Regional aquatic priorities process: combining species data and watershed constraints to determine sub-basin specific priorities

The process of prioritization inherently implies that one places more importance or value of one feature over another. However, in the context of spatial priorities, specific locations may be inherently more valuable than others based on the number of features that are found in any given location. Identification of priorities when considering multiple species, particularly at the regional scale entails selecting those locations that represent the greatest number of species while avoiding those places that are highly impaired or vulnerable to aquatic invasives or effects of climate change. However, in doing so, it's essential to avoid omitting those locations that may be critical for individual species. In this sense merely searching for locations where the most species occur falls short of developing multi-objective solutions. Traditional approaches to watershed priorities tend to default to this "index and weight" approach which tends to pit one species against another and favors those locations where multiple species exist rather than considering each location in the context of a broader specified objective. In the Pacific Northwest, these traditional approaches tend favor west side species that are well understood and mapped and where significant overlap of species ranges exist, however they regularly fail to recognize less well known, isolated and therefore endemic species found mostly on the east side of the Cascades.

There are a multitude of approaches to multi-objective decision making that have gained traction in the last decade that attempt to account for some of the limitations of the more traditional index and weight approach to prioritization. Many of these approaches stem from the decision sciences and have become increasingly more sophisticated as they have been extended to account for geographic space in the context of spatial decisions.   Of the wide array of spatially explicit decision support approaches, we evaluated three separate techniques to determine the most applicable for the problem at hand given the extent and available data. The three approaches we evaluated included: fuzzy logic, Bayesian belief networks and a target based approach known as a computational heuristic. The following table briefly summarizes the pros and cons of each approach.

Method	Pros	Cons
Target Based	Optimal (or close to) solution. Easily re-producible. Handles un-standardized data.	Can be difficult to explain. Difficult to handle uncertainty and missing data.
Fuzzy Logic	Can explicitly model uncertainty and it's effects. Good model for abstract relationships or where data is lacking.	Conceptually difficult to grasp, requires development of a knowledge base (time intensive), difficult to integrate into an on-line system.
Bayesian Belief Networks	Once the model is developed, it's simple to re-run. Easy to explain. Represents uncertainty in terms of probabilities.	Expert driven may require re-convening group of experts if values are used to drive the process. Requires definition of all possible outcomes

We used a multi-objective decision support model based on computational heuristics to identify regional priorities at the 4th field, sub-basin scale. We chose the heuristic because it was able to handle un-standardized data from disparate sources and because it is realitively easy to update as new data become available. While both the fuzzy logic and Bayesian approaches are effective at handling uncertainty, they both are limited in that they require input from a wide variety of experts. These experts then would need to be re-convened as new data becomes available, limiting the flexibility and adaptability of the tool.

The heuristic draws on a simulated annealing algorithm to approximate an optimal configuration (or prioritization schematic) given a mathematically defined set of objectives (referred to as an objective function). This target based approach allows for the selection of a set of priority sub-basins based on avoiding those areas that have poor watershed condition, or are highly vulnerable to climate change effects or aquatic invasives, subject to the condition that targets for all species included in the analysis are met.

We chose a simulated annealing approach as the primary modeling framework imbedded in the decision support tool. We use an existing, well vetted and freely available third party software called Marxan (Ball and Poisingham 2001) that implements a simulated annealing algorithm. The model is used to approximate a close to optimal configuration of high priority watersheds while achieving land management preferences (for example, avoiding sub-basins with a high relative vulnerability to climate change).

This spatial simulated annealing analysis selects discrete fourth field sub-basins defined by a wide array of presence, abundance and persistence of aquatic species as well as vulnerabilities to climate change, aquatic invasives and watershed condition across the study area to achieve goal proportions for each species specified by the user through the decision support tool (DST).

Goal proportions are based on the underlying data specific to each species. The goal therefore represents a proportion of the total number of units for any given species. For example, if data for a given species is collected in terms of presence / absence at the sub-basin scale, a goal of 50% would represent 50% of all sub-basins where that species exists. For a description of the units for each species please see the data dictionary.

An objective function is calculated based on meeting these goal proportions while minimizing "costs" associated with selecting sub-basins in poor health or that are highly vulnerable to aquatic invasives or are at risk effects of climate change. This technique iterates through a million possible priority configurations and recalculates the objective function after each run. Initially, the algorithm *temperature* is high, allowing a wide range of possible priority configurations whether or not the objective function improves. As progress is made through the one million iterations, the *temperature* cools and only changes that improve the objective function are accepted. This process helps to avoid local minima in the early rounds and finds progressively more efficient solutions in later iterations.

The objective function can be expressed as follows:

$$\min Z = \sum_{n=1}^{p} C_c \times \sum_{n=1}^{p} P_s$$

Where:
p: Planning unit (4th field huc)
C: costs associated with priority constrains (c) *(e.g. vulnerability to climate change)*
P: penalty incurred for not meeting the specified target of species n.

The resulting priority sub-basins represent an approximation of the optimum configuration of sub-basins given user specified preferences for specific species.