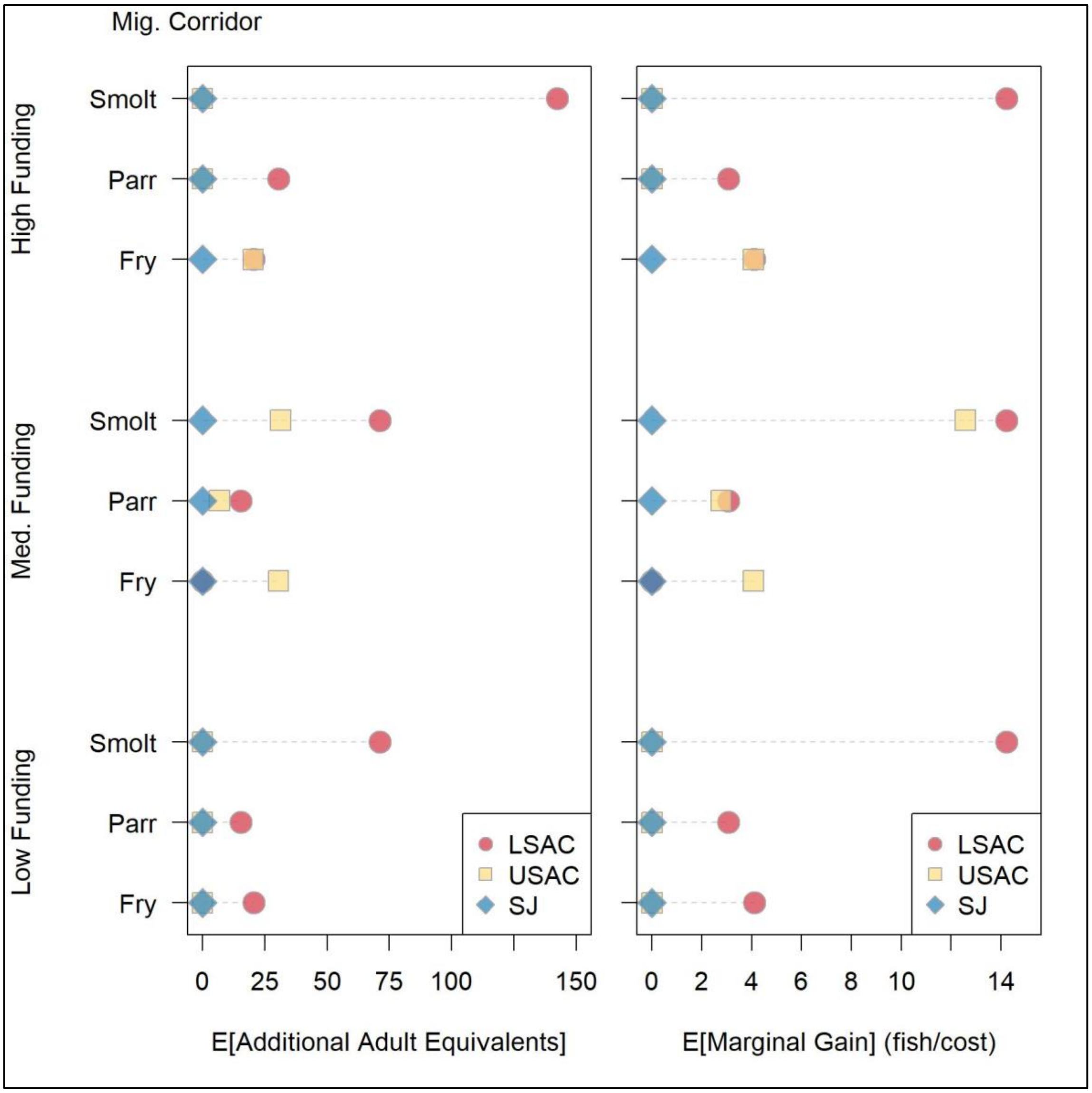

Figure 5.13 – A dot plot that shows how the policy for the upper tier policy for fall-run Chinook salmon in the CVPIA administered streams would translate into adult equivalents for a single time step. The y-axis shows all the different combinations of the two dimensions of state space: funding level and delta condition. The left panel shows how many adult equivalents are produced in a single time step for each watershed in each state. The right panel shows the marginal gain of implementing those actions.

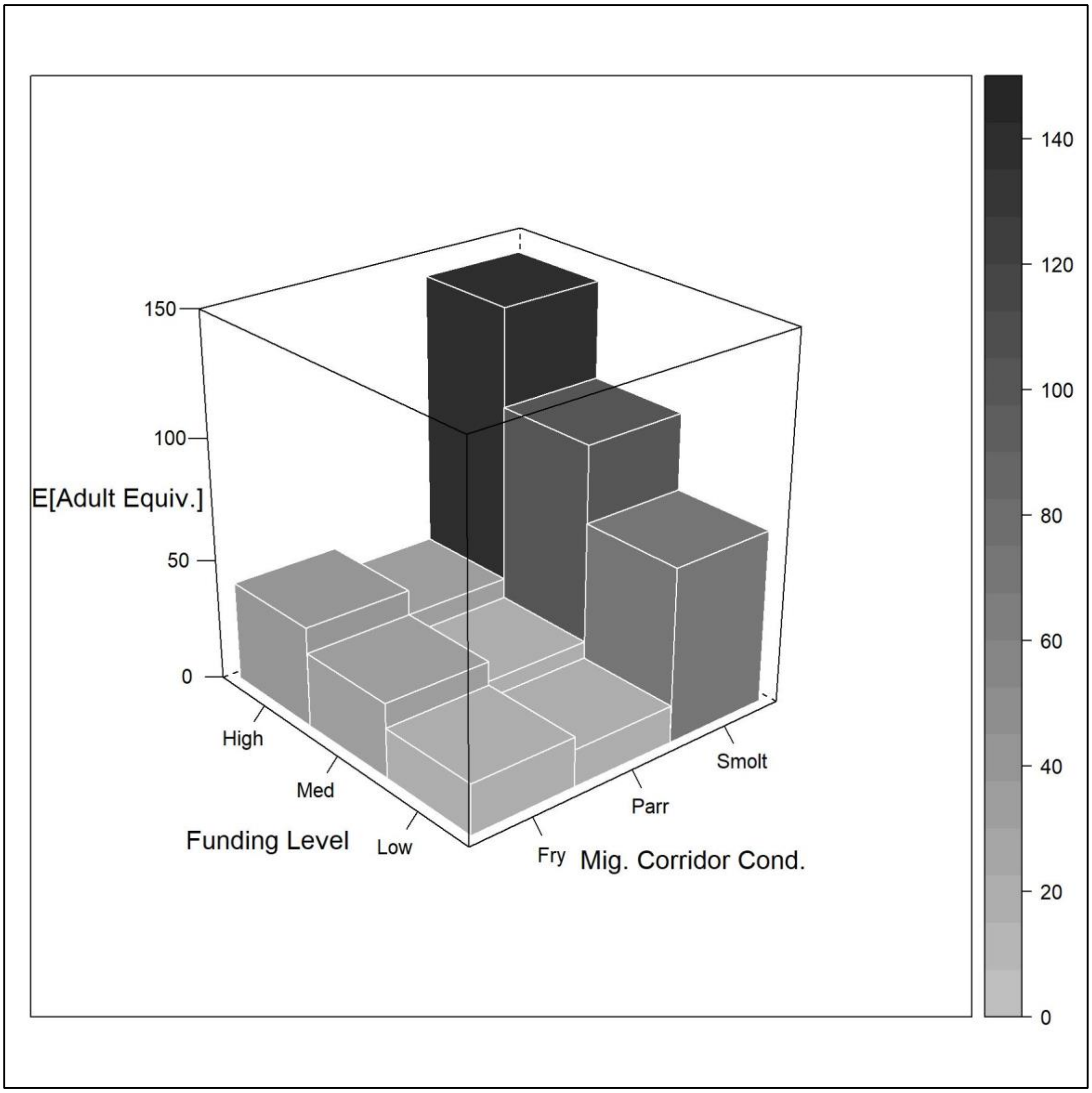

Figure 5.14 – The total expected reward (total number of adult equivalents produced across all three watersheds) from implementing the upper tier policy in a single time step across all funding levels and delta conditions.

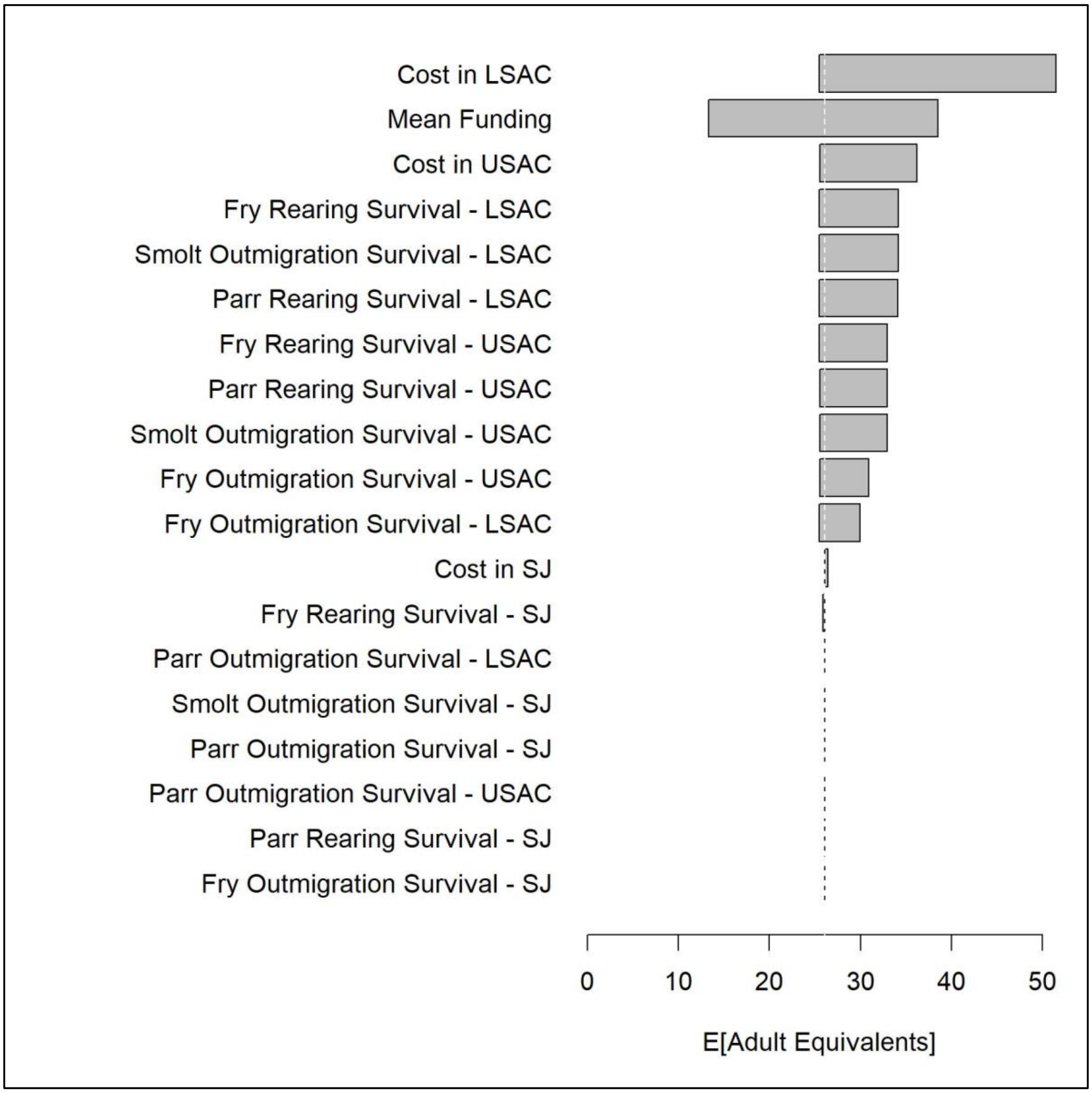

Figure 5.15 – Tornado diagram from the one way sensitivity analysis under fry migratory corridor state. The mean value of each parameter was perturbed ± 50% of its original value and policies for all sets of decision makers were derived. The expected value of the upper tier policy is plotted.

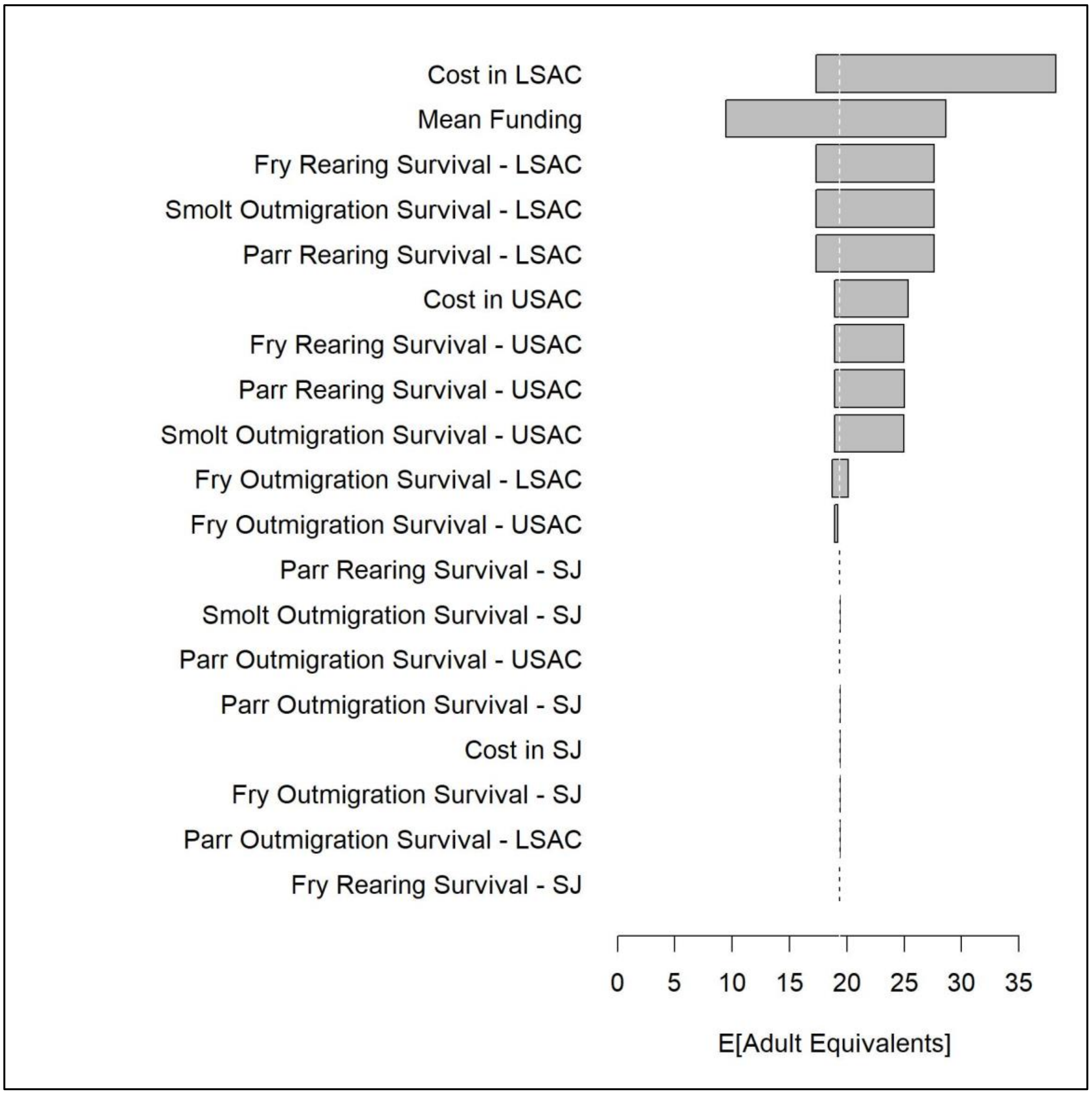

Figure 5.16 – Tornado diagram from the one way sensitivity analysis under parr migratory corridor state. The mean value of each parameter was perturbed ± 50% of its original value and policies for all sets of decision makers were derived. The expected value of the upper tier policy is plotted.

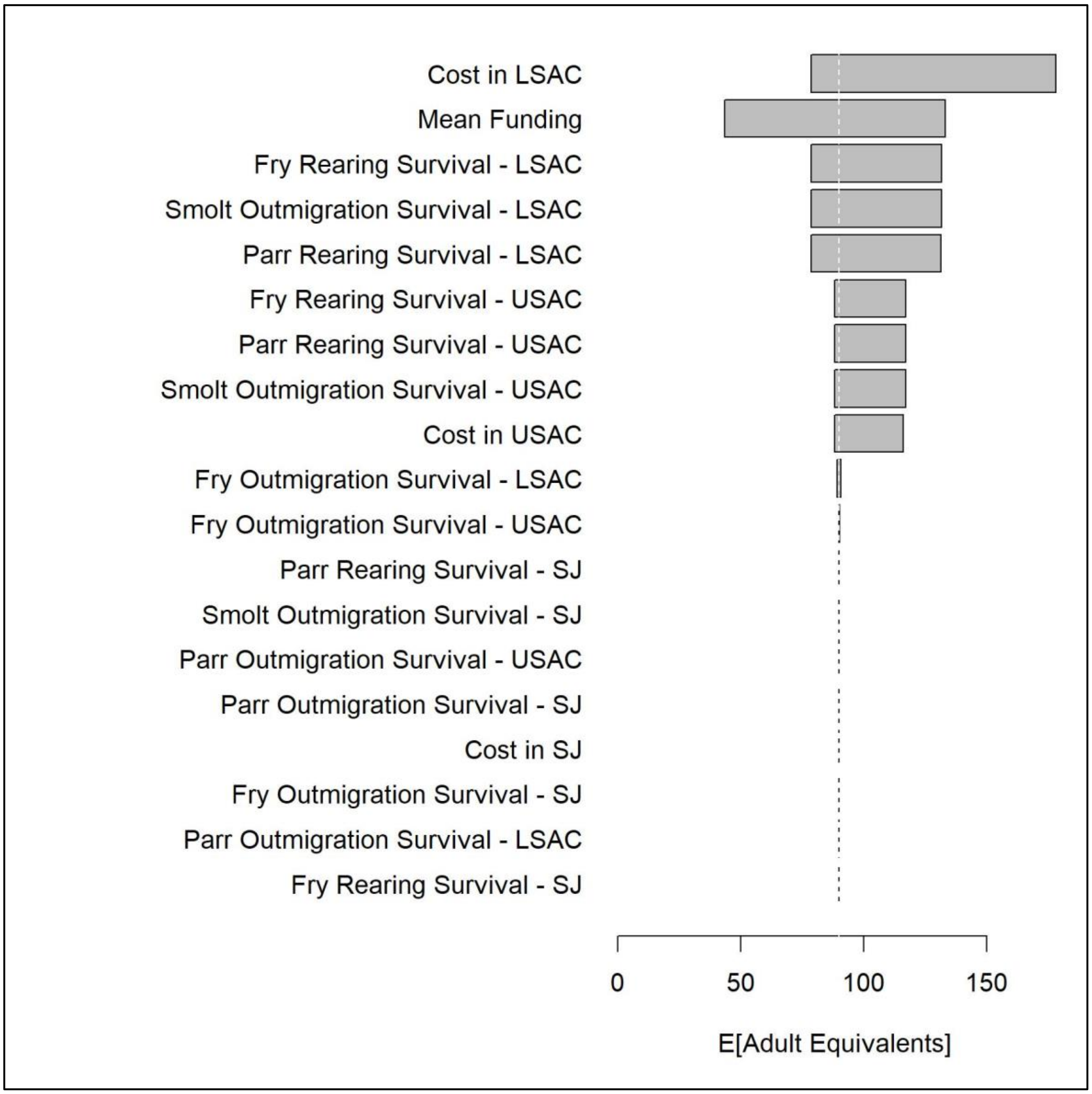

Figure 5.17 – Tornado diagram from the one way sensitivity analysis under smolt migratory corridor state. The mean value of each parameter was perturbed ± 50% of its original value and policies for all sets of decision makers were derived. The expected value of the upper tier policy is plotted.

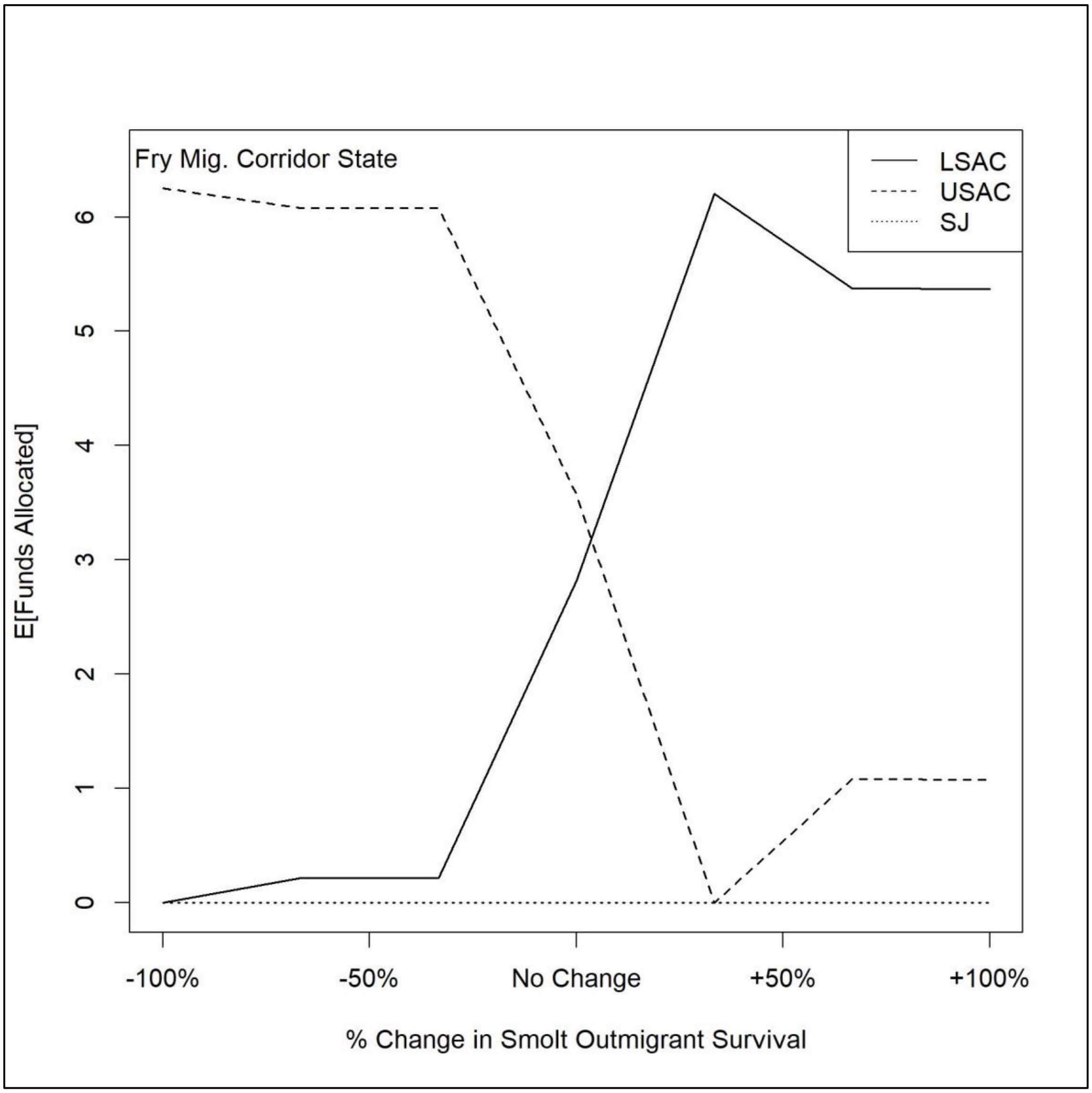

Figure 5.18 – Response profile showing how fund allocation from the upper tier policy changes across a range of values of smolt outmigrant survival in a fry migratory corridor state.

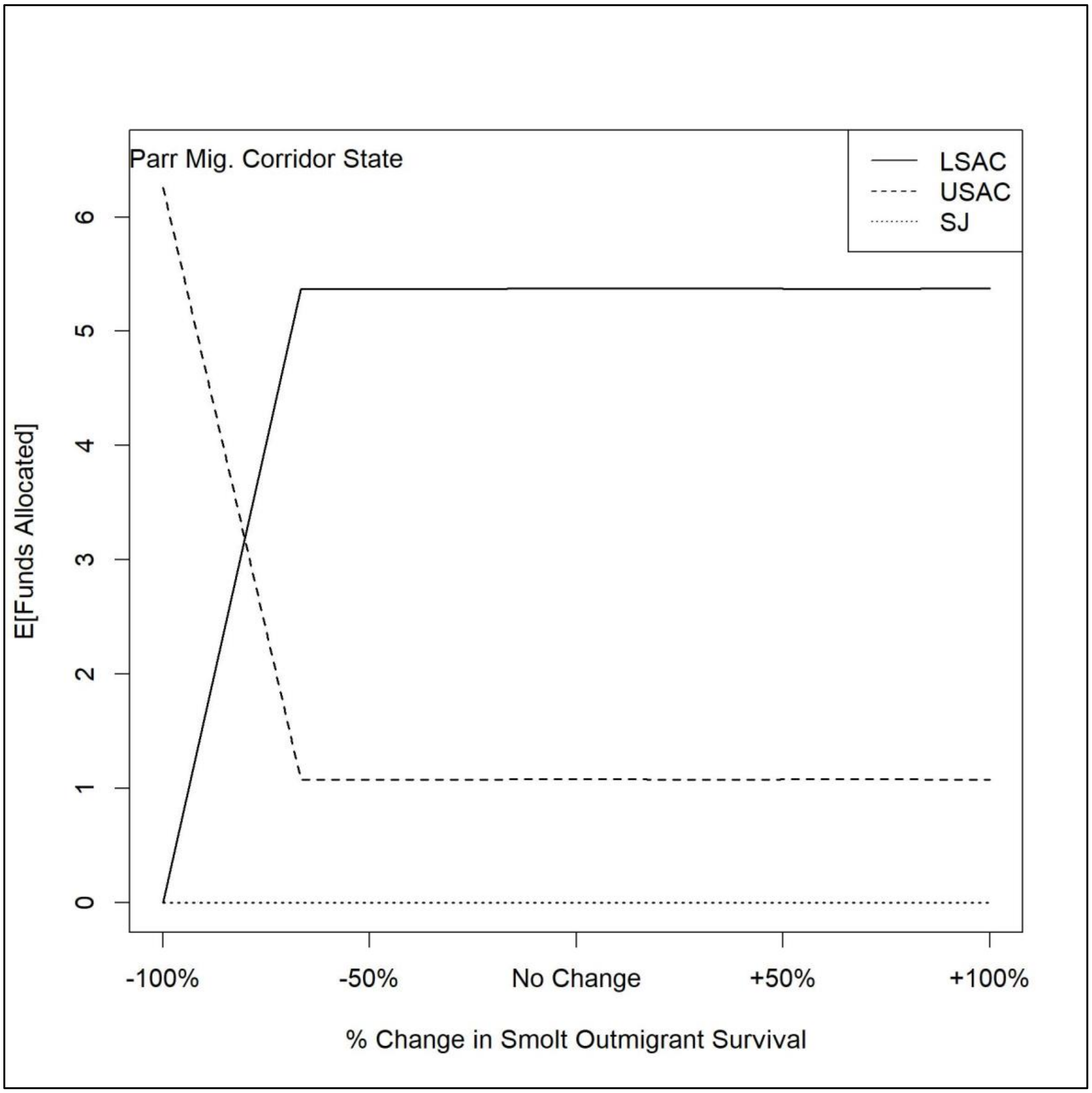

Figure 5.19 – Response profile showing how resource allocation from the upper tier policy changes across a range of values of smolt delta survival in a parr migratory corridor state.

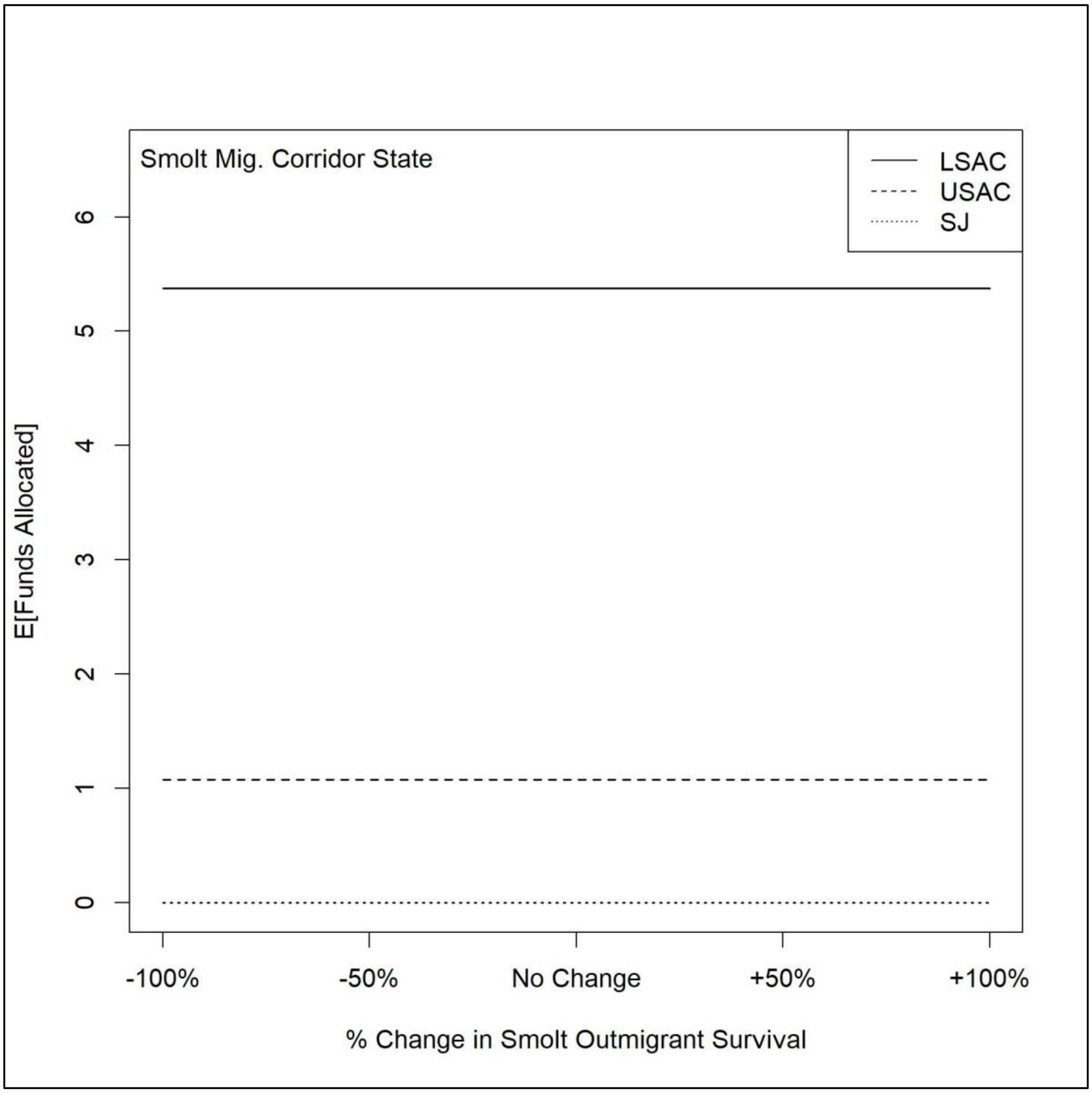

Figure 5.20 – Response profile showing how resource allocation from the upper tier policy changes across a range of values of smolt delta survival in a smolt migratory corridor state.

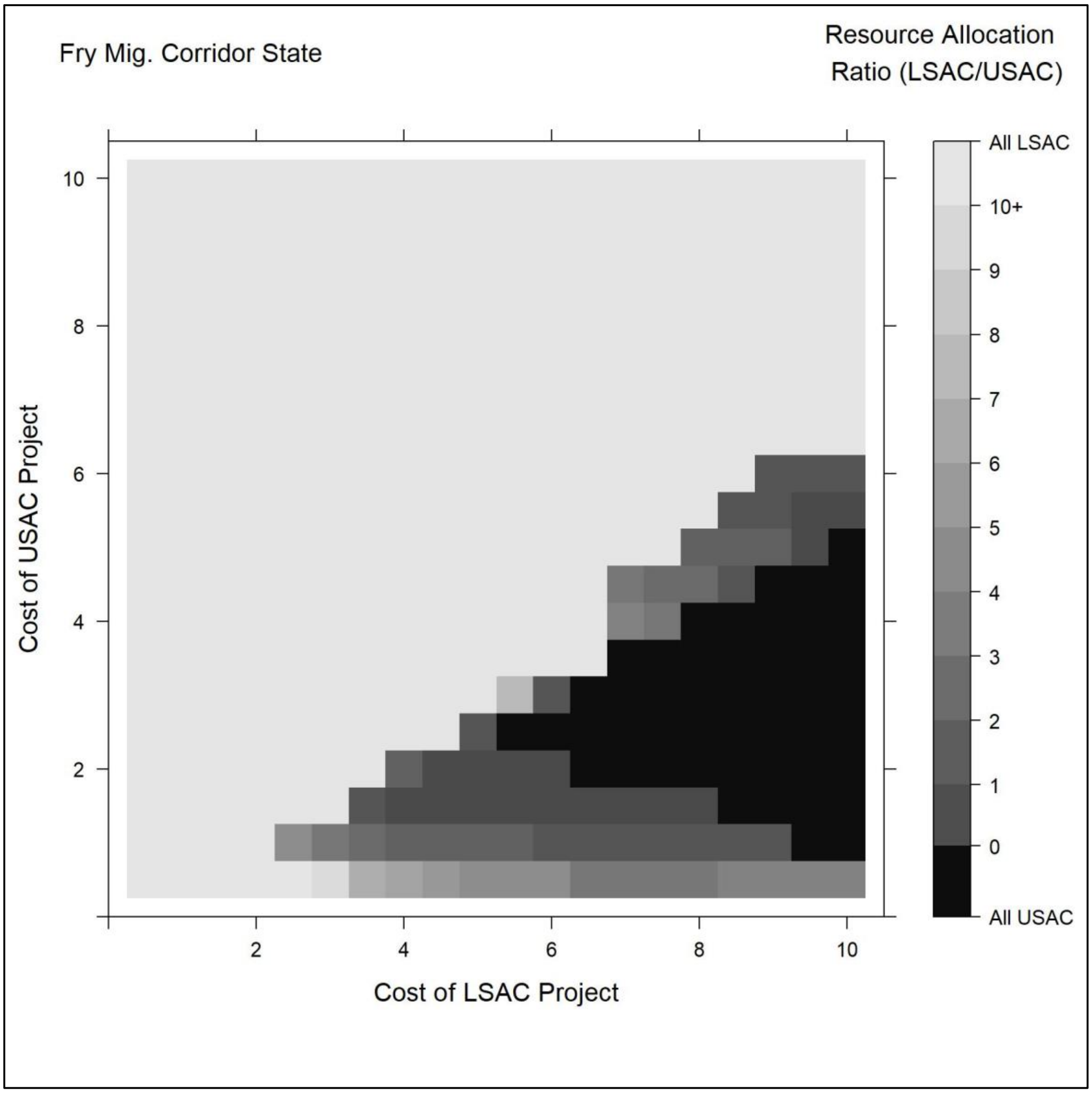

Figure 5.21 – A policy plot showing how the ratio of resources allocated between the LSAC and USAC watersheds changes across different configurations of project costs in the LSAC and USAC. The ratio of resources allocated was determined from the policy that was derived using each cost configuration. This plot was produced under the fry migratory corridor state. The lightest grey represents cost configurations where all the resources would be allocated to the LSAC and black regions represent cost configurations where all the resources would be allocated to USAC.

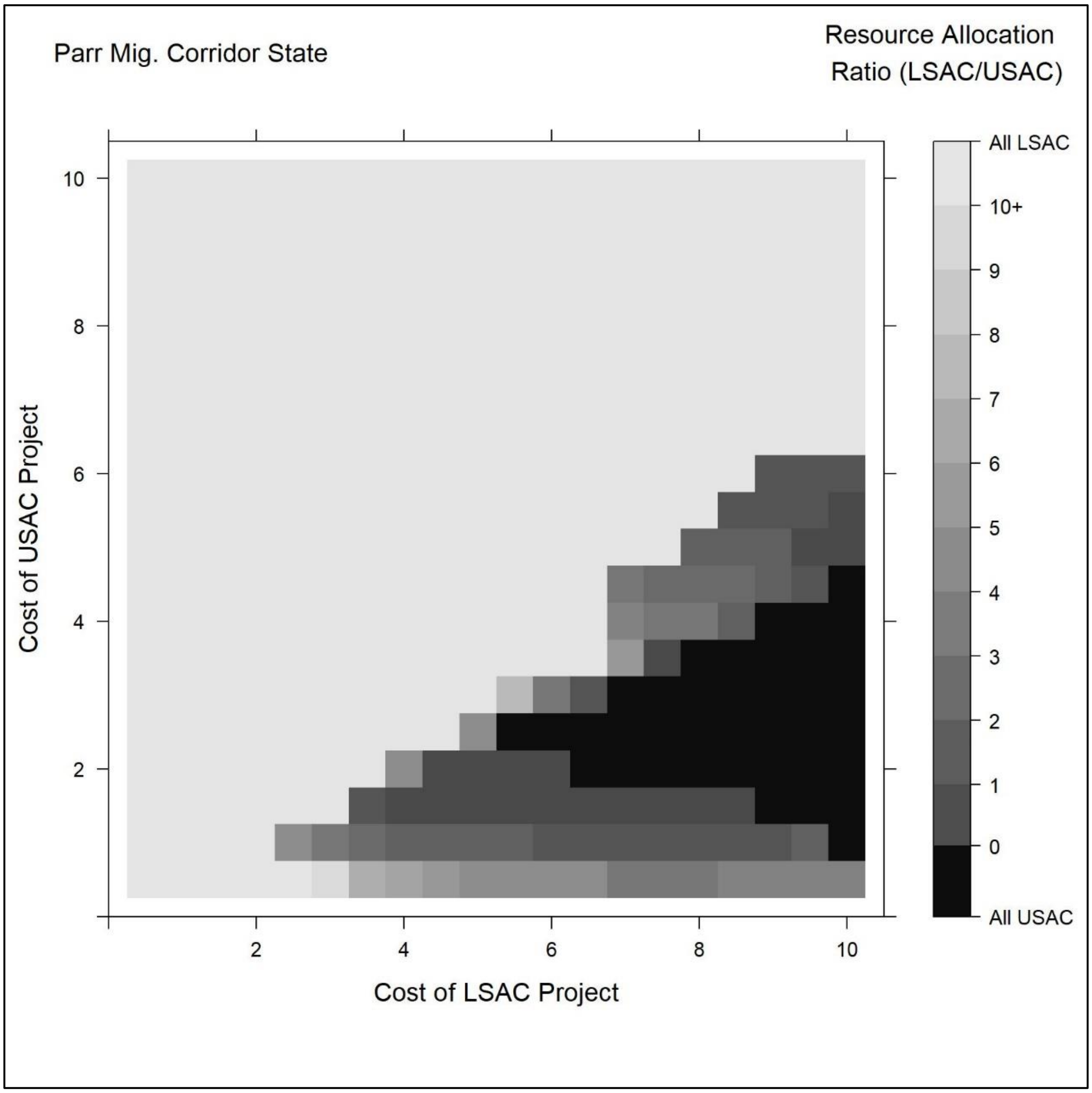

Figure 5.22 – A policy plot showing how the ratio of resources allocated between the LSAC and USAC watersheds changes across different configurations of project costs in the LSAC and USAC. The ratio of resources allocated was determined from the policy that was derived using each cost configuration. This plot was produced under the parr migratory corridor state. The lightest grey represents cost configurations where all the resources would be allocated to the LSAC and black regions represent cost configurations where all the resources would be allocated to USAC.

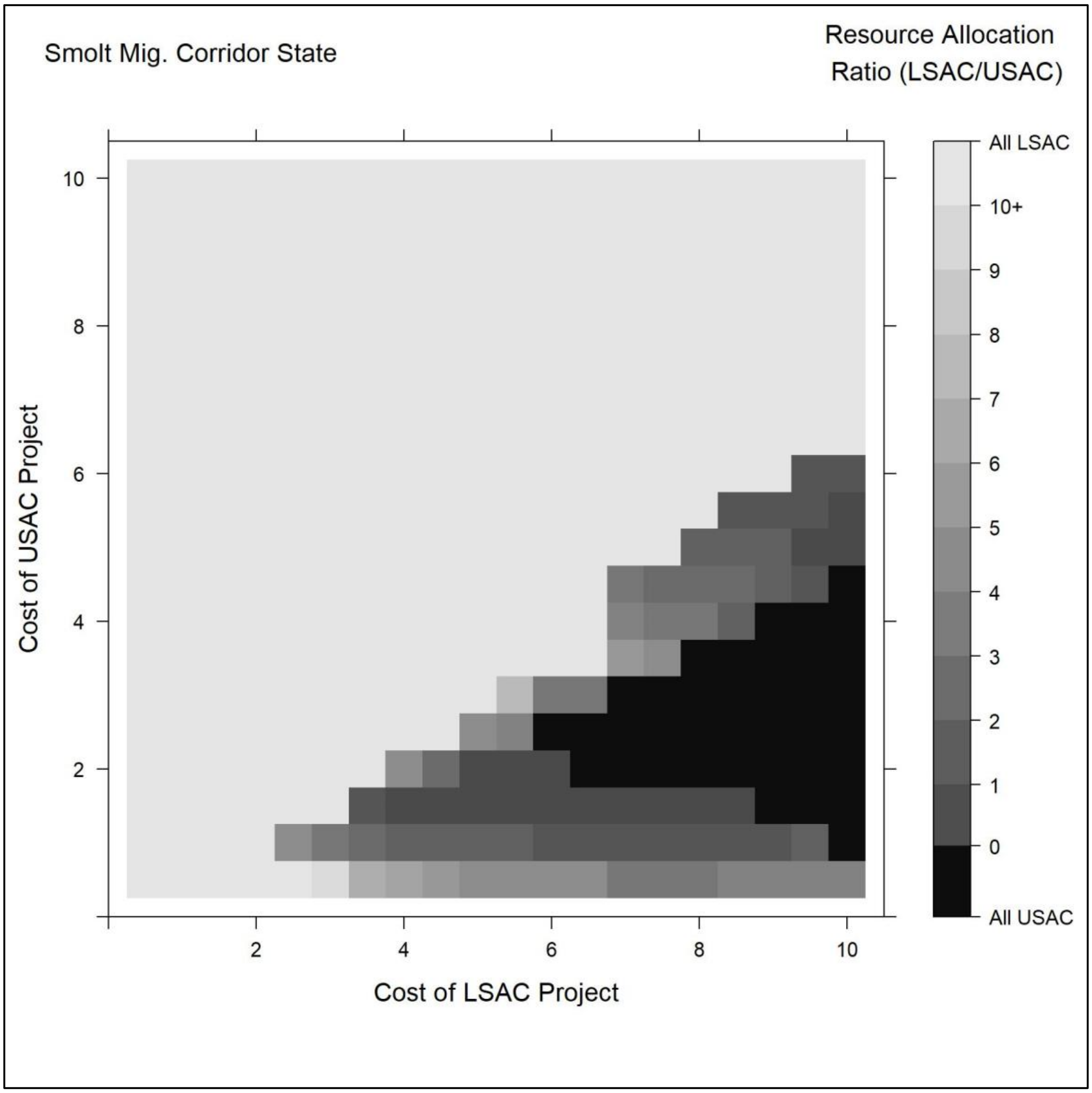

Figure 5.23 – A policy plot showing how the ratio of resources allocated between the LSAC and USAC watersheds changes across different configurations of project costs in the LSAC and USAC. The ratio of resources allocated was determined from the policy that was derived using each cost configuration. This plot was produced under the smolt migratory corridor state. The lightest grey represents cost configurations where all the resources would be allocated to the LSAC and black regions represent cost configurations where all the resources would be allocated to USAC.

CHAPTER 6: GENERAL DISCUSSION

The goal of my dissertation was to explore how scale influences stream restoration prioritization strategies for an anadromous species and to develop dynamic optimization approaches that acknowledge uncertainties that exist at different scales. In each chapter, I examined how spatial scale influenced the decision making process. Chapter 2 evaluated the role that differing spatial scales of management goals and actions played in the history of anadromous fish management in the Central Valley of California. Chapter 3 examined how a large scale decision model can influence optimal decision making at a watershed scale. The fourth chapter applied a small scale decision model to a single river to derive spatially explicit optimal decisions for maximizing natural salmon production. Finally, the fifth chapter combined a large scale decision model and small scale decision model and evaluated how those two spatial scales influence one another.

Scale is a fundamental component of the natural resource management. How scale is defined ultimately determines the sources and amounts of uncertainty in a natural resource management decision problem. Objectives, management alternatives, and ecological processes are all scale dependent. It’s unlikely that an optimal solution to the decision problem can be found if the scale is poorly defined. Effective conservation depends on managers acknowledging the role of uncertainty in the decision making process. Structured decision modeling (SDM) approaches are valuable in natural resource problems because they directly connect quantifiable objectives and explicit alternative decisions with quantitative models to identify optimal management decisions (Clemen 1996, Conroy and Peterson 2013). In my dissertation I used SDM to demonstrate the importance that scale can have on optimal decision making and to identify key uncertainties that exist at different scales.

Issues of scale can create distinct problems in natural resource management. Specifically, natural resource management objectives are often regional (e.g., increase recruitment in a specific population in a watershed), whereas management actions almost always occur on a very small scale relative to the objectives (e.g., rehabilitating 500m of stream habitat). Scale mismatches generally increase uncertainty and inhibit the flow of information (feedback) regarding the effectiveness of management actions making management across a large regional extent even more difficult. In addition, key ecosystem processes occur at different spatial and temporal extents, which can directly influence how any uncertainties about those processes are perceived (Peterson and Dunham 2010).

Decision problems that operate at large spatial scales often require data to be summarized at large spatial extents and grains. Most freshwater fisheries data and assessment methods are focused on much finer resolutions such as at a reach level (Lewis et al. 1996, Frissell et al. 2001). Data observed at smaller spatial resolutions (e.g. reach or tributary) has to be aggregated when objectives occur at larger spatial scales (e.g. population or watershed; Wager et al. 2006). Aggregating data or processes spatially ignores any heterogeneity present in a system and tends to lead to higher levels of variance and bias in parameter estimates (Clark and Avery 1976). This is referred to as “ecological bias,” in which a lot of fine scale data and/or processes (e.g. juvenile rearing and migration) are homogenized in order to be represented at a coarser scale (Greenland and Morgenstern 1989). It’s essential that the variance associated with aggregating data is accounted when evaluating decision alternatives. One strength of the SDM process is it can facilitate a quantitative evaluation of the potential of those uncertainties to influence the optimal decision.

On the other end of the spectrum, fine scale decision problems require data sources to match. Parameterizing fine scale decision problems can be difficult because of the high resolution data that is required. Although data can be aggregated to provide information for coarser resolutions, the opposite isn't always true. For instance, information that is gathered at a coarser scale (e.g. watershed level) may not be appropriate to apply to a fine-scale, spatially explicit decision model. Although fine scale decision problems can be data intensive, structured approaches to decision modeling can identify which data gaps are most critical to decision process which can inform future monitoring.

In natural resource management, uncertainty often manifests itself as a lack of empirical information. A lack of information can paralyze decision making, resulting in no decisions being implemented. I addressed the lack of information by relying on expert judgement to parameterize several of my decision models. Expert judgment may be biased or highly variable, but it still enables managers to model their decision making process. This is important because decision models allow managers to identify the portions of their model that are the most influential to the decision making process. Identifying influential parameters is essential to prioritizing future study and monitoring. In many instances parameterizing a decision model wouldn't be possible without expert judgement. Instead, expert elicited information can serve as a starting place and be used to identify parameters that are highly influential to decision making process. Influential knowledge gaps can then be used to prioritize future monitoring efforts.

Dynamic programming can provide analytic solutions to decision problems as long as the number of dimensions of the state space is kept relatively small. Defining the system states can be perhaps the most difficult part of designing a MDP optimization. Simplification or discretization of the system state space is typically required to solve traditional MDPs due to the "curse of dimensionality" (Bellman and Dreyfus , Bellman 1957). Although this discretization provides an interpretable measure to represent system states, in reality there may exist several, continuous system states that may prove to be important to determining optimal decisions. MDPs that include multiple continuous state-spaces are known as general state-space MDPs, and require more advanced algorithms to accurately depict state-space transitions and rewards (Feng et al. 2004, Li and Littman 2005). Solving larger, more complex decision problems may not be possible, or at least practical, with dynamic programming due to the computational requirement of calculating the objective function for every combination of the discretized state-space. However, reinforcement learning and other heuristic methods provide tools to approximate solutions to MDPs or MMDPs with high dimensionality (Barto and Mahadevan 2003, Sutton and Barto 2018).

MDPs have some limitations in the application to natural resource decision problems. Infinite horizon MDPs, such as those found in my analyses, require stationary reward vectors and transition matrices. The stationarity assumption is violated when state-specific transition rates or reward values shift through time. In these analyses I assumed habitat transition rates and the number of salmon produced from decision alternatives were static through time. Climate change is an example of a large scale stressor that could influence those parts of this decision problem. Non-stationary resource dynamics create new issues in decision optimization and dynamic programming (Nichols et al. 2011, Williams 2011). Heuristic approaches (e.g. reinforcement learning, genetic algorithms) can handle nonstationary decision problems, but they do not provide always provide the optimal decision set. Another solution is to assume stationarity for short periods of time and revising solutions optimal solutions periodically (Nichols et al. 2011, Williams and Johnson 2013).

Migratory species pose unique challenges to natural resource decision problems. Often local managers only have influence on a portion of the migratory species life cycle. However, processes that occur outside spatial extent that managers administer can still be highly influential to management goals. In the decision problem in Chapter 4, the local watershed managers could only influence habitats within their own watershed. However, ocean and migratory corridor survival rates were among the most important factors in determining natural production and optimal habitat restoration policies. MMDPs are a tool that can transparently connect processes that occur at different scales to decision making. The benefits of monitoring and resolving uncertainties can be shared indirectly across scales and decision making hierarchy.

I've demonstrated how local processes, such as juvenile survival, can influence not only local decision making, but also regional decision making. This is an example of indirect feedback between decision tiers in a MMDP. Techniques that deconstruct complex decision problems into a smaller set of problems, such as MMDPs and other hierarchical approaches, make intuitive sense for problems that span multiple spatial scales (Parr and Russell 1998, Lane and Kaelbling 2001). MMDPs are essentially just generalized versions of a single level MDP, however they allow problems to be framed in a more logical and relatable fashion. The biggest appeal of a hierarchical approach is how it creates individualized policies for every decision maker at each level. It would be possible to frame a MMDP as an equivalent traditional single level MDP, however that would require the single state space to increase exponentially in size because it would cover the state space of each decision maker in the problem. The resulting state-space would be almost uninterpretable and any decision rule or policy that was derived from it would not be uniquely applicable to individual levels and associated decision makers.

Taken together these chapters help expand the knowledge base of fisheries management, especially in California's Central Valley. Each of my chapters provides a look at how optimal habitat restoration was influenced by how the scale was defined. Much is known about how scale can influence how we view ecological processes, conversely little is known on how scale influences decision making in natural resource management. The work presented here expands our understanding of how scale influences decision making in natural resource management and how scale should be acknowledged when deriving optimal decisions.

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