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Optimizing the removal of small fish passage barriers

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Removing small artificial barriers that hinder upstream migrations of fish is a major problem in riparian habitat restoration. Because of budgetary limitations, it is necessary to prioritize barrier removal and repair decisions. These have usually been based on scoring and ranking procedures, which, although simple to use, can be very inefficient in terms of increasing the amount of accessible instream habitat. We develop a novel decision-making approach, based on integer programming techniques, which optimizes repair and removal decisions. Results show based on real datasets of barrier culverts located in Washington State that scoring and ranking is over 25% below the optimum on average and a full 100% below in the worst case, producing no net habitat gain whatsoever. This is compared to a dynamic programming method that was able to find optimal solutions in less than a second, even for problems with up to several hundred variables, and a heuristic method, which found solutions with less than a 1% average optimality gap in even less time.

Keywords: salmon habitat restoration, fish passage barrier removal, nonlinear integer programming, dynamic programming

1. Introduction

Wild salmon have shown dramatic population and range declines worldwide over the past two centuries. In the United States alone, wild salmon stocks have been extirpated from over 40% of their historical range in the Pacific Northwest [1] and over 80% in the Atlantic Northeast [2]. In areas that still support wild salmon runs, most populations are heavily depressed. For example, it is estimated that adult annual production has fallen by as much as 85% in the Columbia River basin during the past 150 years [3]. Even more drastic declines have been experienced recently such as the in Inner Bay of Fundy, Canada, where salmon runs have fallen from 40,000 adults to only several hundred (over a 99% decline) in just the past 20 years [4].

One of the biggest sources of salmon decline, and one which still presents a major obstacle to recovery, is the presence of an extremely large number of small artificial barriers, such as small dams, culverts, dikes, levees, floodgates and weirs, which reduce or block access of salmon to large portions of their historical habitat. Small barriers have a wide variety of negative effects on salmon and resident fish. Some barriers, like small dams and levees, may completely block fish from accessing high quality rearing and spawning habitat in side channels or upper tributaries to a river. Full barriers also reduce the distribution of resident fish and can cause an increased risk of extinction among small, isolated populations. In contrast, partial and temporal barriers, like floodgates and many culverts, may block migration some of the time or simply reduce access to weaker fish or fish at younger life stages. Consequently, both full and partial/temporal barriers reduce population growth rates through a combination of increased mortality and predation and decreased egg production.

Besides their direct impacts on fish demographics, passage barriers have other less well-known biological and ecological impacts. These include increasing the level of inbreeding among resident fish, lowering nutrient inputs to upstream reaches provided by the carcasses of anadromous adults and causing artificial selection for stronger swimming fish species. A more thorough review of the various problems associated with reduced fish migration due to artificial passage barriers is given in Meehan [5].

Given the magnitude and severity of the problem, reconnecting isolated stream habitat has become an important priority for the restoration of impaired anadromous salmon stocks. Indeed, Roni et al. [6] rank it as the most important type of restoration activity in their prioritization hierarchy due to its high cost-effectiveness. They cite various studies attributing the majority of increases in local salmon populations to barrier removal as opposed to other types of restoration like the placement of instream structures and sediment reduction. Furthermore, these increases were frequently demonstrated within one year after removal of barriers. For example, Beechie et al. [7] estimated that impassable culverts and other artificial barriers have reduced coho summer and winter smolt production by as much as 24–34% in the Skagit River basin in Washington State. What is more, this loss was considered greater than the combined effect of other adverse forest management activities and hydropower generation within the basin.

Extensive engineering guidelines for the building of new instream structures and the retrofitting of existing barriers to enhance fish passage have been developed by various state, tribal and federal management agencies [8–11]. Unfortunately, few formal methods exist for deciding which barriers to repair or replace when multiple barriers are present.

Because budget limitations often preclude the removal of all barriers, the most common method for making repair and replacement decisions is based on a scoring and ranking scheme. The simplest methods assign scores to each barrier according to a set of key physical, ecological and economic attributes *independently* of their spatial arrangement. Most include some measure of the following parameters: (1) habitat quantity, (2) habitat quality, (3) degree to which a barrier impairs movement, and (4) cost of repair. A barrier's benefit–cost ratio is a typical example. Benefit is usually based on the potential gain in quality-weighted upstream habitat or equivalent fish production gain multiplied by the percentage increase in fish passability. Upstream habitat is usually taken as the total length of stream, or some combination of spawning and rearing area, up to the first natural point barrier. Passability is usually given as a single value representing the average passability for all fish species and life stages, but can be stratified according to different species or life stages if sufficient data are available. These values are typically obtained using professional judgment or through more sophisticated modeling techniques, e.g. with the *FishXing* software [12]. Given a specified budget amount, the basic premise of scoring and ranking procedures is to move down an ordered list selecting barriers to repair in decreasing order of rank until the budget is exhausted.

Examples of scoring and ranking methods can be found in [11,13,14]. Pess et al. [13] use rankings of benefit–cost ratios based on the potential gain in upstream smolt production divided by the cost to repair a barrier. Changes in fish passability are not considered by the authors. The Washington Department of Fish and Wildlife [14] uses a somewhat different prioritization scheme based on a function of upstream production gain that is adjusted for species interactions, repair cost, change in fish passability and the mobility and threat status of the species affected by a barrier. Taylor and Love [11] suggest a similar scoring system that accounts for species' threat status, current level of passability, total quality-weighted habitat gain, barrier maintenance status and risk of structural failure. Unlike [13] and [14], however, Taylor and Love do not consider the fiscal impacts of repair in their rankings.

The major advantage of scoring and ranking techniques is that they are easy to implement and can be used to find solutions to complex problems having large numbers of barriers with multiple fish species and assessment criteria. The major disadvantage associated with them comes from their inherently static nature and the frequently limited consideration given to the spatial arrangement of barriers. Scores are usually assigned with no regard for the levels of passability at upstream and downstream barriers. As a result, a prioritized list may produce solutions in which upstream barriers should be fixed prior to one or more impassable barriers located downstream, despite the fact that this would produce no habitat gain whatsoever. Further, even when spatial context is taken into account, because lists have a fixed ordering, they still do not readjust for changes in the system caused by each successive repair decision. For example, the relative impact of fixing an upstream barrier usually increases once one or more of its downstream barriers have been repaired. This occurs because access to this barrier, which may formerly have been very low or even completely inaccessible, may be greatly improved, thus making it more of a bottleneck to upstream migration. Taken together, repair and replacement decisions based on scoring ranking have the potential to be highly inefficient.

By contrast, optimization models do not suffer the same shortcomings. Optimization provides a normative and systematic framework for making decisions that guarantees achievement of the maximum possible benefit (or minimum cost) given one or more operational/resource constraints [15]. In spite of this, however, it has been suggested by some that because optimization models never completely capture all forms of risk or limitations imposed by administrative process, their practical value in real-world planning situations is limited. Although this really appears to be more of a critique of modeling in general, which by necessity requires some abstraction of reality, the fact is alternatives like scoring and ranking certainly fare no better at incorporating real-world complexities. Usually they are worse in this regard, as discussed previously, and are almost always less cost-effective than optimization whatever the level of knowledge or data quality may be. What is more, even when a solution to an optimization model may not be ideal in light of all possible uncertainties and political realities, the model may still be useful for screening out particularly bad solutions or illustrating important tradeoffs among different management objectives. At the very least, optimization models provide a baseline with which to compare to more politically agreeable management alternatives.

Perhaps the only real drawbacks of using optimization are its technical complexity, often necessitating expert mathematical and computer programming knowledge, and the computational burden required to solve problems to optimality. Structural complexity is unavoidable but potentially lengthy solution times can often be overcome with better formulations and the use of heuristic techniques [15] that do not guarantee optimality but can usually generate optimal to near-optimal solutions much more quickly. In this context, scoring and ranking procedures can be viewed as very simple heuristics that frequently produce far less efficient solutions, albeit much faster, than more intelligent types of heuristics. Thus, it would seem that the advantages of optimization, vis-à-vis its ability to handle many important real-world complexities and produce cost-effective results, outweigh any of its limitations.

A diverse array of problem applications employing optimization techniques exist within the wider environmental resource management field such as forestry, natural reserve selection and reservoir and river system management, to name a few [16–18]. Unfortunately, the use of optimization in the conservation and restoration of salmon habitat, however, has been extremely limited. The work by Paulsen and Wernstedt [19], therefore, is noteworthy. They examine the use of linear programming for integrated salmon recovery planning in the Columbia River basin. The objective of their problem is to find a "least-cost" solution, consisting of various combinations of higher fish passage, habitat improvements and harvesting levels that meet stock-specific goals on harvest and recruitment population sizes. Their formulation, however, is limited in scalability due to how mitigation decisions are handled in their model. Because mitigation alternatives, such as alternative hydroelectric dam operating strategies and small barrier removal, have cumulative effects that cannot be expressed as closed-form equations, individual projects must be modeled in combination with each other using a simulation model. Consequently, problems quickly become intractable as the number of possible project combinations grows exponentially with increasing numbers of individual mitigation projects.

What is needed is a general-purpose optimization model for planning the removal of small barriers that is more scalable and avoids the immense difficulty of relying upon simulation. In response to this, the goal of this paper is to demonstrate how fish passage barrier removal problems can be sufficiently modeled and solved using optimization techniques. To this end, the remainder of this paper is organized into five main sections. First, we give a detailed description of the problem of fish passage barrier removal and then formalize it mathematically using a nonlinear binary formulation that maximizes the net gain in quality-weighted habitat above passage barriers given a budget constraint. In section two we show using an example how a simple scoring and ranking method may yield particularly poor results. This is followed in the third section by the description of two new solution approaches: an exact method based on dynamic programming techniques and a heuristic method that uses a greedy mechanism to construct an initial solution followed by a local search procedure to improve it. Fourth, a practical case study is presented in which the different algorithms are compared to each other based on computation results from several datasets of barrier culverts located in Washington State. Finally, we provide some concluding remarks and suggest some important areas for further research.

2. Problem formulation

In fish passage barrier removal planning, the most common explicitly or implicitly stated goal of public agencies and private organizations is to maximize the net increase in accessible habitat, in terms of quality-weighted area or length [11], or similarly potential gain in fish production [14]. The obstructions themselves, which might include culverts, small dams, levees and other small structures, usually vary in terms of the percentage of fish that are able to pass through them. Although hydroelectric dams and other large hydro-modifications may represent significant fish passage barriers, these are generally excluded from consideration given that they are more or less permanent structures whose removal involves a whole host of competing social and economic concerns beyond just environmental interests. As such, we concern ourselves with small structures that have relatively little effect on the downstream passage of fish but do impair upstream passage.

The scope of any particular problem may range widely from a handful of barriers along a few tributaries up to thousands of barriers scattered across one or more highly reticulated river basins. By definition, barrier passability is taken as the fractional rate, within the range [0, 1], at which fish are able to pass through a barrier while migrating upstream. Access to habitat above a barrier, which we term accessibility, is taken as the product of all downstream barrier passability values. Accessibility represents the percentage of fish that are able to reach a particular area by swimming upstream, passing through each and every barrier starting at the mouth of the river. It is assumed, based on this definition of accessibility, that barrier passability values are independent of each other. Consequently, fish that are able to pass beyond one barrier are neither more nor less likely to pass beyond any successive upstream barriers. In general, multiple repair or replacement alternatives may be available at any given barrier, each having a variable effect on passability, e.g. low cost/low passability improvements versus high cost/high passability improvements. Of course at most one repair option can be implemented. This, however, does not exclude multi-stage projects, with later stages possibly being optional, since these too can be represented mathematically as a single combined project. While political or other administrative constraints may sometimes be important, we focus only on the most important type of restriction, a budget. Also, we assume that barriers are arranged as a tree network similar to the one shown in figure 1, which depicts six different passage barriers arranged along several adjoining streams. With an underlying tree structure, it is assumed that streams never diverge as they flow downstream, thereby excluding braided rivers and deltas that allow multiple paths to same upstream location. While not strictly necessary, this

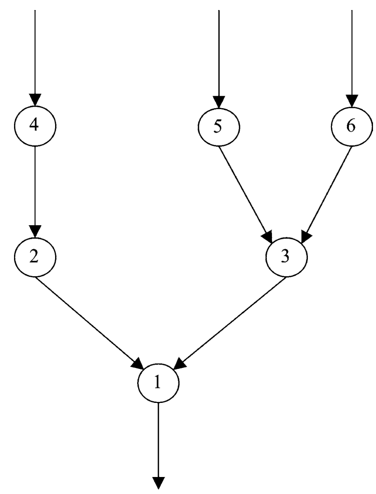

Figure 1. An example fish passage barrier network. Barriers are represented as nodes. Arcs indicate the direction of stream flow and represent areas of stream habitat between barriers.

assumption is realistic and makes the problem easier to formulate and solve.

To formulate the problem mathematically, consider the following notation. Let J be the set of all barriers, with indices j and k. The set D_j denotes all barriers downstream from and *including* barrier j. Current passability at barrier j is given by $\bar{p}_j$. Let A_j be the set of repair and replacement projects with index i that can be implemented at barrier j. The parameters p_{ij} and c_{ij} represent, respectively, the increase in passability and cost of project i at barrier j. Also, let v_j be the *net* amount of habitat between barrier j and its nearest set of artificial or natural upstream barriers. The amount of available budget is represented by b. Finally, the variables of the model are given by,

$$x_{ij} = \begin{cases} 1 & \text{if project } i \text{ is chosen at barrier } j, \\ 0, & \text{otherwise,} \end{cases}$$

$\alpha_j =$ level of accessibility to habitat immediately above barrier j.

Fish passage barrier removal problem

$$\max z = \sum_{j \in J} v_j \alpha_j, \tag{1}$$

s.t.

$$\alpha_j = \prod_{k \in D_j} \left(\bar{p}_k + \sum_{i \in A_k} p_{ik} x_{ik} \right) - \prod_{k \in D_j} \bar{p}_k \quad \forall j \in J, \tag{2}$$

$$\sum_{i \in A_j} x_{ij} \leqslant 1 \qquad \forall j \in J, \tag{3}$$

$$\sum_{j \in J} \sum_{i \in A_j} c_{ij} x_{ij} \leqslant b, \tag{4}$$

$$x_{ij} \in \{0, 1\} \qquad \forall j \in J,\ i \in A_j. \tag{5}$$

The Fish Passage Barrier Removal Problem (FPBRP) maximizes the total net gain in accessible habitat that can be achieved by removing or repairing fish passage barriers given a limited budget. The objective (1) measures the sum of accessibility-weighted net habitat upstream from each barrier. For each barrier j, the net amount of accessible upstream habitat is equal to the net amount of habitat v_j located between barrier j and its nearest net increase in set of artificial or natural barriers upstream from j times the accessibility α_j immediately above j. Equation (2) calculates the level of accessibility α_j to habitat immediately above barrier j, where $0 \leqslant \alpha_j \leqslant 1$. It is the product of adjusted passability at j times adjusted passability at all downstream barriers $k \in D_j$, $k \neq j$, minus initial accessibility $\prod_{k \in D_j} \bar{p}_k$. For each barrier, adjusted passability is equal to initial passability $\bar{p}_k$ plus the increase in passability $\sum_{i \in A_k} p_{ik} x_{ik}$ given any repairs. Of course equation (2) could just as easily be substituted directly into the objective (1) thereby eliminating the need for the α_j variables. It is shown separately here for purposes of clarity. The set of constraints (3) mandate that at most one passage improvement project can be chosen for site j. Naturally, it is assumed that A_j contains only *undominated* projects, where a project h is dominated by i if $p_{hj} \leqslant p_{ij}$ and $c_{ih} > c_{ij}$. If, as is often the case, only one repair option exists, i.e. $|A_j| = 1$, so that the only decision is to either fix a barrier completely or not, constraints (3) could be dropped from the model entirely. Constraint (4) is a budget constraint, which simply requires that the total cost of barrier improvement projects not exceed available funds. Finally, constraints (5) stipulate that all decision variables be binary. Figure 2 shows an illustration of how FPBRP would be formulated for the example fish passage barrier network shown in figure 1 based on the problem data provided in table 1.

Table 1
Parameter values for the example fish passage barrier network.

J	v_j	$\bar{p}_j$	$\lvert A_j \rvert$	c_{ij}	p_{ij}	D_j
1	200	0.3	1	200	0.7	1
2	300	0.0	3	60, 70, 100	0.25, 0.5, 1.0	1, 2
3	150	0.6	2	30, 70	0.2, 0.4	1, 3
4	1000	0.4	1	30	0.6	1, 2, 4
5	500	0.0	1	80	1.0	1, 3, 5
6	100	0.8	2	10, 40	0.1, 0.2	1, 3, 6

Frequently, a multi-objective approach is required for the problem of barrier repair and removal. Other ecological, economic or management issues in addition to the amount of habitat gain or increase in fish production can play a significant role in deciding which barriers to fix. Factors such as environmental quality, the importance of certain areas to threatened and endangered species, the risk of structural failure, and improved fishing in specific locales are some common decision criteria that policy makers consider when evaluating repair options. Many of these issues can be handled in the model by weighting them in the objective function. For example, habitat quality can be handled by scaling the amount of habitat by a quality rating score q_j, using perhaps some sort of habitat suitability index model [20]. The new objective function values $q_j v_j$ can then more broadly represent measures of quality-adjusted habitat. Likewise, greater emphasis can be placed on increasing the amount of habitat for threatened or endangered stocks, when multiple stocks are being considered, by simply giving more weight to the critical areas they are expected to occupy. This could be done by assigning weights w_s to each individual species s among a group of species S and setting the objective values $v_j = \sum_{s \in S} w_s v_{js}$, where v_{js} is the net amount of habitat available for species s above barrier j.

FPBRP presumes one rate of passage at each barrier. This single value might represent the average of all fish species and life stages or the critical passage rate of a single target species or life stage. To be more realistic, FPBRP could easily be adjusted to account for different rates of passage for each species or life stage by indexing the values for passability $\bar{p}_{js}$ and p_{ijs}, habitat v_{js} and accessibility α_{js} over each species or life stage s. Besides having to sum the objective function $z = \sum_{s \in S} \sum_{j \in J} w_s v_{js} \alpha_{js}$ over this new index s, an expanded formulation would require a commensurate increase in the number of accessibility equations (2) for each species or life stage. Accounting for different pas-

$$\max z = 200\alpha_1 + 300\alpha_2 + 150\alpha_3 + 1000\alpha_4 + 500\alpha_5 + 100\alpha_6$$

s.t.

$$\alpha_1 \leqslant 0.3 + 0.7x_{11},$$
$$\alpha_2 \leqslant (0.3 + 0.7x_{11})(0.25x_{12} + 0.5x_{22} + x_{32}),$$
$$\alpha_3 \leqslant (0.3 + 0.7x_{01})(0.6 + 0.2x_{13} + 0.4x_{23}) - 0.18,$$
$$\alpha_4 \leqslant (0.3 + 0.7x_{11})(0.25x_{12} + 0.5x_{22} + x_{32})(0.4 + 0.6x_{14}),$$
$$\alpha_5 \leqslant (0.3 + 0.7x_{11})(0.6 + 0.2x_{13} + 0.4x_{23})x_{15} - 0.18,$$
$$\alpha_6 \leqslant (0.3 + 0.7x_{11})(0.6 + 0.2x_{13} + 0.4x_{23})(0.8 + 0.1x_{16} + 0.2x_{26}) - 0.144,$$
$$x_{11} \leqslant 1,$$
$$x_{12} + x_{22} + x_{32} \leqslant 1,$$
$$x_{13} + x_{23} \leqslant 1,$$
$$x_{14} \leqslant 1,$$
$$x_{15} \leqslant 1,$$
$$x_{16} + x_{26} \leqslant 1,$$
$$200x_{11} + 60x_{12} + 70x_{22} + 100x_{32} + 30x_{13} + 70x_{23} + 30x_{14} + 80x_{15} + 10x_{16} + 40x_{26} \leqslant 100,$$
$$x_{11}, x_{12}, x_{22}, x_{32}, x_{13}, x_{23}, x_{14}, x_{15}, x_{16}, x_{26} \in \{0, 1\}.$$

Figure 2. Formulation of FPBRP for the example fish passage barrier network (figure 1) given a \$100,000 budget.

sage rates of each species or life stage is intentionally left out of the model here both for ease of presentation and since most management organizations themselves generally consider only one passage rate for planning purposes.

As mentioned previously, it is assumed that rivers have an underlying tree structure. To handle the more general case, in which rivers can split and then rejoin as they move downstream, would require a more complicated formulation. Such a formulation would need to consider the minimum or weighted average of the passability values at each group of barriers constituting a multipath barrier. Because few real-world examples exist in which barriers are located along all branches of a diverging river, consideration of multi-path barriers, in our view, is an unnecessary complication to include in the model.

3. Example problem

Having outlined the problem, we now describe, through the use an example, how inefficient the status quo method of making repair and replacement decisions based on scoring and ranking can be compared to an optimal approach based on FPBRP. Consider the example fish passage barrier network shown in figure 1 with associated problem data provided in table 1. A list of barrier repair options in descending order of priority is shown in table 2. Although many different scoring procedures are possible, we use the following rule, which is structurally similar to the ones described in [11] and [14],

$$S_{ij} = \frac{p_{ij}(v_j + \sum_{k \in U_j} v_k)}{c_{ij}}. \tag{6}$$

Table 2
Rankings of barrier repair options based on equation (1) for the example fish passage barrier network.

Barrier (j)	Repair option (i)	Score (S_{ij})	Cost (c_{ij})
4	1	20.00	30
2	3	13.00	100
2	2	9.29	70
1	1	7.88	200
5	1	6.25	80
2	1	5.42	60
3	1	5.00	30
3	2	4.29	70
6	1	1.00	10

The set U_j represents the collection of all barriers located *upstream* from barrier j. The value S_{ij} represents the benefit–cost ratio of barrier j given implementation of repair project i. The benefit of project i at barrier j is thus calculated as the total amount of habitat upstream from j, $v_j + \sum_{k \in U_j} v_k$, multiplied by the net change in passability p_{ij} given implementation of repair i. Note that this rule completely ignores passability at downstream and even upstream barriers.

Using the scoring and ranking procedure with a fixed budget, one simply proceeds from the top to the bottom of table 1, making all affordable repairs until no more barriers can be fixed. Once a barrier has been repaired, one can either (1) remove all the other repair options associated with it from the list or (2) replace the current repair if and when a better (i.e. higher p_{ij}) and affordable one is encountered while moving down the list. For example, with a budget of \$100,000, one would start by making the single repair option at barrier 4, located at the top of the list. This, however, would produce no net gain in accessible habitat since passability at downstream barrier 2 is still zero. With \$70,000 remaining, the next and last affordable repair is the second repair option at barrier 2, yielding a total net gain of 135 m of habitat (i.e. $0.3 \times 0.5 \times [300 \text{ m} + 0.6 \times 1000 \text{ m}]$). This is substantially less than the optimal solution found with FPBRP (figure 2), which consists of doing only the third repair option at barrier 2 to produce a net gain of 210 m of habitat (i.e. $0.3 \times 1.0 \times [300 \text{ m} + 0.4 \times 1000 \text{ m}]$). Methods for finding optimal and near optimal solutions to FPBRP are discussed in the following section. While results will of course vary depending upon the particular problem data and the type of scoring rule that is used, this simple example clearly illustrates the deficiencies that can and generally do arise with scoring and ranking procedures.

4. Solution methods

4.1. Dynamic programming

Since FPBRP is a nonlinear integer program, solving it exactly presents an especially challenging problem. Existing commercial nonlinear solvers, like MINOS, are generally better suited for problems with continuous variables and are only guaranteed to find local optima, not global ones. Fortunately, a dynamic programming (DP) formulation [15,21] can be devised that is guaranteed to find a global optimal solution. DP essentially works by breaking a problem down into a series of smaller subproblems, which can then be solved in an iterative fashion to find a solution to the original problem. To do so, a problem is first divided into a number of stages with a set of discrete states defined for any stage. For each stage and state combination pair, an optimal decision is made by determining its value with respect to the current state and the change in state that it would produce at latter stages. With DP, therefore, an optimal policy is produced for all possible states at any given stage. For FPBRP, stages correspond to barriers while states correspond to the amount of budget. At any given barrier and budget amount, the best repair decision is made taking into account both the potential gain in habitat produced by a repair and the remaining budget that would be available for repairs at any upstream barriers.

For the rest of what follows, we use standard graph theory terminology to describe the DP algorithm. A *node* is used to refer to a barrier. A *parent* node is defined as any node with at least one upstream node incident to it. Likewise, a *child* node is defined as the node incident to a parent node and s*iblings* are any group of nodes having the same downstream parent. For example, with respect to the example in figure 1, which shows a set of fish passage barriers represented as nodes in a tree, node 1 is the parent to two children, nodes 2 and 3. Node 2, therefore, is the sibling of node 3 and vice versa. In a similar fashion, node 4 is the child of node 2, its parent. Throughout, it is assumed that a barrier network is oriented vertically, with the root node at the bottom of the tree as shown in figure 1. For problems having multiple individual networks of barriers located in different river basins or subbasins, a dummy node can always be created to serve as the root for all subtrees, i.e. the root nodes of each tree can be redefined as the children of the dummy root node.

The DP algorithm for FPBRP operates by evaluating nodes from right to left, starting from the uppermost layer of a tree and working downward to the root node. Thus, a parent node is always evaluated after a child node, which is located further up in the tree. There are four different types of recursive value functions depending on (1) a node's relative position with respect to its siblings and (2) whether a node has any children. A childless node that is either an only child or the youngest sibling, where youngest is defined as occupying the rightmost position among a group of siblings, is referred to as *terminal leaf* node. A *nonterminal leaf* node is any other childless node that is not the youngest sibling. Likewise, a parent node that is either an only child or the youngest sibling is known as a *terminal branching* node while any other parent node is termed a *nonterminal branching* node.

To begin, let $F_j(d)$ denote the value function for barrier j at state d, where states represent the amount of remaining budget. Without loss of generality, it is assumed that states are integer-valued in the range $[0, b]$. For each parent node j, let $F_{kid(j)}(\cdot)$ denote the value function of j's oldest child, where oldest is defined as the leftmost node among a group of siblings. For each nonterminal node j, let $F_{sib(j)}(\cdot)$ be the value function of j's next older sibling. Finally, let T_{jd} be the set of barrier repair and replacement activities that are affordable for barrier j at state d, i.e. $T_{jd} = \{i \in A_j \mid c_{ij} \leqslant d\}$. By definition, assume $\max\{\emptyset\} = -\infty$. The DP equations for each type of node over all states $d = 0, 1, \ldots, b$ are given by:

Terminal leaf

$$F_j^1(d) = \max\Big\{0; \max_{i \in T_{jd}}\{p_{ij} v_j\}\Big\}, \tag{7}$$

Nonterminal leaf

$$F_j^2(d) = \max\Big\{F_{sib(j)}(d); \max_{i \in T_{jd}}\big\{p_{ij} v_j + F_{sib(j)}(d - c_{ij})\big\}\Big\}, \tag{8}$$

Terminal branch

$$F_j^3(d) = \max\Big\{\bar{p}_j F_{kid(j)}(d); \max_{i \in T_{jd}}\big\{p_{ij} v_j + p_{ij} F_{kid(j)}(d - c_{ij})\big\}\Big\}, \tag{9}$$

Nonterminal branch

$$F_j^4(d) = \max_{0 \leqslant u \leqslant d}\big\{F_j^3(u) + F_{kid(j)}(d - u)\big\}. \tag{10}$$

For a terminal leaf node, equation (7) stipulates that the optimal value in terms of accessible upstream habitat for any budget value d is the maximum of not making a repair, or making the most profitable repair, $\max_{i \in T_{jd}}\{p_{ij} v_j\}$. If T_{jd} is empty, then no repair is made since all types of repair are unaffordable. On the other hand, if T_{jd} is nonempty, one chooses the most profitable, affordable repair. In equation (8) for nonterminal leafs, unlike (7), one must also consider the tradeoff in the value of the cost-to-go function $F_{sib(j)}(\cdot)$ when making a repair decision. When all repairs are unaffordable, the null decision is simply to do nothing. When one or more repairs are affordable, however, one must decide whether to repair the barrier, considering that fewer funds will be available for any subsequent repairs $F_{sib(j)}(d - c_{ij})$, or leave the barrier as is so that more funding will be available for later decisions $F_{sib(j)}(d)$. The equation for terminal branches (9) is structurally similar to (8), with the exception that the cost-to-go function $F_{kid(j)}(\cdot)$ for j's oldest child must be used in place of $F_{sib(j)}(\cdot)$ and must also be multiplied by the passability value, $\bar{p}_j$ or p_{ij}, depending on whether or not repairs are made. Finally, when evaluating nonterminal branches, equation (10) requires one to compute the best allocation of funds u assigned to it and any of its upstream nodes, based on the value of $F_j^3(\cdot)$ assuming it were a terminal branch, and the compliment $d - u$ assigned to its next older sibling $F_{sib(j)}(\cdot)$. The function $F_j^3(\cdot)$, calculated by means of equation (9), determines the value of the best repair decision at a nonterminal branch given any possible budget amount. The use of $F_j^3(\cdot)$ inside equation (10) is justified by the fact that once a budget amount has been allocated to a nonterminal branch, it can effectively be treated as a terminal branch.

Each of the equations (7) through (9) can be solved with little computational effort. Finding the optimal decision at each state d simply involves a comparison of all feasible actions, i.e. no repair and all affordable repairs. Finding a solution to equation (10), however, is considerably more complicated as it requires a linear search on the value u to find the best allocation of repair funds assigned to nodes on two different branches of the tree.

To illustrate, again consider the example in figure 1. The order of operations for the DP algorithm is in descending order of node labels: $6, 5, \ldots, 1$. Nodes 6 and 4, which are both terminal leaf nodes, are evaluated using equation (7). Node 5 is a nonterminal leaf node and consequently is evaluated using equation (8). Nodes 3 and 1 are evaluated using equation (9) since these are both terminal branching nodes. Finally, node 2, the only nonterminal branching node in the network, is evaluated with equation (10). It is important to note that because of the dependencies among barriers, other orderings for the DP formulation will not work.

It should be noted that our specific implementation of the DP algorithm was fashioned in such a way that states that could never be reached, e.g. budget amounts in between the cost of two repairs, were eliminated from consideration. This allowed us to greatly reduce the computational time involved for many of the nodes by not having to compute the objective function values for all budget values d between 0 and b. Details of this technique are discussed for the related knapsack problem in Martello and Toth [22].

4.2. Heuristic method

Greedy type algorithms for integer programs, which are designed to quickly construct solutions of reasonably good quality, have been well studied in the operations research literature [15,22]. The basic premise underlying these greedy heuristics is to iteratively set the decision variable with the highest "utility" to one so long as the cost of the variable does not exceed the remaining budget. For FPBRP, the most straightforward measure of utility is the benefit-to-cost ratio, which is equal to the accessibility weighted net habitat gain over repair cost.

The greedy add with branch pruning (GABP) heuristic uses a greedy adding procedure to construct an initial solution and then tries to improve this solution through the use of a local search technique we refer to as *branch pruning* (figure 3). The construction phase GABP, uses a basic greedy scheme for making barrier repair decisions. At each iteration, benefit-to-cost ratios are computed for all affordable repairs and the repair with the highest value is chosen. Obviously, when computing benefit-to-cost ratios, it makes sense that information on any impassable downstream barriers should also be taken into account. More specifically, if current accessibility at a barrier is zero due to the presence of one or more impassable downstream barriers, a barrier should be repaired only if all impassable downstream barriers are repaired as well. Thus, if impassable downstream barriers are detected when computing the benefit-to-cost ratio of a repair, GABP computes this ratio as the net amount of all accessibility-weighted habitat above the barrier's most downstream impassable barrier, given the least cost repair of all impassable barriers along the path between the barrier and its furthest downstream impassable barrier, divided by the total cost of all such repairs. Barriers for which no repair is affordable are permanently fixed to their initial passability values and removed from further consideration. In the special case where initial passability is zero and no repairs are affordable, all upstream barriers can be also fixed to their current values, since no fish will be able to reach them.

When no more repairs are affordable, the construction phase terminates and a simple local search procedure is initiated. The local search routine consists of making alternating destructive and constructive moves on an incumbent solution until an improving solution is found. If an improving solution is found, the incumbent is replaced with the new solution and the destructive/reconstructive moves repeated. Specifically, during a destructive move, a branch of the network is selected and "closed", whereby the passabilities values for all repaired barriers in the closed branch are reset to their initial values. The resulting cost savings from "unrepairing" these nodes is added back to the residual budget. A constructive move then follows in which the same greedy scheme used in the initial construction phase is carried out.

To force the algorithm away from the incumbent solution, the closed branch is temporarily pruned from the network during reconstruction so that repairs are only made to barriers in the remaining "open" branches of the network. This

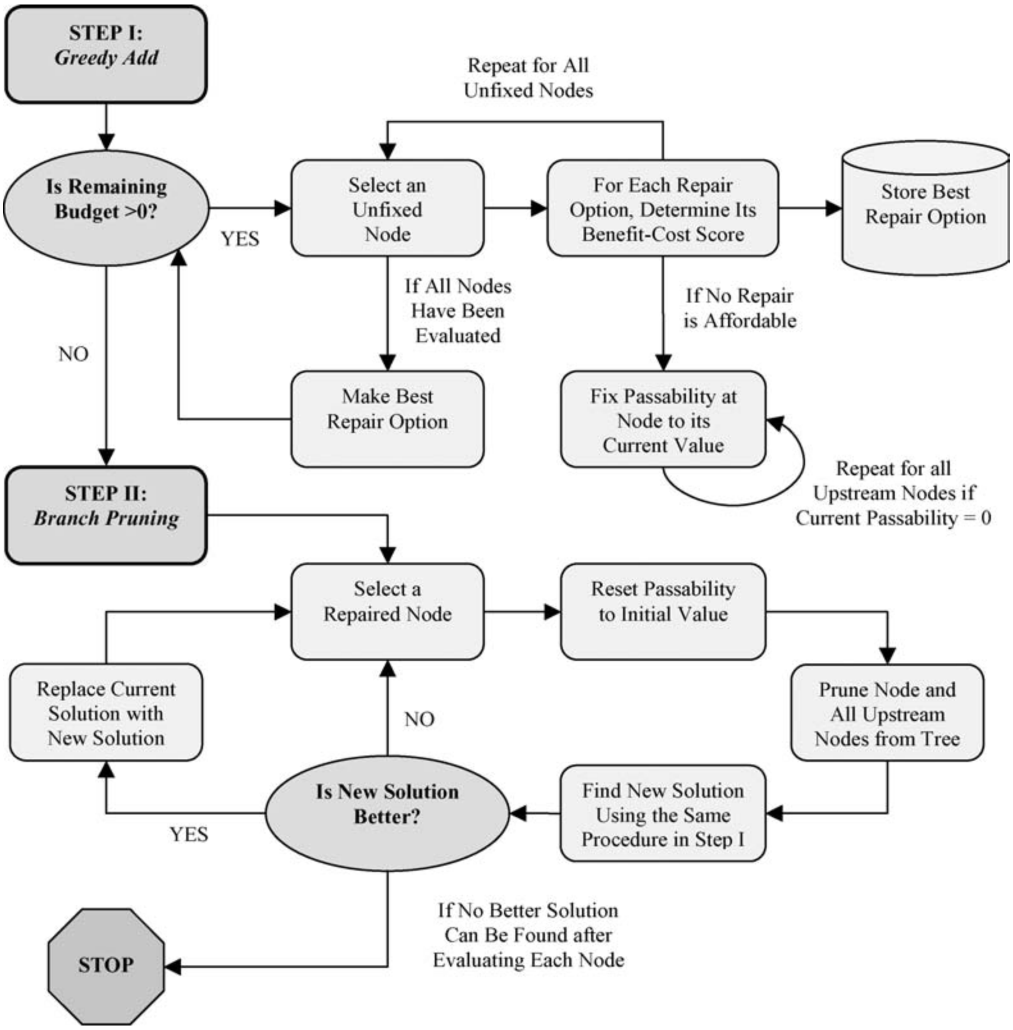

Figure 3. Flowchart showing an outline of the heuristic GABP.

type of strategy was chosen based on preliminary tests which showed it to be preferable to one in which repairs were also allowed along the closed branch. Finally, for the results presented below, only repaired nodes were considered for pruning. This reduced the overall computational time of the local search by excluding pruning moves at unrepaired nodes as well. Again, preliminary tests showed this modification to be faster while still producing quite satisfactory results.

5. Case study: Culvert replacement in Washington State

5.1. Background

Culverts are far and away the most common type of fish passage barrier in the State of Washington. It is estimated that as much as 7,700 river kilometers of habitat in Washington is currently blocked by impassable culverts [6]. Frequently, these barrier culverts are created by improper design or installation, subsequent changes to the stream channel, or lack of proper maintenance. The two most frequently encountered problems are undersized and high-sloped culverts. These types of culverts are impassable to juvenile or adult fish due to high internal flow velocities that exceed the swimming ability of fish. Others can have too little flow and may even run completely dry during certain periods of the year. Culverts with outflow heights greater than the maximum fish jumping ability are another common problem. In some cases, culverts can become blocked by debris accumulation or become so damaged that fish are maimed or killed while entering or exiting a culvert. Besides acting as barriers, culverts can have other deleterious effects that include altering stream morphology and limiting the downstream flow of sediment, large woody debris and other organic materials. Especially problematic is the catastrophic failure of culverts during heavy storm events. This can cause flooding, severe sediment scour and deposition, bank destabilization and damage to riparian vegetation.

In order to amend the situation, the Washington Department of Fish and Wildlife (WDFW) and the Washington State Department of Transportation (WSDOT) have spent nearly $14 million dollars since 1991 on the inventory, prioritization and correction of fish passage barriers. The sheer number of culverts in Washington State makes this a daunting task. Based on their latest report [23], over 4,500 cul-

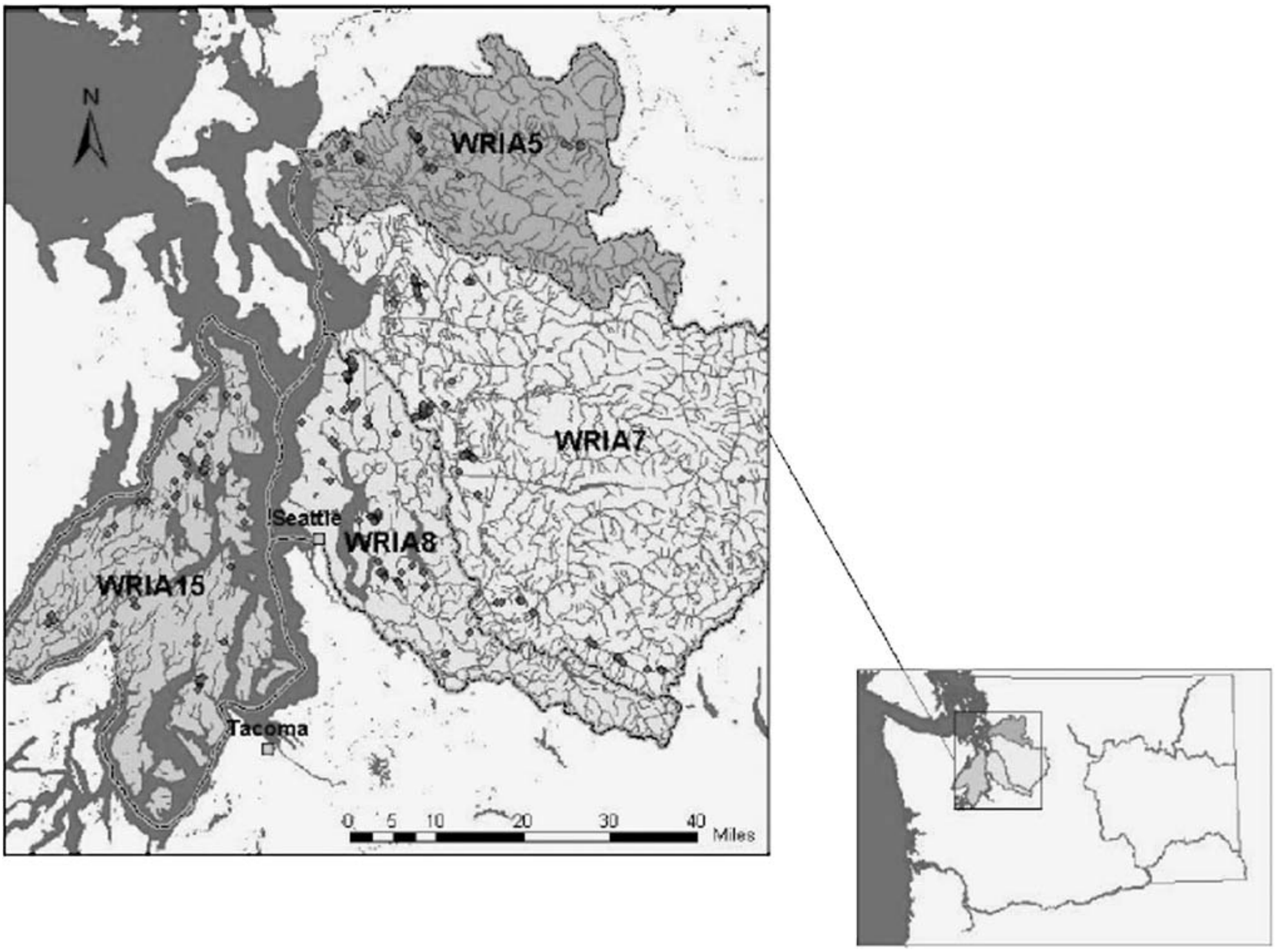

Figure 4. Map showing the layout of the study area. Culvert locations are indicated by small dots.

verts have been surveyed throughout the state with many more still remaining to be surveyed. Over half of them have been found to be fish-bearing crossings and over 1,100 are thought to be passage barriers. Of these, 754 have enough upstream habitat to justify repair, yet only 124 have actually been fixed. These findings are somewhat better than what might be extrapolated from [24], which found that up to 75% of culverts in some forested watersheds were full or partial impediments to fish passage. Summary results of the WSDOT/WDFW fish passage barrier assessment project have been compiled within the Salmonid Screening, Habitat Enhancement, and Restoration (SSHEAR) database maintained by WDFW.

To examine the performance of the three solution methods for FPBRP (DP, GABP and scoring and ranking), eight culvert network datasets were created based on GIS data obtained from the SSHEAR database, WDFW's Fish Program and the Snohomish County Surface Water Management department. The data layers are organized based on a system of watershed management areas used by the State of Washington known as Water Resource Inventory Areas (WRIAs). In all, there are 62 nonoverlapping WRIAs spanning the state. Four core culvert datasets: *wria5*, *wria7*, *wria8* and *wria15*, were created by overlaying the locations of barrier culverts within WRIAs 5, 7, 8 and 15, respectively, on top of 1 : 24,000 scale stream hydro-layers to determine the network connectivity of culverts. One barrier in *wria7* for which complete SSHEAR habitat survey data was unavailable was excluded from the analysis. The remaining four datasets: *wa1*, *wa2*, *wa3* and *wa4*, are based on composites of the four core datasets from WRIAs 5 and 7, WRIAs 8 and 15, WRIAs 7 and 8, and WRIAs 5, 7, 8, and 15, respectively. A map showing the locations of barrier culverts for each of the different WRIAs is provided in figure 4.

Habitat values v_j (derived from the SSHEAR database) were taken as the length in meters of river habitat between each barrier j and its nearest artificial or natural upstream barriers. This metric was chosen for its simplicity and because it is the primary metric used by WSDOT. Of course, some weighted combination of spawning and rearing habitat, which is also supplied in the SSHEAR database, could just as easily have been used instead. Estimated costs to *fully* repair barriers are denoted by values of 1, 2 or 3 in the SSHEAR database. These values correspond in dollar figures to the three ranges $\leqslant$\$100,000, (\$100,000, \$500,000] and $>$\$500,000, respectively. More precise estimates do exist, but for legal reasons are kept confidential. Instead of simply fixing a dollar amount to each value 1, 2 or 3, we chose to randomly generate repair costs in tens of thousands of dollars rounded to the nearest thousand from the uniform distributions [1, 10], (10, 50] and (50, 100], respectively. Thus, in line with WSDOT, only two types of barrier repair decisions were considered: full repair versus no repair.

5.2. Results

The four algorithms dynamic programming (DP), greedy add (GA), i.e. without the branch pruning local search routine, greed add with branch pruning (GABP), and scoring and ranking (SR) according to equation (6), were implemented in JAVA 2 (JDK 1.3.1). All experiments were conducted on the same 3.06 GHz Pentium 4 processor with 512 MB of RAM. It is important to point out that the results presented below are for demonstration purposes only. They should not be construed to represent the best allocation of repair funds or be used to form comparisons with past or existing repair programs since the cost data were randomly generated and since a known barrier culvert was excluded from one of the test datasets for lack of habitat survey data. This, however, in no way invalidates the types of conclusions that can be drawn from this exercise. Obviously, more precise costs are necessary to make real policy recommendations. However, better data will certainly not change the inherent differences among the solution methods in terms of overall quality (as measured by total net habitat gain) or in terms of computational time. Any observed differences are purely due to the quality and robustness of the solution techniques themselves, i.e. the way in which information is used, since no solution method requires any greater data requirements than any other.

Table 3 shows, for each dataset, a comparison of the different solution methods at four different budget values. Budgets, expressed in hundreds of thousands of dollars, are roughly equally spaced at 20% increments of the maximum possible budget given under "Max Budget", which represents the cost to repair all barriers in a dataset. The column labeled "Barriers" indicates the total number of barriers present. The columns labeled "Obj" report the objective values of the different solution methods in terms of the net gain in meters of habitat. Solution times, under the heading

Table 3
Performance of each solution technique at various budget amounts.

Dataset	Barriers	Max budget	Budget	DP		GA			GABP			SR		
				Obj	Time	Obj	%Gap	Time	Obj	%Gap	Time	Obj	%Gap	Time
wria5	47	2,139	450	34,596	0.02	34,596	0	0.03	34,596	0	0.00	30,642	11.43	0.00
			900	40,354	0.00	39,071	3.18	0.00	40,254	0.25	0.02	39,309	2.59	0.00
			1,350	44,001	0.03	42,029	4.48	0.00	44,001	0	0.09	43,442	1.27	0.00
			1,800	46,495	0.02	46,495	0	0.00	46,495	0	0.00	46,495	0	0.00
wria15	66	2,058	450	28,612	0.02	28,249	1.27	0.02	28,249	1.27	0.00	25,880	9.55	0.00
			900	37,162	0.02	36,019	3.08	0.00	36,279	2.38	0.03	36,408	2.03	0.00
			1,350	42,645	0.08	42,610	0.08	0.00	42,612	0.08	0.02	42,583	0.14	0.00
			1,800	45,176	0.05	45,176	0	0.00	45,176	0	0.02	45,176	0	0.00
wria7	85	3,020	650	32,739	0.06	32,439	0.92	0.00	32,539	0.61	0.02	25,306	22.70	0.02
			1,300	40,939	0.03	40,581	0.87	0.02	40,915	0.06	0.03	35,880	12.36	0.02
			1,950	46,071	0.05	43,714	5.12	0.00	44,960	2.41	0.03	44,066	4.35	0.02
			2,600	48,637	0.08	46,755	3.87	0.00	48,459	0.37	0.02	48,637	0	0.02
wria8	91	3,170	650	47,416	0.05	47,114	0.64	0.00	47,114	0.64	0.02	41,846	11.75	0.00
			1,300	55,897	0.05	55,549	0.62	0.00	55,822	0.13	0.00	52,449	6.17	0.00
			1,950	61,066	0.08	59,741	2.17	0.00	61,066	0	0.08	58,721	3.84	0.00
			2,600	63,994	0.06	63,994	0	0.02	63,994	0	0.02	63,927	0.10	0.00
wa1	132	5,176	1,050	67,498	0.06	67,498	0	0.02	67,498	0	0.02	55,828	17.29	0.00
			2,100	80,523	0.09	79,006	1.88	0.00	79,322	1.49	0.03	74,798	7.11	0.00
			3,150	89,337	0.11	86,899	2.73	0.00	87,816	1.70	0.05	87,051	2.56	0.02
			4,200	94,909	0.12	94,815	0.10	0.00	94,909	0	0.05	94,466	0.47	0.00
wa2	157	5,236	1,050	75,573	0.08	75,358	0.28	0.00	75,358	0.28	0.02	63,088	16.52	0.00
			2,100	93,699	0.11	93,197	0.54	0.00	93,531	0.18	0.03	89,313	4.68	0.00
			3,150	102,801	0.12	102,524	0.27	0.00	102,524	0.27	0.02	100,575	2.17	0.00
			4,200	108,585	0.14	108,211	0.34	0.00	108,258	0.30	0.05	108,490	0.09	0.00
wa3	176	6,214	1,250	80,708	0.08	80,387	0.40	0.02	80,480	0.28	0.05	66,821	17.21	0.02
			2,500	96,732	0.12	94,766	2.03	0.00	96,534	0.20	0.06	89,696	7.27	0.02
			3,750	106,309	0.16	104,102	2.08	0.00	105,283	0.97	0.08	102,018	4.04	0.02
			5,000	112,211	0.17	108,722	3.11	0.00	112,195	0.01	0.06	112,050	0.14	0.02
wa4	289	10,805	2,200	146,759	0.30	145,392	0.93	0.02	145,445	0.89	0.06	123,674	15.73	0.00
			4,400	175,135	0.36	173,130	1.14	0.02	173,311	1.04	0.11	166,953	4.67	0.00
			6,600	192,904	0.44	188,515	2.28	0.02	189,093	1.98	0.23	187,896	2.60	0.00
			8,800	203,809	0.50	203,002	0.40	0.02	203,362	0.22	0.14	203,538	0.13	0.00

"Time", are expressed in CPU seconds. Finally, "%Gap" indicates for each heuristic method the percent gap (error) of its objective relative to the optimal value found by DP, where gap is calculated as the difference of the optimal and heuristic objectives divided by the optimal objective.

One of the first observations about table 3 is that for each dataset, the increase in the optimal objective value, given by the value under DP, increases at a decreasing rate with increases in budget. For example, 32,739 m of accessible habitat could be gained for *wria7* with a budget of $650,000. By increasing the budget by $650,000 to $1.3 million, the amount of accessible habitat only increases by 8,200 m to 40,939 m. The next two increments of $650,000 produce increases of 5,132 m and 2,567 m, respectively. A similar pattern plays out for each of the other data sets. This behavior is more clearly seen in figure 5, which shows the efficient frontier of maximum net increase in accessible habitat versus budget for three different datasets. Each curve is roughly concave. Results such as this can be very informative to decision makers during the budget proposal and allocation process for determining a good level of tradeoff in situations with decreasing returns on investment.

In terms of computational time, DP solved very rapidly, usually in a few tenths of a second and never more than half a second for the largest dataset and budget value. As one would expect, solution time increased with both budget amount and the number of barriers in a dataset. For example, keeping the budget roughly fixed, DP found an optimal solution for *wria5* in 0.03 seconds with a budget of $1.35 million, while for *wria8*, which is roughly double the size of *wria5*, solution time went up by less than a factor of two to 0.05 seconds at a comparable budget of $1.3 million. A similar pattern is found for fixed problem size, as well. Solution time increased only incrementally between the lowest and highest budget values for the smaller datasets (*wria5*, *wria7*, *wria8* and *wria15*) and almost doubled for the larger datasets (*wa1*, *wa2*, *wa3* and *wa4*).

GABP found solutions of very high quality with low computational effort. Solutions for GABP were generally only 1 to 3% below the optimum. For small problem sets, there was practically no difference in time between the heuristic and DP. As problem size and budget amount increase, however, the ratio of DP to GABP solution time did increase, though in absolute terms the difference was rather negligible. The greedy adding heuristic GA (without branch pruning) is shown only for comparative purposes. The occasionally considerable improvement in optimality gap between GA and GABP demonstrates the utility of performing the local search routine.

By comparison, the scoring and ranking procedure SR, in spite of requiring virtually no computational effort, frequently produced much lower quality solutions than GABP or GA. When budget values were relatively low, the percent gap was quite high: frequently greater than 9% and as much as 22% in the worst case based on table 3. As the budget increased, however, the percent gap dropped markedly. For the first three datasets, in fact, SR was able to find an optimal solution for the largest budget value. This pattern can be attributed to the underlying assumptions of the barrier scoring procedure. Using equation (6), the passability at upstream barriers is not directly taken into account, presupposing that habitat above upstream barriers is freely accessible. Consequently, scoring and ranking solutions generally get closer to optimal as more and more barriers have been fixed and scores become more globally accurate in terms of each barrier's overall importance to an optimal solution. This pattern of high percent gap at low budget values is more clearly seen in figure 6, which shows for SR the percent gap versus budget amount for datasets *wria5*, *wria7* and *wria8*. Looking at the results for *wria7*, SR performed especially poorly with a maximum gap of over 60% at a budget of $100,000 and was still nearly 20% for budgets as high as $1 million. With even finer gradations of the budget, SR was a full 100% below the optimum, producing no gain whatsoever for *wria7* at a budget of $5,000, as seen in figure 7.

To get a better understanding of the performance of the different heuristics, a total of 19 budget values (at 5% increments of the maximum budget) were evaluated for each of the eight datasets. Table 4 presents summary results of the average percent gap (Avg %Gap), the maximum percent gap

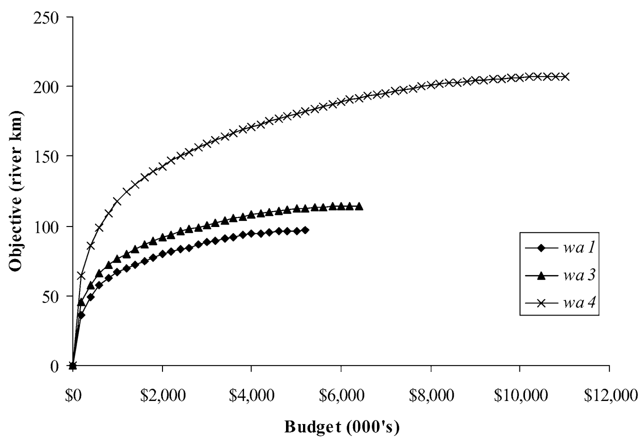

Figure 5. Maximum net habitat gain versus budget amount for select datasets.

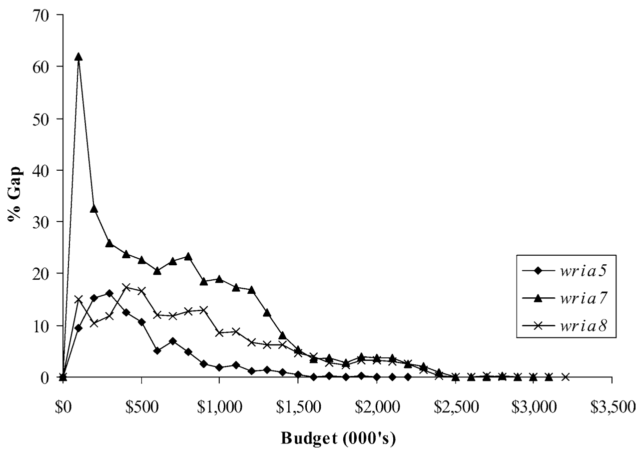

Figure 6. Percent gap of SR at budget increments of $100,000 for select datasets.

Table 4
Overall performance of each heuristic for 19 different budget values.

Dataset	GA			GABP			SR		
	Avg %Gap	Max %Gap	Num Opt	Avg %Gap	Max %Gap	Num Opt	Avg %Gap	Max %Gap	Num Opt
wria5	1.36	4.34	9	0.75	3.44	13	4.12	18.16	3
wria15	1.18	3.67	4	0.66	2.39	10	5.80	26.94	3
wria7	3.00	7.20	3	0.65	3.27	4	10.94	31.80	3
wria8	0.67	2.65	10	0.12	0.63	12	7.04	32.58	3
wa1	1.45	3.74	4	0.96	2.85	4	7.81	30.80	1
wa2	0.70	2.72	3	0.35	1.93	4	6.18	18.43	2
wa3	1.64	3.36	4	0.60	2.63	6	7.71	22.80	1
wa4	1.07	2.56	3	0.67	2.08	3	7.04	25.43	2
Avg	1.38	3.78	5.00	0.60	2.40	7.00	7.08	25.87	2.25
SD	0.74	1.52	2.83	0.26	0.89	4.04	1.97	5.73	0.89

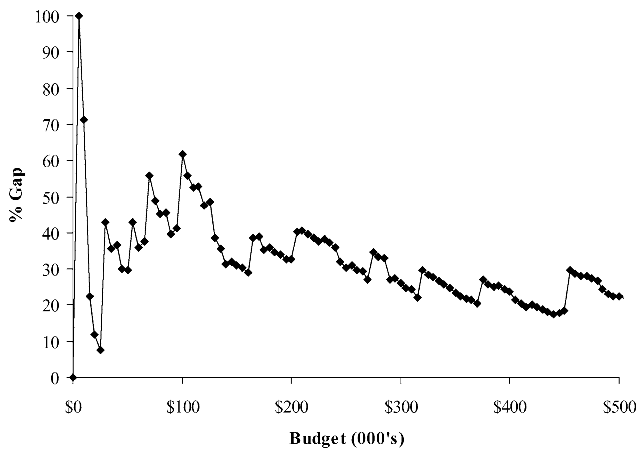

Figure 7. Percent gap for SR at budget increments of $5,000 for dataset *wria7*.

(Max %Gap) and the number of times an optimal solution was found (Num Opt) across all 19 budget values. On average, GABP was only 0.6% off the optimum (1.38% for GA) but was more than an order of magnitude worse for SR at a 7.08% optimality gap. And even if a 7% average gap may not seem like much, when one looks at the worst-case performance of SR as measured by the maximum percent gap, the potential disadvantage of a scoring and ranking procedure is clearly evident. On average, the maximum gap for the three heuristics was 26%, 4% and 2%, for SR, GA and GABP, respectively. Another indication of SR's inferiority is the number of times the heuristics found an optimal solution. On average, GABP found an optimum 37% of the time over all budget values. This is somewhat better than GA, which found an optimum 26% of the time, and considerably better than SR, which only found an optimum 12% of the time.

The results indicate two important findings. First, for a nominal amount of computational time, the heuristics GABP and GA strictly outperformed the scoring and ranking procedure SR in all three performance measures: average gap, maximum gap and frequency of finding an optimum. This is particularly noteworthy, showing that the use of better algorithms provides a sort of insurance against the worst instances of miss planning. Second, using a heuristic with a local search routine (GABP) produced solutions of significantly higher quality with little added computational effort than one without (GA).

6. Conclusion

The problem of reconnecting inaccessible stream habitat is a major concern throughout the North America and elsewhere due to the presence of large numbers of small artificial stream barriers that block the upstream movements of fish. This problem is especially relevant to salmon stocks because of their extensive use of upstream areas during adult spawning and juvenile rearing. To combat the problem, public resource agencies and private environmental organizations have spent and continue to spend millions of dollars each year to inventory and fix fish passage barriers.

Because of the absence of more formal procedures like optimization models, current methods for making barrier repair and replacement decisions generally rely on simple scoring and ranking techniques. Though quick and simple to use, scoring and ranking techniques can give arbitrarily bad solutions due to their generally limited consideration of spatial dependencies among barriers and their inability to readjust rankings as some barriers are repaired. In their defense, some would argue that scoring and ranking is the only available method that can account for multiple decision criteria, like the amount and quality of habitat, the presence of endangered or threatened species, regulatory requirements and the presence of special political backing or funding certain areas. Yet, almost all of these factors can be incorporated into an optimization model by directly including them as constraints that the model must satisfy or by adding them into the objective function through the use of weights.

To overcome the shortcomings of scoring and ranking, we have presented a novel decision-modeling approach for deciding which fish passage barriers to repair or replace. Referred to as the Fish Passage Barrier Removal Problem (FPBRP), this nonlinear, binary model maximizes the gain in accessible habitat above barriers subject to a budget constraint. The formulation is quite general in that many different types of fish passage barriers may be considered such as small dams, culverts, dikes, levees, floodgates, weirs and many others. Additionally, multiple repair options at these barriers can be considered. With simple modification, the model can also handle multiple passage rates for different fish species and life stages. Though it assumes that component river networks have an underlying tree structure, extensions of FPBRP that consider several barriers arranged in parallel along the same stretch of stream, as might exist with deltas and braided rivers, are possible. Speaking more generally, what makes FPBRP especially appealing is that compared to other classes of optimization models used in environmental planning, which generally make a lot of strong simplifying assumptions, FPBRP is quite robust in terms of capturing an accurate description of the problem faced by restoration managers. In this, FPBRP is well suited to give actionable results, not just informative results.

Because it is a nonlinear integer model, existing commercial solvers are ill suited to solving FPBRP optimally. To overcome this, a dynamic programming (DP) formulation was given that is guaranteed to find a global optimal solution. To examine the performance of the dynamic programming routine, two alternative solution methods were investigated. The first method, called GABP, is based on a greedy construction heuristic combined with a local search procedure that utilizes a branch pruning mechanism to improve an initial solution. The second method, called SR, is based on a simple scoring and ranking procedure that uses a benefit–cost ratio for ordering repairs.

Computational results on eight real datasets of barrier culverts located in Washington State show the dynamic programming method to be very acceptable in terms of solution time. For problems with up to several hundred barriers, DP found a solution in less than half a second. The results also confirm the potentially poor performance of scoring and ranking methods. SR frequently produced solutions that were 25% below the maximum and in the worst case were 100% suboptimal, producing zero net gain.

By comparison, the more intelligent and robust heuristic GABP found in almost all cases optimal or near optimal solutions with relatively low computational effort. On average the heuristic was less than 1% below the optimum and usually never more than a few percentage points below in the worst case. Although it was found that GABP had really little advantage over DP in terms of reduced solution time, especially for the smaller datasets, this method may still be useful for several reasons. First, while there is no evidence to confirm this, we believe that GABP could have promise when dealing with large datasets having a thousand or more variables that might be time consuming to solve using DP. Second, the basic GABP structure can be quite easily adapted to solve more complex barrier removal problems having additional constraints besides a budget. In this, GABP may have especially useful applications.

There are several areas of further research we suggest for extending the model. One natural extension could be to incorporate stochastic issues into the problem. With FPBRP, it is assumed that barrier repair costs and passability values are known with certainty, yet rarely does this actually hold in practice. Handling uncertainty in passability is a very simple matter assuming one is using a maximum expected value objective. It can be shown quit easily that one only need replace the "known" change in passability of project i at barrier j, p_{ij}, with its expected value $\hat{p}_{ij}$. Thus, no structural changes to the basic model or the solution algorithms are required with this type of uncertainty. Cost uncertainty is more difficult to deal with, especially using a heuristic method. With a heuristic it is necessary at the very least to minimize budget overruns or more appropriately to find an order of repairs and set of policies that determine when and when not to fix different barriers depending on the amount of budget remaining. Cost uncertainty, however, can be easily handled using a stochastic dynamic programming framework. Taking this approach would require only minor changes to the deterministic dynamic programming formulation above. One would simply need to take the expectation of the cost-to-go functions $E_c\{F_{sib(j)}(d - c_{ij})\}$ and $E_c\{F_{kid(j)}(d - c_{ij})\}$ on right-hand side of equations (8) and (9), respectively, in order to find the best repair option. It is unlikely that this more general formulation would require any drastic increase in solution time.

Another interesting line of research might be to consider the tradeoff between habitat quantity and quality. The current model addresses only one piece, albeit an important one, of the larger problem faced in restoration planning: how to choose among many different types of restoration activities to achieve the greatest benefit of fish and their ecosystems. Habitat values are static using FPBRP. Although habitat can be easily adjusted for current environmental quality, direct control of this quality is not handled within the scope of the model presented here. More generally, however, managers need flexibility in trading off habitat quantity and quality. As such, it may make little sense to open a large tract of inaccessible stream habitat if environmental quality is so poor that additional restoration efforts need to be undertaken. These might include rehabilitating riparian zones, lowering stream temperatures, reducing pollution and sediment inputs and increasing channel complexity through placement of instream structures and large-woody debris.

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