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# Optimal Fish Passage Barrier Removal - Revisited

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**Abstract**

Infrastructure, such as dams, weirs and culverts, disrupt the longitudinal connectivity of rivers, causing adverse impacts on fish and other aquatic species. Improving fish passage at artificial barriers, accordingly, can be an especially effective and economical river restoration option. In this article, we propose a novel, mixed integer programing model for optimizing barrier mitigation decisions given a limited budget. Rather than simply treating barriers as being impassable or not, we consider the more general case in which barriers may be partially passable. Although this assumption normally introduces nonlinearity into the problem, we manage to formulate a linear model via the use of *probability chains*, a newly proposed technique from the operations research literature. Our model is noteworthy in that it can be readily implemented and solved using off-the-shelf optimization modeling software. Using a case-study from the US State of Maine, we demonstrate that the model is highly efficient in comparison to existing solution methods and, moreover, highly scalable in that large problems approaching 7,000 barriers can still be solved optimally. Our analysis confirms that barrier mitigation can provide substantial ecological gains for migratory fish species at low levels of investment.

**Keywords:** fish passage barriers, river connectivity, probability chains, optimization, MILP.

## 1 Introduction

River systems comprise some of the most complex, dynamic and bio-diverse ecosystems on earth, as well as playing an essential role in the transport of organisms and matter through the landscape (Dynesius and Nilsson, 1994). At the same time, river systems across the globe have been modified extensively in order to provide socioeconomic benefits like water supply, flood suppression, power generation and transportation infrastructure. A global review of large river systems identified more than 50% as being affected by river barriers such as dams, culverts and weirs (Nilsson et al., 2005). In the United States, only 2% of streams are believed to be free flowing and relatively undeveloped (Pringle, 2003). River barriers fragment the continuity of rivers and substantially alter their natural flow, thereby transforming the biological, morphological and physio-chemical characteristics of rivers and associated ecosystems (Bednarek, 2001). The presence of physical obstructions to migratory fish (e.g., salmon and eel) can reduce or eliminate their ability to reach high quality spawning and rearing grounds (Stanford et al., 1996).

While large head dams do impose major obstacles, the cumulative effect of low head dams, road crossings and other smaller barriers can be even greater due to their large number (Januchowski-Hartley et al., 2013).

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Numerous studies have demonstrated the negative effects small artificial barriers have on migratory and resident fish populations (Sheer and Steel, 2006; Catalano et al., 2007; Fullerton et al., 2010; Nislow et al., 2011). Culverts, for example, can hinder fish passage due to high water velocities, inadequate depths, debris jams or large outflow drops (Kemp and Williams, 2008). This can result in fish expending significant additional energy when migrating upriver as well as increased predation, angling mortality and disease in pooling areas below barriers. Individuals that are unsuccessful in passing barriers may be forced to spawn or rear in less suitable habitat downstream (e.g., in areas of increased risk of siltation or predation of eggs and larvae), thus further depressing population numbers (de Leaniz, 2008).

Removing migratory fish passage barriers has been demonstrated to result in increased spawning (Burdick and Hightower, 2006), fish density (Gardner et al., 2013), diversity (Catalano et al., 2007) and rapid colonization of formerly impounded upstream reaches (Roni et al., 2008). Moreover, there is good evidence that river barrier mitigation is one of the most cost-effective means of improving fish populations at the watershed scale (Roni et al., 2002, 2008). Putting economics aside, there are often important legislative drivers for improving river connectivity, such as the Endangered Species Act in the US and the Water Framework Directive in the EU.

Traditionally, studies on river barrier mitigation have concentrated on the assessment of localized connectivity improvements. Scoring and ranking procedures are a typical example and are commonly employed to prioritize barriers for mitigation action (e.g., Kocovsky et al., 2009 and Nunn and Cowx, 2012). However, scoring and ranking approaches consider each barrier independently and fail to account for the cumulative effects on longitudinal connectivity from improving passage at downstream barriers. Their use in prioritization typically results in sub-optimal subsets of barriers being targeted for action (Kemp and O'Hanley, 2010). Understanding how passage improvement at multiple river barriers interact to affect fluvial connectivity is key to the sustainable management of rivers and the conservation of migratory fish species (Fullerton et al., 2010).

In broad terms, two general approaches can be identified in the literature that consider interactive effects of barrier mitigation, namely graph theoretic (e.g., Erős et al., 2011; Segurado et al., 2013) and optimization modeling frameworks (e.g., O'Hanley and Tomberlin, 2005; Kuby et al., 2005). Both of these methodologies model watersheds as Dendritic Ecological Networks (DENs), where the river network is characterized by a branching architecture with branches forming as one moves in the upstream direction (Grant et al., 2007).

## 1.1 Graph Theoretic Modeling

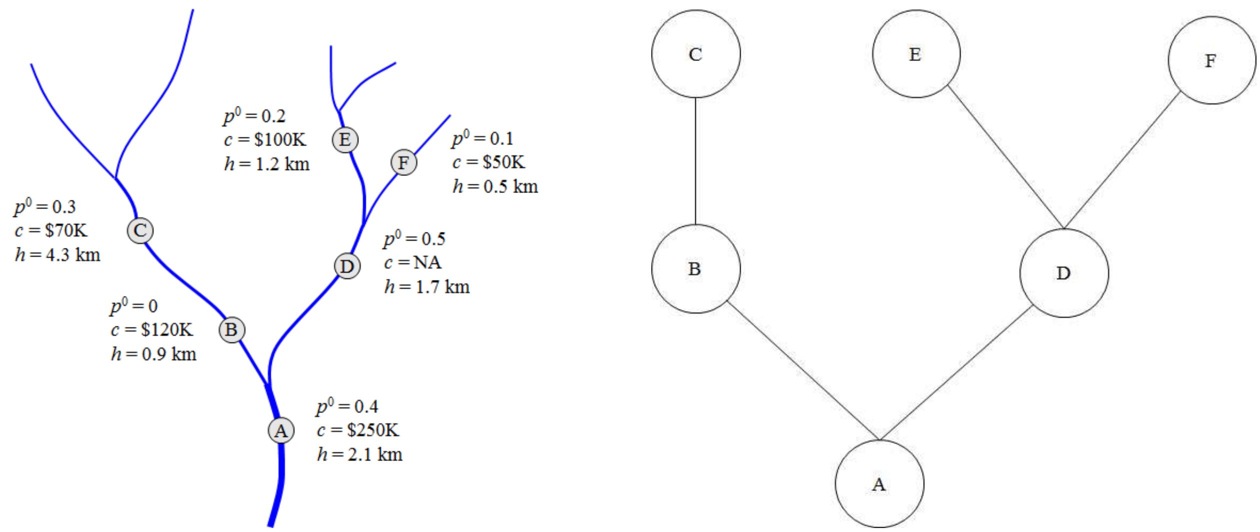
Graph theoretic approaches typically model river DENs as a set of river segments or habitat patches (nodes) and river confluences (arcs) (Padgham and Webb, 2010; Erős et al., 2011; Segurado et al., 2013). Barriers within the network can either be total (i.e., passability 0), thus splitting the graph into separate sub networks (Erős et al., 2011; Segurado et al., 2013) or partial (i.e., passability between 0 and 1), in which case transition between nodes is modeled via a transition probability matrix (Padgham and Webb, 2010). The positional importance of any habitat node can be evaluated using metrics like the Betweeness Centrality Index (BCI), which measures the number of shortest paths going through it (Pascual-Hortal and Saura, 2006). Overall habitat availability within a watershed can be captured by different metrics like the Integral Index of Connectivity (IIC), which takes into account both connectivity between habitat patches and habitat amount (Pascual-Hortal and Saura, 2006). The importance of any given barrier, in turn, can be identified by calculating the effect that restoring connectivity between nodes has on IIC (Erős et al., 2011; Segurado et al., 2013).

Whilst less common in the literature, an alternative approach in which DENs are constructed using barriers (nodes) and adjacencies between barriers (arcs) has proven insightful for assessing river connectivity (Cote et al., 2009; McKay et al., 2013; Diebel et al., 2014). Figure 1, presents an example of this approach with natural and artificial barriers represented as lettered nodes (A-F). Assuming individual barrier passabilities are independent, connectivity from any given point in the network to habitat immediately above a barrier is simply taken as the product of the passabilities for all intervening barriers. This is more generally referred to as cumulative passability for barriers in series (Kemp and O'Hanley, 2010). To quantify habitat availability at the watershed level, various metrics have been proposed. Cote et al. (2009) describe the Dendritic Connectivity Index (DCI), which is calculated as sum of the relative amount of net habitat above a barrier adjusted by the cumulative passability of the barrier. McKay et al. (2013) examine a conceptually similar index (the HCIU index) specifically for the case of upstream migrating fish. Diebel et al. (2014) present a more general connectivity metric (the C metric) specific to resident fish, which further accounts for multiple habitat types and the travel distance between habitat areas.

Examining the effect of barrier mitigation on river connectivity using indicies such as IIC, DCI, HCIU and C can allow decision makers to choose the best course of action among an identified set of alternatives. Graph based approaches for prioritizing barrier mitigation action are certainly more insightful than traditional scoring and ranking approaches in that they consider basin-wide barrier impacts on river connectivity and the effect of coordinated mitigation action. However, they are "descriptive", rather than "prescriptive," in that they do not produce a recommended solution. The chosen subset of barriers targeted for mitigation has no guarantee of being optimal unless all possible permutations of barrier mitigation action have been evaluated. While this is possible when dealing with a small number of barriers (i.e., a few dozen at most), for problems involving large numbers of barriers (i.e., in the 100s to 1000s), considering every possible combination becomes computationally intractable.

## 1.2 Optimization Modeling and Connectivity

Optimization models also normally employ graph structures to model DENs in the format presented in Figure 1 (i.e., barriers represented as nodes with arcs between adjacent barriers). Unlike simple graph theory models, optimization approaches provide a scalable means of exploring all possible combinations of barrier mitigation action so that an optimal solution can be identified which maximizes restoration gains given available resources. In addition, models can be formulated to address a variety of different objectives and or include various planning constraints. For example, O'Hanley (2011) present a model particularly suited to resident fish species that maximizes the size of the largest barrier free sub-network within a river system subject to a budget. Kuby et al. (2005) present a bi-objective model for removing hydropower dams that maximizes accessible habitat gains, while simultaneously minimizing economic losses associated with reduced power generation and water storage capacity. Zheng et al. (2009) optimize no less than 9 ecological and socio-economic objectives through the use of multicriteria value analysis, including fish biomass changes, ecosystem structure, function and productivity responses, and both dam removal and invasive species control costs. The approach is noteworthy for the combined use of optimization, multicriteria analysis, simulation and habitat suitability modeling. Zheng and Hobbs (2013) consider a similar type of multi-objective framework, focusing in particular on dam safety issues.




(a) (b)

Figure 1: Example of a river barrier network represented as a simple map (a) and as an equivalent DEN (b). In (a), basic information pertaining to each barrier is listed next to each node, including current passability ($p^0$), the cost ($c$) in thousands of dollars to fully repair/remove the barrier (i.e., increase passability to 1), and the amount of river habitat ($h$) immediate above the barrier. Barrier D is a natural barrier with no mitigation option available (i.e., $c = \text{NA}$).

Structurally O'Hanley (2011), Kuby et al. (2005), Zheng et al. (2009) and Zheng and Hobbs (2013) formulate their optimization models as mixed integer linear programs (MILPs), in which the primary decision variables are binary to indicate whether any particular barrier should be repaired/removed or not. In order to maintain linearity of the models, these studies all assume that passability is also binary (i.e., barriers are either completely impassable or passable). In contrast, O'Hanley and Tomberlin (2005) adopt the more general view, as done in Cote et al. (2009), Diebel et al. (2014) and McKay et al. (2013), that barriers may be partially passable (i.e., anywhere in the range 0 to 1). In the context of diadromous fish, access to river habitat above a barrier is taken (assuming barriers are independent) as the product of all downstream barrier passability values. Unfortunately, multiplying barrier passabilities together introduces nonlinear interactions among the decision variables. This normally makes such optimization models hard to solve. O'Hanley and Tomberlin (2005) resort to the use of specialized dynamic programming (DP) and heuristic methods.

In this paper, we propose an efficient *linear* model for optimizing river barrier repair and removal decisions in order to maximize upstream habitat gains for migratory fish. We reformulate the Fish Passage Barrier Removal Problem (FPBRP) model proposed by O'Hanley and Tomberlin (2005) as a MILP based on a newly proposed technique of using probability chains (O'Hanley et al., 2013) to evaluate cumulative passability terms. The benefits of a linear model are twofold. First, it allows FPBRP to be coded using high-level algebraic modeling languages such as OPL, AMPL or GAMS and subsequently be solved using off-the-shelf optimization software solvers like CPLEX and GUROBI. Second, the increased efficiency and scalability of the model, in comparison to DP, allows far larger problems to be solved optimally.

The remainder of the paper is organized as follows. In Section 2, we present the original nonlinear version of FPBRP as well as our new linear reformulation. In Section 3, we provide some simple examples to demonstrate how the linear model works. In Section 4, we compare the linear model to existing solution methods and demonstrate the insight the FPBRP can provide using a case study from the US. In Section 5, we provide concluding remarks. In a set of online appendices, we provide an OPL implementation of the model and an example dataset that can be readily translated into other modeling languages.

# 2 The Fish Passage Barrier Removal Problem (FPBRP)

FPBRP selects barriers for repair or removal in order to maximize the amount of accessible habitat for diadromous fish. It is assumed that barrier passabilities can take on fractional values in the range 0 to 1. Passability represents the probability that fish are able to pass through, over or around a particular barrier. Given that fishes naturally vary in their ability to negotiate barriers, the model allows for multiple barrier passability values to be specified for each "restoration target" of interest (e.g., a species, guild or ecologically significant unit). Cumulative passability to habitat above any given barrier (a.k.a. accessibility) is taken as the product of the passability at that barrier and all barriers downstream to the river mouth. Cumulative passability is equivalent to longitudinal connectivity with the river mouth. The model assumes that multiple mitigation options (e.g., removal, replacement, fitting baffles, installing fish passes) may be available at any given barrier with varying cost and passability improvement but that only one project can be carried out at a barrier. Lastly, there is assumed to be a budget, which limits total expenditure on river barrier mitigation actions.

## 2.1 Nonlinear Formulation

In order to formulate the nonlinear version of FPBRP, we use the notation provided in Table 1 and following decision variables.

$$x_{ji} = \begin{cases} 1 & \text{if mitigation project } i \text{ is carried out at artifical barrier } j \\ 0 & \text{otherwise} \end{cases}$$

$$z_{jt} = \text{cumulative passability to habitat immediately above barrier } j \text{ for restoration target } t$$

A nonlinear formulation for FPBRP is then given as follows:

$$\text{FPBRP} \;\; \max \sum_{t \in T} w_t \sum_{j \in J} v_{jt} z_{jt} \tag{1}$$

*s.t.*

$$z_{jt} = \prod_{k \in D_j} \left( \bar{p}_{kt} + \sum_{i \in A_k} p_{kti} x_{ki} \right) \qquad \forall j \in J, t \in T \tag{2}$$

$$\sum_{i \in A_j} x_{ji} \leq 1 \qquad \forall j \in J^* \tag{3}$$

$$\sum_{j \in J^*} \sum_{i \in A_j} c_{ji} x_{ji} \leq b \tag{4}$$

$$x_{ji} \in \{0, 1\} \qquad \forall j \in J^*, i \in A_j \tag{5}$$

Table 1: Notation used in FPBRP.

| Symbol | Definition |
|---|---|
| $T$ | Set of restoration targets, indexed by $t$ |
| $J$ | Set of all artificial and natural barriers, indexed by $j$ and $k$ |
| $J^*$ | Set of barriers for which at least one mitigation project exists (i.e., $\|A_j\| \geq 0$) indexed by $j$ |
| $D_j$ | Set of all barriers downstream from and including barrier $j$ |
| $A_j$ | Set of mitigation projects available at barrier $j$, indexed by $i$ |
| $w_t$ | Objective weight for restoration target $t$ |
| $v_{jt}$ | Net amount of habitat above barrier $j$ for restoration target $t$ |
| $c_{ij}$ | Cost of implementing mitigation project $i$ at barrier $j$ |
| $b$ | Available budget for carrying out mitigation actions |
| $\bar{p}_{jt}$ | Initial passability of barrier $j$ for restoration target $t$ |
| $p_{jti}$ | Increase in passability at barrier $j$ for restoration target $t$ given implementation of mitigation project $i$ |

The objective (1) calculates the sum of cumulative passability weighted habitat $v_{jt}z_{jt}$ for each barrier $j$ and restoration target $t$. Target-specific weights $w_t$ allow certain targets to be prioritized over others. Cumulative passability $0 \leq z_{jt} \leq 1$ above barrier $j$ for target $t$ is calculated via the first set of constraints (2). They specify for a given barrier $j$ and target $t$ that $z_{jt}$ is equal to the product of the passabilities in set $D_j$, namely barrier $j$ and all barriers downstream from $j$ to the river mouth. If no project is selected at a given barrier $k \in D_j$, then passability at $k$ for restoration target $t$ is $\bar{p}_{kt}$. If project $i$ is selected, then passability at $k$ for restoration target $t$ becomes $\bar{p}_{kt} + p_{kti}$. Note that equations (2) are nonlinear. Constraints (3) ensure only one mitigation project $i$ can be carried out at any given barrier. If at most one project is available at barrier $j$ (i.e.,$|A_j| \leq 1$), then (3) can be dropped for that particular barrier. Inequality (4) stipulates that the total cost of barrier mitigation actions cannot exceed the total available budget $b$. Constraints (5) impose binary restrictions on the $x_{ji}$ decision variables.

It is worth pointing out that net habitat amounts $v_{jt}$ can be given in any relevant unit such as length (e.g., river miles or kilometers) or area (e.g., wetted area). Habitat can also be quality-adjusted, if so desired, by taking the raw amount of habitat $h_{jt}$ for target $t$ and barrier $j$ and then multiplying it by a habitat suitability score $q_{jt} \geq 0$ (i.e., $v_{jt} = q_{jt}h_{jt}$). Habitat quality can be based on any number of environmental correlates such as flow, temperature, water quality, bank/substrate condition, local land use, etc.

We also note that the above model can be easily adapted to account for downstream passage by redefining parameter $\bar{p}_{jt}$ (likewise for $p_{jti}$) as the product of upstream passability $\bar{p}_{jt}^{up}$ and downstream passability $\bar{p}_{jt}^{dwn}$ for each barrier $j$ and target $t$ (i.e., $\bar{p}_{jt} = \bar{p}_{jt}^{up} \times \bar{p}_{jt}^{dwn}$ and $p_{jti} = p_{jti}^{up} \times p_{jti}^{dwn}$). In this way, $\bar{p}_{jt}$ and $p_{jti}$ can be used to represent *bi-directional* passability terms, thus allowing one to handle (using salmon as an illustrative example) both upstream passage of spawning adults and downstream passage of juvenile smolts.

## 2.2 Linear Reformulation

To reformulate FPBRP as a MILP, we introduce the additional following variable:

$$y_{jti} = \text{change in cumulative passability at barrier } j \text{ for target } t \text{ given implementation of project } i$$

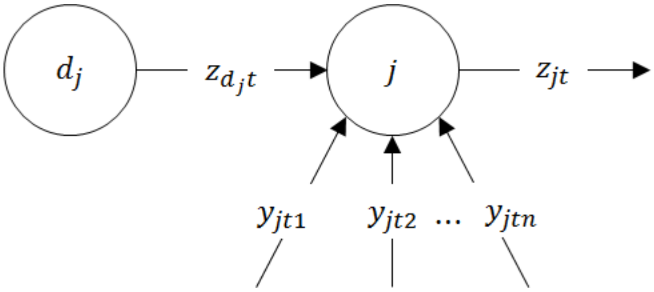



Figure 2: Probability chain for a hypothetical barrier $j$ whose initial passability $\bar{p}_{jt}$ for restoration target $t$ can be improved via implementation of mitigation projects $i = 1, 2, \ldots n \in A_j$, thereby resulting in an increase in cumulative passability $z_{jt}$ to the area upstream of $j$.

Further, let $d_j$ refer to the barrier immediately downstream of $j$. A linear version of FPBRP can be derived by replacing (2) with the following.

$$z_{jt} = \bar{p}_{jt} + \sum_{i \in A_j} y_{jti} \qquad \forall j \in J | d_j = \emptyset, t \in T \tag{6}$$

$$z_{jt} = \bar{p}_{jt} z_{d_j t} + \sum_{i \in A_j} y_{jti} \qquad \forall j \in J | d_j \neq \emptyset, t \in T \tag{7}$$

$$y_{jti} \leq p_{jti} x_{ji} \qquad \forall j \in J^*, t \in T, i \in A_j \tag{8}$$

$$y_{jti} \leq p_{jti} z_{d_j t} \qquad \forall j \in J^* | d_j \neq \emptyset, t \in T, i \in A_j \tag{9}$$

Nonlinearity is removed from the model through the use of flow-balance constraints (6) and (7) for the determination of $z_{jt}$ combined with bounding constraints (8) and (9) on $y_{jti}$. Collectively, variables $z_{jt}$ and $y_{jti}$ and constraints (6)-(9) form a probability chain that iteratively propagates cumulative passability values from each barrier $j$ to its next upstream barrier (O'Hanley et al., 2013). Specifically, equations (6) specify for restoration target $t$ that cumulative passability $z_{jt}$ at a barrier $j$ for which there is no downstream barrier ($d_j = \emptyset$) is equal to initial passability $\bar{p}_{jt}$ plus the potential increase in passability $y_{jti}$ for target $t$ resulting from the implementation of any project $i$ at $j$. Equations (7), meanwhile, specify for target $t$ that the cumulative passability $z_{jt}$ at any barrier $j$ located above another barrier ($d_j \neq \emptyset$) is the product of $\bar{p}_{jt}$ and the cumulative passability at downstream barrier $d_j$ ($z_{d_j t}$) plus the potential increase in cumulative passability $y_{jti}$ of any project $i$ at $j$. Inequalities (8) specify that if project $i$ is not selected ($x_{ji} = 0$), then $y_{jti}$ must equal 0. If project $i$ is selected, then $y_{jti}$ is bounded above by $p_{jti}$, the maximum potential increase in cumulative passability at barrier $j$. For barriers without a downstream barrier, the value $p_{jti}$ provides the exact increase in cumulative passability. Finally, inequalities (9) limit the increase in cumulative passability $y_{jti}$ to be $p_{jti}$ times cumulative passability at downstream barrier $d_j$ ($z_{d_j t}$). Inequalities (9) become binding at upstream barriers $j$ ($d_j \neq \emptyset$) when $x_{ji} = 1$. Figure 2 provides an illustrative example of a generic probability chain represented in graph form.

## 2.3 Negative Weight Targets

An implicit assumption of FPBRP is that increased river connectivity invariably provides a positive ecological benefit. In some planning situations, however, there may be certain targets (e.g., invasive species) for which habitat gain is undesirable and therefore should be limited. For each such target, a negative weight $w_t$ can be assigned in the objective function (1). In order to accommodate “anti-restoration” targets into a MILP structure, additional constraints need to be derived. Specifically, constraints (8)-(9) would not be sufficient to produce correct values for the $y_{jti}$ variables (and by extension the $z_{jt}$ variables) when a negative weight $w_t$ is given to target $t$. A negative weight favors the smallest possible values for $y_{jit}$. However, (8)-(9) only place upper bounds on these variables and so do not constrain them to increase as they should when mitigation occurs. To overcome this, one simply needs to substitute the following constraints in place of (8)-(9) for each negatively weighted target.

$$y_{jti} \geq p_{jti}x_{ji} \qquad \forall j \in J^*|d_j = \emptyset, t \in T, i \in A_j \tag{10}$$

$$y_{jti} \geq p_{jti}z_{d_jt} + x_{ji} - 1 \qquad \forall j \in J^*|d_j \neq \emptyset, t \in T, i \in A_j \tag{11}$$

$$y_{jti} \geq 0 \qquad \forall j \in J^*|d_j \neq \emptyset, t \in T, i \in A_j \tag{12}$$

Inequalities (10) ensure that if project $i$ is implemented at a barrier with no downstream barrier ($d_j = \emptyset$) then the change in cumulative passability $y_{jti}$ is forced up to $p_{jti}$. Inequalities (11) similarly force $y_{jti}$ up at any barrier $j$ with at least one downstream barrier ($d_j \neq \emptyset$) when mitigation is carried out (i.e., $x_{ji} = 1$ for some project $i$). Finally, inequalities (12) ensure that $y_{jit}$ remains non-negative at upstream barriers whenever mitigation is not carried out (i.e., the right hand side of each constraint (11) would potentially be negative if $x_{ji} = 0$, $\forall i \in A_j$).

# 3 Simple Example Problem

In order to illustrate how cumulative passability terms $z_{jt}$ are evaluated along a probability chain, consider a simple example of three artificial river barriers 1-3 located in series above the river mouth, as shown in Figure 3. For simplicity, we assume that there is a single restoration target, which allows us to drop index $t$ from the notation. Initial passabilities for barriers 1-3 are given as $\bar{p}_1 = 0.5$ , $\bar{p}_2 = 0.7$ and $\bar{p}_3 = 0.2$, respectively. We also assume that only a single mitigation project is available at any given barrier, allowing us to drop $i$ from the notation, and that this restores a barrier to full passability (i.e., $p_1 = 0.5$, $p_2 = 0.3$ and $p_3 = 0.8$).

## 3.1 Case 1: No Mitigation

If no mitigation projects are carried out at any of the barriers (i.e., $x_1 = x_2 = x_3 = 0$), then cumulative passability of barrier 3, according to equation (2), is simply the product of the initial passabilities of the

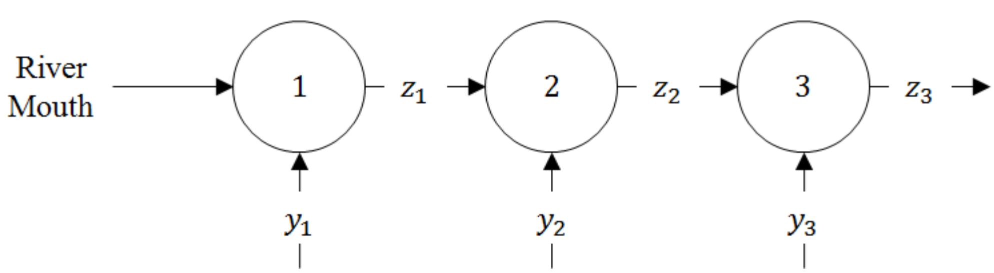



Figure 3: Single stream channel with three artificial barriers located in series above the river mouth.

three barriers (i.e., $z_3 = 0.5 \times 0.7 \times 0.2 = 0.07$). Alternatively, using the linear model, $z_3$ can be determined iteratively using probability chain (6)-(9). Since no mitigation is carried out, we have based on (8) that $y_1 = y_2 = y_3 = 0$. According to (6), we have for barrier 1:

$$z_1 \;=\; \bar{p}_1 + y_1 \;=\; 0.5 + 0 \;=\; 0.5$$

while based on (7), we have for barriers 2 and 3:

$$z_2 \;=\; \bar{p}_2 z_1 + y_2 \;=\; 0.7 \times 0.5 + 0 \;=\; 0.35$$

$$z_3 \;=\; \bar{p}_3 z_2 + y_3 \;=\; 0.2 \times 0.35 + 0 \;=\; 0.07$$

As demonstrated above, the linear model produces a cumulative passability value for barrier 3 that is equivalent to the nonlinear model. Simple inspection shows that the same also holds for barriers 1 and 2.

### 3.2 Case 2: Mitigation of Barriers 1 and 3

Suppose that mitigation is undertaken at barriers 1 and 3 (i.e., $x_1 = x_3 = 1$ and $x_2 = 0$). According to the nonlinear model, $z_3 = 1 \times 0.7 \times 1 = 0.7$. In Box 1, we demonstrate how the linear model produces the same value for $z_3$.

Barrier 1

Based on (8): $y_1 \;\leq\; p_1 x_1 \;=\; 0.5 \times 1 \;=\; 0.5 \quad \therefore y_1 \;=\; 0.5$

Based on (6): $z_1 \;=\; \bar{p}_1 + y_1 \;=\; 0.5 + 0.5 \;=\; 1$

Barrier 2

Based on (8): $y_2 \;\leq\; p_2 x_2 \;=\; 0.3 \times 0 \;=\; 0 \quad \therefore y_2 \;=\; 0$

Based on (7): $z_2 \;=\; \bar{p}_2 z_1 + y_2 \;=\; 0.7 \times 1 + 0 \;=\; 0.7$

Barrier 3

Based on (8): $y_3 \;\leq\; p_3 x_3 \;=\; 0.8 \times 1 \;=\; 0.8$

Based on (9): $y_3 \;\leq\; p_3 z_2 \;=\; 0.8 \times 0.7 = 0.56 \quad \therefore y_3 \;=\; 0.56$

Based on (7): $z_3 \;=\; \bar{p}_3 z_2 + y_3 \;=\; 0.2 \times 0.7 + 0.56 \;=\; 0.7$

Box 1: Evaluation of variable $z_3$ based (6)-(9) given mitigation at barriers 1 and 3.

## 4 Case Study

In order to examine the performance of the linear FPBRP model, barrier data were obtained from the US State of Maine. To provide a benchmark for comparison, the nonlinear version of FPBRP was solved at various budget amounts using the dynamic programming (DP) and greedy add with branch pruning (GABP) algorithms presented in O'Hanley and Tomberlin (2005). The DP formulation is guaranteed to provide an optimal solution to FPBRP, whereas GABP is a heuristic that provides optimal to near optimal solutions. A full discussion of these methods is provided in O'Hanley and Tomberlin (2005). The linear version of FPBRP presented in Section 2.2 was coded in OPL using CPLEX studio version 12.5. The CPLEX model (.mod file) along with a data file (.dat file) for the example network shown in Figure 1 are provided in a set of online appendices. All experiments were run on the same dual-core Toshiba Satellite Pro R850-15F laptop (Intel i3 processor, 2.10 GHz per chip) with 4 GB of RAM.

## 4.1 Background

Watersheds in the State of Maine are impacted by numerous artificial barriers, including culverts and both small and large-head dams. In order to assess the problem in a systematic way, the US Fish and Wildlife Service Gulf of Maine Coastal Program has compiled an inventory of barriers across the state, including their location and a qualitative estimate of migratory fish passability. This dataset consists of a total of 6,989 natural and artificial barriers, as shown in Figure 4. Qualitative passability values (full or partial barrier) were converted into quantitative values (0 and 0.5, respectively). A single mitigation project was considered for each artificial barrier. At small to medium sized dams ($\leq$ 25ft) and culverts, costs were estimated to restore full passability by either dam removal or replacement with a new bottomless arch culvert, respectively. At large dams ($>$25 ft), the cost of installing a fish pass with a passability of 0.75 was estimated. The amount of habitat above any given barrier is characterized as the river length between the barrier and its immediate upstream barriers or the limits of diadromy. The current amount of accessible habitat above barriers (i.e., given a zero budget) for the Maine dataset is 1,816.4 km. The cost of fixing all 6,761 artificial barriers is estimated to be \$721.9M and would result in 23,731.1 km of accessible habitat. Consequently, only 8% of the potential amount of river habitat above barriers is currently accessible within Maine.

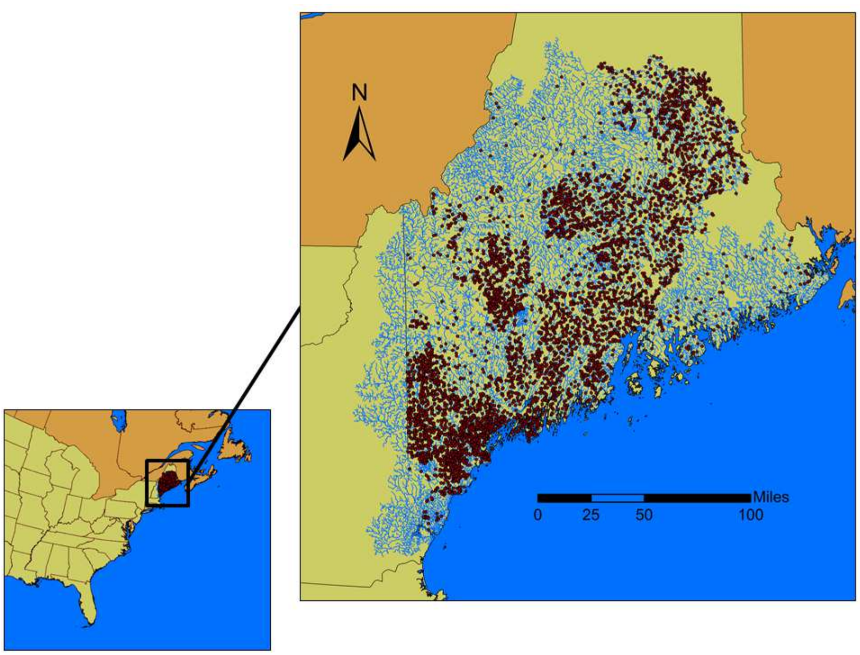



Figure 4: Location of artificial and natural barriers (represented by small dots) across the State of Maine.

Table 2: Performance of CPLEX, DP and GABP on the Maine dataset for selected budget values. Under "Objective," the amount of maximum connectivity weighted habitat is given both in terms of river length (km) and as a percentage relative the maximum gain given mitigation of all barriers (% Max). The column "% Gap" denotes the percentage difference and the column "Diff" the absolute difference between the objective value found with GABP and the optimal objective.

| | Objective | | CPLEX | DP* | GABP | | |
|---|---|---|---|---|---|---|---|
| Budget ($M) | (km) | (% Max) | Time (s) | Time (s) | Time (s) | % Gap | Diff (km) |
| 5 | 8,133.5 | 34.3 | 9.70 | 0.50 | 1.47 | 1.10 | 89.1 |
| 10 | 9,804.5 | 41.3 | 11.27 | 0.70 | 2.84 | 0.26 | 25.4 |
| 15 | 10,781.1 | 45.4 | 8.75 | 0.89 | 5.84 | 1.50 | 161.6 |
| 20 | 11,547.8 | 48.7 | 10.35 | 1.31 | 12.29 | 0.16 | 18.9 |
| 25 | 12,172.0 | 51.3 | 10.67 | - | 6.86 | 0.32 | 39.1 |
| 50 | 14,337.0 | 60.4 | 12.63 | - | 28.10 | 0.14 | 20.4 |
| 100 | 17,074.6 | 72.0 | 12.52 | - | 79.65 | 0.21 | 35.2 |
| 150 | 18,882.8 | 79.6 | 15.56 | - | 108.45 | 0.31 | 57.9 |
| 300 | 21,690.3 | 91.4 | 39.71 | - | 179.65 | 0.33 | 71.8 |
| 450 | 23,077.2 | 97.2 | 36.11 | - | 138.28 | 0.09 | 20.9 |
| 600 | 23,711.3 | 99.9 | 16.92 | - | 123.27 | 0.04 | 9.9 |
| Avg | | | 16.74 | - | 62.43 | 0.41 | 50.0 |

*A "-" indicates that the DP algorithm was unable to find a solution at the specified budget level.

## 4.2 Results

The performance of the CPLEX implementation of FPBRP and the DP and GABP algorithms on the Maine dataset is provided in Table 2. For large datasets such as this, solving the DP algorithm becomes more and more computationally intensive as the total budget rises. Above a certain budget threshold, in fact, the problem becomes intractable and the DP algorithm fails. This threshold was reached at a budget level of between $20M and $25M on the computer used to run our experiments.

Table 2 identifies the DP algorithm as being highly efficient at low budget levels (≤$20M), in which case it is able to find optimal solutions within 2 seconds. Above the $20M threshold, however, DP could not generate a solution. GABP, by contrast, was able to return near optimal solutions often within 30 seconds (180 seconds in the worst case). The optimality gap for the GABP heuristic is generally small at higher budget levels (>$25M), with a maximum gap of only 0.33% (71.8 km) at $300M. For lower budget levels (≤$20M), the optimality gap reached a maximum of 1.50% (161.1 km) at $15M. Whilst less efficient than the DP algorithm at lower budget levels, the CPLEX implementation was nonetheless able to return optimal solutions within 40 seconds for *all* budget levels. It also consistently out performed GABP in terms of solution quality and time at budget levels of $50M and higher. This is a important finding as it means that not only is the linear model capable of providing optimal solutions for large datasets comprising many thousands of barriers, but it also provides them quicker than the GABP heuristic.

A pattern of diminishing marginal improvements in accessible habitat with increasing budget was observed for the Maine dataset. This is illustrated in Figure 5, which shows substantial gains in accessible habitat for modest investments ($5-10M) and small increases in accessible habitat when moving up to larger levels of investment (e.g., at $300M to $600M). More importantly, what the results show is that the majority of potential ecological gain can be achieved at relatively low budget levels. Accessible habitat above barriers could be improved from its current level of 1,816.4 km to 8,133.5 km (more than a fourfold increase) with an investment of just $5M and to 12,172.0 (more than a sixfold increase) given $25M. These budgets represent,

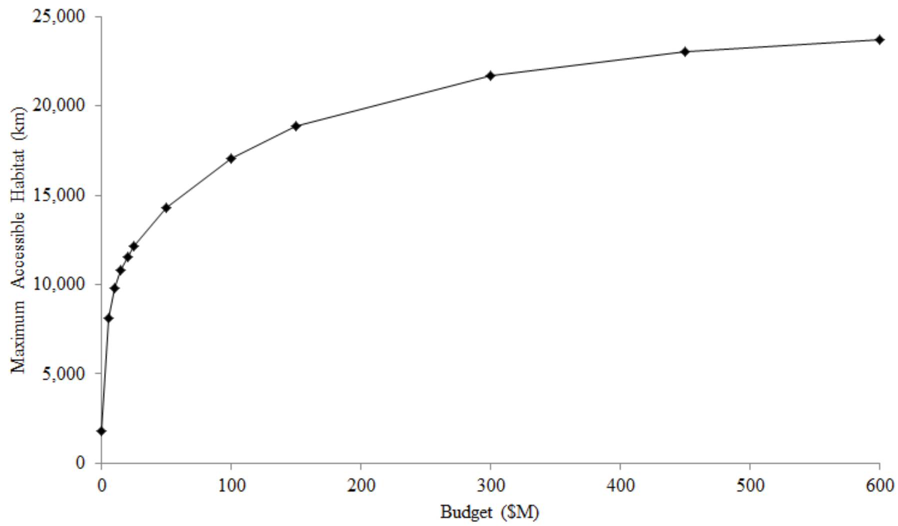



Figure 5: Maximum accessible habitat versus budget for the Maine dataset.

respectively, only 0.7% and 3.5% of the total amount required to mitigate all known artificial barriers within Maine.

Table 3 provides a detailed breakdown of solution characteristics at different budget levels. The first observation that can be made is that at low to moderate budgets (≤$50M), full barriers tend to be selected more than twice as often compared to partial barriers. At a budget of $25M, for example, 215 full barriers (73% of total) are selected versus 79 partial barriers (27% of total). At higher budgets (>$50M), partial barriers begin to dominate within the solution, due primarily to the fact that there are considerably more partial barriers (3,956) than full barriers (2,805).

Another finding, albeit unsurprising, is that barriers selected for mitigation, particularly at lower budgets (≤$50M), are generally located close to the mouths of the river networks. Selected barriers have a relatively few number of downstream barriers, a considerably higher number of upstream barriers, and a large amount of river upstream (Total USL). At a budget of $5M, for example, mitigated barriers have an average of 2.8 downstream barriers and 322.9 upstream barriers. This contrasts sharply with the average 5.4 downstream barriers and 5.3 upstream barriers for artificial barriers as a whole. It is also clear that barriers with higher amounts of net upstream habitat (Net USL) are top priorities for mitigation at low budgets levels. At a budget of $5M, barriers selected for mitigation have a mean of 184.7 km of net upstream habitat, a value substantially higher than 6.2 km for the average artificial barrier.

In terms of cost, barriers selected for mitigation are considerably more expensive than average when the budget is fairly tight (≤$15M). At a budget of $5M, the average cost of mitigation for selected barriers is roughly $45,000 more than the $107,000 needed to mitigate an average barrier. This represents a 42% premium. At budgets of $10-15M, the increased cost is much less pronounced but still 9-12% higher than average. Beyond $15M, selected barriers are cheaper than average, going from -13% at $20M to -45% at $150M. Beyond this budget value, the cost of mitigation relative to the average begins to rise again. This, in combination with the lower than average amount of net upstream habitat for selected barriers at budgets ≥$300M implies that there is a large number of relatively expensive barrier mitigation actions that are not

Table 3: Key attributes of barrier mitigation solutions at selected budget levels. The column "All" provides a breakdown, by attribute, of the 6,761 artificial barriers in the Maine dataset. The upper portion of the table shows for each solution the number of barriers of a given structure type (large dams, small dams and culverts) and their passability level (full versus partial barriers). In lower portion of the table, average values for selected attributes are provided. This includes the cost of barrier mitigation (Cost), the net upstream length of river (Net USL) immediately above a barrier, the total length of river above a barrier to the limits of the system (Total USL), the number of downstream barriers (No. DS Barriers) and the number of upstream barriers (No. US Barriers).

| | | Budget ($M) | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Attribute | All | 5 | 10 | 15 | 20 | 25 | 50 | 100 | 150 | 300 | 450 | 600 |
| No. Barriers | 6761 | 33 | 86 | 125 | 216 | 294 | 647 | 1534 | 2559 | 4693 | 5011 | 6033 |
| Full Barriers | 2805 | 21 | 60 | 89 | 159 | 215 | 453 | 879 | 1219 | 1938 | 2079 | 2476 |
| Partial Barriers | 3956 | 12 | 26 | 36 | 57 | 79 | 194 | 655 | 1340 | 2755 | 2932 | 3557 |
| Large Dams | 58 | 0 | 0 | 1 | 1 | 1 | 6 | 10 | 12 | 22 | 33 | 45 |
| Small Dams | 688 | 30 | 63 | 81 | 100 | 119 | 171 | 237 | 280 | 416 | 476 | 567 |
| Culverts | 6015 | 3 | 23 | 43 | 115 | 174 | 470 | 1287 | 2267 | 4255 | 4502 | 5421 |
| Cost ($k) | 106.8 | 151.5 | 116.3 | 120.0 | 92.6 | 85.0 | 77.3 | 65.2 | 58.6 | 63.9 | 89.8 | 99.5 |
| Net USL (km) | 6.2 | 184.7 | 91.4 | 73.4 | 46.2 | 36.3 | 21.9 | 11.7 | 7.9 | 5.4 | 6.1 | 5.6 |
| Total USL (km) | 44.4 | 1932.6 | 828.5 | 609.7 | 371.1 | 278.6 | 232.4 | 104.8 | 65.2 | 45.7 | 51.8 | 46.9 |
| No. DS Barriers | 5.4 | 2.8 | 2.4 | 2.3 | 2.4 | 2.4 | 3.0 | 3.3 | 3.7 | 4.3 | 4.4 | 5.0 |
| No. US Barriers | 5.3 | 322.9 | 143.4 | 101.8 | 63.2 | 47.8 | 31.33 | 14.4 | 9.4 | 6.6 | 6.4 | 5.8 |

substantially restricting habitat access for migratory fish.

Indeed, looking at the results more closely, we observe that nearly 70% of artificial barriers in Maine can be mitigated with \$300M. This would deliver over 90% of the maximum possible accessible habitat for only 40% of the maximum budget. A very large sum, both in relative and absolute terms, would therefore need to be spent beyond this point for little added benefit, which, in turn, is reflected in the rising average cost per mitigated barrier at \$300M and above. One of the central messages from all this is that barrier mitigation needs to be carefully planned out if substantial connectivity gains are to be achieved. Simply removing barriers opportunistically (as is often the case in practice) will almost invariably result in large amounts of money being spent for minimal benefit (i.e., the vast majority of barriers within this study region have large repair/removal cost combined low amounts of blocked upstream habitat). In this regard, optimization models are an ideal tool for cost-effectively targeting mitigation action.

Perhaps the most significant insight from Table 3 is that small dams play an essential role in optimal mitigation strategies, especially at low to moderate budgets, but large dams do not. At \$25M or below, only a single large dam (>25 ft) is selected for mitigation. None are selected at \$5M or \$10M. Only when the budget reaches \$50M are more than a handful of large dams selected for mitigation but still never exceed 1% of selected barriers. Small dams, on the other hand, are the dominate type of selected barrier for budgets \$15M or less and are considerably over represented in the optimal solution for budgets ≤\$100M. Whereas small dams represent just 9% of all artificial barriers, they nonetheless comprise 91% of selected barriers at \$5M, 40% at \$25M and 15% at \$100M. While culverts are under represented for budgets ≤\$100M, they still represent a majority of selected barriers at budgets ≥\$20M and so constitute a core element in connectivity restoration.

These findings are rather surprising given the popular perception among scientists, policy makers, and the general public that removing large dams holds the key to the recovery of diadromous fish populations. What our analysis shows is that large dams are not the main drivers of connectivity impairment within Maine. On the contrary, mitigating large dams is a costly exercise, which in many cases, may deliver only moderate benefit to migratory fish. Given their cumulatively greater impact on connectivity (due to their vastly larger number) and comparatively low cost of mitigation, targeting small dams and culverts has the real potential to provide a far more effective and economical means of improving river connectivity within this system.

# 5 Conclusions

The negative ecological effects caused by the presence of artificial barriers within rivers are well documented. Barrier mitigation actions aimed at restoring fish passage is widely seen as a highly effective way of improving the integrity of river ecosystems. In this paper, we present a linear version of the Fish Passage Barrier Removal Problem (FPBRP) for optimizing barrier mitigation decisions. The paper contributes to the existing literature by providing a framework for identifying cost-effective solutions to tackle the impacts of river infrastructure on diadromous fish. The model is highly efficient, scalable, and can be readily implemented using off-the-shelf optimization software. We demonstrate the usefulness of our linear model using barrier data from the US State of Maine. The model consistently provides optimal barrier mitigation strategies for any given budget within seconds.

It is anticipated that our model will be of direct benefit to practitioners involved in river barrier mitigation. As Kemp and O'Hanley (2010) discuss, techniques that deliver optimized solutions offer substantial benefits over more traditional planning methods like scoring and ranking. Furthermore, the ability to produce prescriptive solutions that are guaranteed to maximize accessible river habitat highlights the advantage of an optimization based framework over alternative graph theoretic approaches, particularly when analyzing realistically sized datasets.

The model presented here should also prove insightful to watershed managers by clarifying how potential habitat gain varies with different levels of investment. Pareto-optimal trade-off curves, such as Figure 5, can be constructed to identify levels of investment that deliver high environmental returns at suitable cost (O'Hanley, 2011). Indeed, our analysis reveals that substantial habitat gains for migratory fish species can be achieved at markedly low levels of investment. Specifically, within Maine, a budget of $5M would result in more than a fourfold increase in accessible river habitat above barriers. This finding should lend strong support to the notion that barrier mitigation is, in fact, a highly cost-effective form of river restoration.

A natural extension of our present work is to formulate a linear model that accounts for the dispersal needs of resident fish. Research is ongoing in this regard. Looking more broadly, decisions to invest in environmental improvement programs are increasingly being informed by cost-benefits analysis. Incorporating FPBRP or models like it into a bio-economic framework to estimate the dollar value of river connectivity improvements would be informative for both river managers and policy makers and provide an interesting line of future research.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