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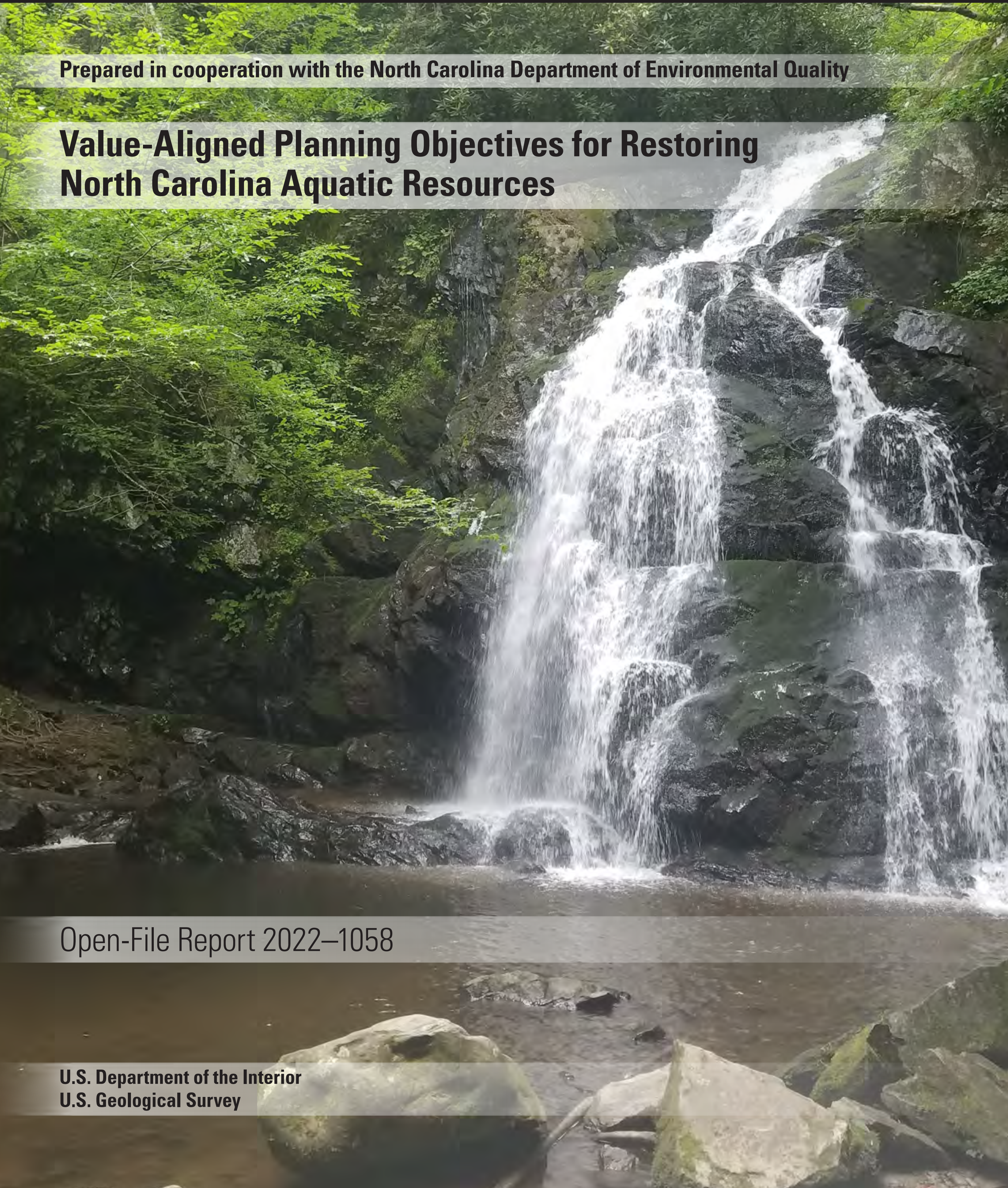
Value-Aligned Planning Objectives for Restoring North Carolina Aquatic Resources



Open-File Report 2022–1058

U.S. Department of the Interior
U.S. Geological Survey

Cover. A headwater stream in the Great Smoky Mountains of North Carolina. Photograph by Mitchell Eaton, U.S. Geological Survey, 2018.

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Contents

Figures

Tables

Abbreviations

DMS	Division of Mitigation Services (of the North Carolina Department of Environmental Quality)
HCZ	hydrologically connected zone
HUC–8	8-digit hydrologic unit code
MCDA	multicriteria decision analysis
NHD	National Hydrography Dataset
PrOACT	Structured decision framework identifying Problem, Objectives, Alternatives, Consequences, and Tradeoffs
SPARROW	SPAtially Referenced Regression On Watershed attributes
USGS	U.S. Geological Survey

Value-Aligned Planning Objectives for Restoring North Carolina Aquatic Resources

By Ana María García,[1] Mitchell Eaton,[1] Georgina M. Sanchez,[1,2] Jennifer L. Keisman,[1] Kirsten Ullman,[3,4] and James Blackwell[3]

Abstract

Rapid population growth and development in the southeastern United States have resulted in substantial impairment to freshwater aquatic ecosystems. National or regional restoration policies strive to address impaired ecosystems but can suffer from inconsistent and opaque processes. The Clean Water Act, for example, establishes reallocation mechanisms to transfer ecosystem services from sites of disturbance to compensation sites to offset aquatic resource functions that are unavoidably lost through land development. However, planning for the prioritization of compensatory mitigation areas is often hampered by unstructured decision-making processes that are narrowly framed because they are not co-produced with stakeholders affected by, or having an interest in, the impacts and mitigation. This summary report represents the collaborative efforts of the U.S. Geological Survey and the North Carolina Department of Environmental Quality, Division of Mitigation Services, to co-develop an applied decision framework following the principles of structured decision-making for prioritizing watershed catchments by their potential for realizing a range of beneficial outcomes from future mitigation projects. The framework focuses on supporting the State's nationally recognized stream and wetlands compensatory mitigation program by clarifying a discrete decision problem and specifying agency and stakeholder values to formulate fundamental and means objectives for prioritizing restoration sites. The co-development of this decision framework resulted in a number of useful insights from the perspective of the decision maker, including recognition (1) that the problem is a multi-objective decision driven by values beyond restoring lost functionality of ecosystems (that is, biogeophysical goals), (2) that the decision comprises a linked and sequential planning-to-implementation process, and (3) that future risk associated with land-use and climate change must be considered. The outcomes of this collaboration can serve as a systematic and transparent framework to prioritize a wide range of restoration, conservation, and resource-allocation activities in similar environmental contexts across the Nation.

Introduction

Ecosystems in the southeastern United States have been disturbed by the substantial and rapid population growth of recent years. Several studies predict environmental damage, including a recent U.S. Geological Survey (USGS) study that estimated 61 percent of streams in the southeastern Piedmont will have extensive losses in invertebrate taxa because of projected urban growth (Van Metre and others, 2019). As a result of the known deleterious effects of rapid development, the Clean Water Act (33 U.S.C. §1251 et seq.) establishes the authority for States to develop reallocation mechanisms such as mitigation banks and in-lieu fee mitigation programs. Such programs frequently attempt to transfer ecosystem services from areas of disturbance to compensation sites as an offset of aquatic resource functions that are lost through land conversion (Short, 1988; Palmer and Filoso, 2009). Damages are tracked and quantified, and compensation credits are generated at locations within the service area but not where the damage was incurred (Widis and others, 2015). This reallocation requires a mechanism for the spatial distribution of accrued mitigation credits (Cipollini and others, 2005).

Within the State of North Carolina, the Department of Environmental Quality, through the Division of Mitigation Services (DMS), administers an in-lieu fee mitigation program to offset effects to streams, wetlands, and riparian buffers associated with development in the State. This program sells compensatory mitigation credits to developers and infrastructure builders who are affecting the aquatic resource and later implement compensation activities (Bronner and others, 2013). Transfer of aquatic resource functions, which for the purposes of this study were broadly described as water quality, hydrology, and habitat, from one place to another often involves complex planning and decision making. Recognizing the need to connect holistic aquatic health to site-specific restoration projects, the DMS has implemented a structured decision-making approach to characterize elements of their decision process, to

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identify relevant knowledge gaps, and to develop potential forward-looking strategies. The U.S. Department of the Interior has recently engaged in decision-science applications to efficiently integrate scientific findings and data in natural resource management (Williams and others, 2009). This report documents elements of a decision framework that was developed during a 2-year cooperative project between the DMS and USGS. The framework development began by first working with the DMS to articulate the decision problem and specifying DMS and stakeholder values to formulate fundamental and means objectives for prioritizing restoration sites. The foundation of this framework is a hierarchy of objectives that captured DMS values and can be evaluated via quantifiable attributes. These attributes can evaluate progress towards meeting DMS goals while recognizing that elements of the decision framework are likely to be revised and updated as more information becomes available.

Applying Structured Decision Making

Structured decision making is a widely used and well-tested framework for addressing complex problems through systematic decomposition of a decision process (Runge and others, 2016). Applying the Problem, Objectives, Alternatives, Consequences, and Tradeoffs (PrOACT; fig. 1) decision process (Gregory and Keeney, 2002) involved multiple workshops aimed at formulating an initial decision prototype and associated components; mainly, decision problem, objectives, and measurable attributes. The process was iterative with multiple revisions of the foundational elements and progressively adding complexity to the framework.

Between February 2019 and May 2020, the USGS and DMS had three in-person, full-day workshops and monthly 1-hour phone call meetings. For the first set of meetings and the first workshop, the goal was to characterize the decision problem. The following workshops were organized around prototypes of the decision process. The elicitation process involved reacting to the prototypes to iteratively refine elements. Within the project timespan, it was possible to clarify the decision problem and iteratively identify quantifiable objectives and measurable attributes and identify knowledge gaps.

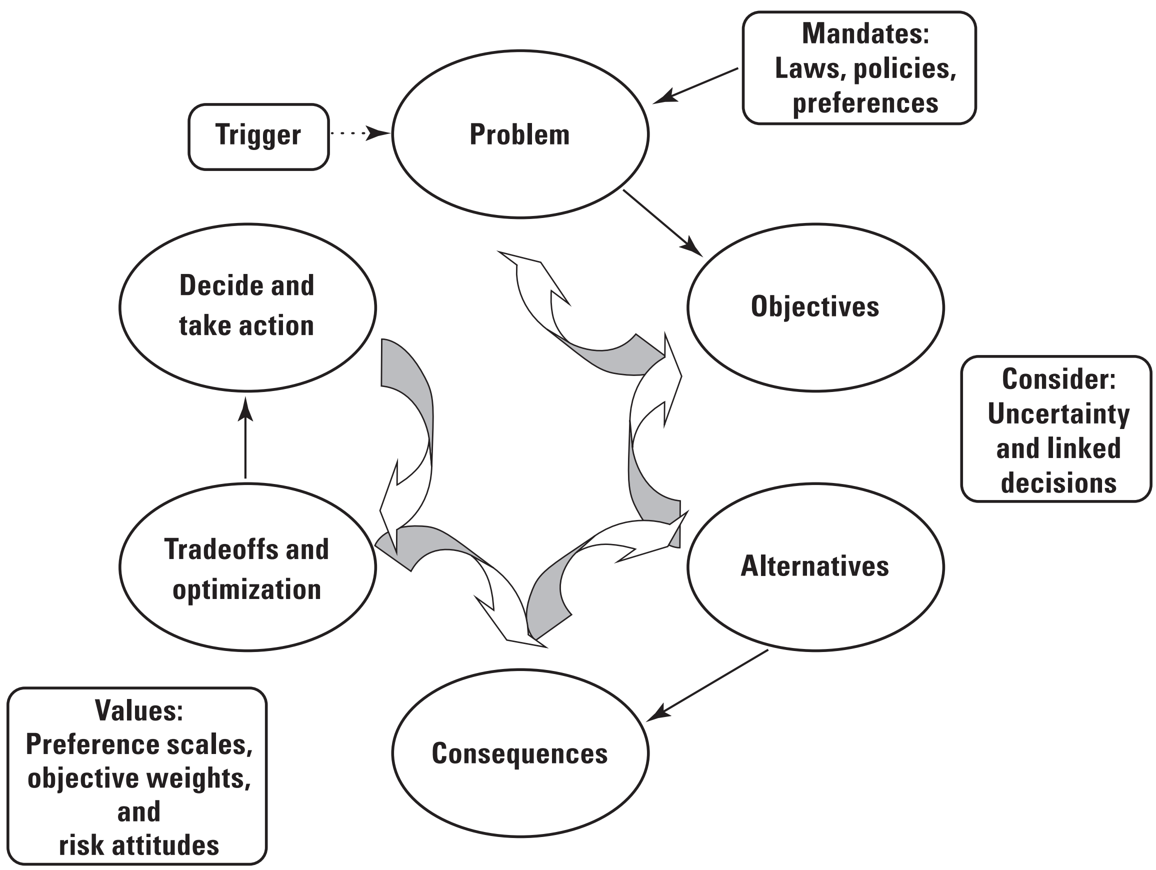

Figure 1. Diagram depicting the sequence of structured decision-making elements using the Problem, Objectives, Alternatives, Consequences, and Tradeoffs (PrOACT) process. Diagram credit: Jean Fitz Cochrane, U.S. Fish and Wildlife Service; used with permission.

Decision Problem

As defined in decision science, a decision is characterized as a choice between two or more actions, requiring an irrevocable allocation of resources towards that choice. A decision problem is a concise articulation of the decision needing to be made and serves to outline the nature and scope of the decision-making process. The DMS uses a sequential decision process to allocate financial resources to restoration projects in the State. Within the DMS, a group of decision makers that are identified herein as the “watershed planning group” prioritizes areas within a defined space for stream and wetland restoration projects to be implemented by a separate subgroup of decision makers, the “operations group.” In this study, we focused on the watershed planning group’s decision, which is further complicated in that the prioritization occurs ahead of full knowledge of the extent of compensatory mitigation needs. The procurement process involves private sector firms that propose projects to fulfill the mitigation needs; therefore, implementation decisions are recommended by private firms and landowners.

The decision problem spans several spatial scales. The “sub-basin scale” (also termed “service area”) is defined as a broad, hydrologically contained region within which mitigation credits are generated and expended. For planning purposes, the 8-digit hydrologic unit code (HUC–8) as defined within the Watershed Boundary Dataset (U.S. Geological Survey and U.S. Department of Agriculture, Natural Resources Conservation Service, 2013) is the spatial unit that defines the “sub-basin scale.” The watershed planning group identifies priorities for restoration by developing scores for watersheds within the larger sub-basin. What constitutes a watershed can vary depending on points of interest and physiographic characteristics of the landscape. Currently, the DMS uses watersheds defined by the National Hydrographic Dataset (NHD) version 2 catchments for decision making. In this document, we will use the word “catchment” to refer to NHD catchments and “watershed” as a generic term. The scale of the catchment is still substantially larger than the scale of restoration project implementation, which is often referred to as the “reach scale.” An additional spatial definition is the concept of mitigable areas. Mitigable areas include historical stream corridors and wetlands suitable for generating mitigation credits via nature-based restoration methods (natural channel design, wetland restoration and enhancement, and riparian buffer restoration and establishment). In summary, restoration needs are broadly accrued or anticipated at a large (HUC–8) sub-basin scale, and reach-scale restoration projects are elicited by, among other things, prioritizing watersheds for restoration.

The watershed planning approach augments the accumulated benefits of a potential collection of projects by establishing a systematic, spatially explicit evaluation of valued restoration interests rather than estimating the performance of individual projects in isolation. This aspect of the mitigation framework is critically important; the scientific consensus (for example, Bernhardt and others, 2005) is that reach-scale restoration alone can often yield small and localized ecosystem benefits but, when integrated with catchment scale planning framework, the likelihood of improved ecosystem health is improved.

To provide additional context for the DMS decision process, we elicited and discussed various elements that constitute a “problem statement,” which provides a foundation and guide for the later steps of the prototype decision model. The decision context is primarily characterized by identifying the decision maker and the authority by which they act. Additional elements described in problem framing include the scope (that is, the spatial and temporal extent of the decision), the timing and frequency (that is, whether the decision happens once or is repeated at regular or irregular intervals), whether a specific event or action triggered the need for a decision to be made, and other relevant background information such as knowledge of primary sources of uncertainty or statutory constraints. We captured these elements in a brief problem statement (sidebar 1) that was used to keep subsequent discussions on track and to communicate the goals of the project to others.

Sidebar 1. Problem Statement

The watershed planning group (decision maker) participates in a linked and sequential decision process that acts to satisfy compensatory mitigation requirements associated with permits accepted from customers of the Stream and Wetland In-Lieu Fee Mitigation Program and from the North Carolina Department of Transportation. Compensatory mitigation is required to replace aquatic resource functions that are unavoidably lost as a result of development permits (triggers). The Division of Mitigation Services Planning evaluates and scores (action) catchments to elicit mitigation projects within the service areas (8-digit hydrologic unit codes) across North Carolina (decision scope). The scoring is independent among 8-digit hydrologic unit codes and based on a 10-year planning cycle (frequency and timing). Ranking is performed ahead of full knowledge of the extent of compensatory needs (constraint and uncertainty).

Fundamental Objectives

Evaluating the potential to achieve one or more fundamental objectives or “ends” provides the foundation for all decision-making processes. Fundamental objectives describe the decision maker’s desired future conditions and serve as the primary motivation for making any decision. Predicting the degree that any alternative course of action will meet stated objectives is how one action is selected over another. Fundamental objectives are essential, nonsubstitutable, and comprehensive in that they capture the full set of decision maker and stakeholder values. Conditional on the problem statement articulated during this project, the DMS initially identified a single objective that provided the fundamental rationale for their role in the mitigation planning process (sidebar 2).

Sidebar 2. Management Objectives

Initial fundamental objective.—Score catchments based on the most relevant available information to elicit mitigation projects and maximize aquatic resource health now and into the future.

The fundamental objective was revisited during workshops 1 and 2, and eventually a multi-objective framework was developed such that the fundamental objectives are as follows:

1. Maximize the feasibility of mitigation projects,
2. Maximize aquatic resources health, and
3. Minimize future risk of impairment.

Component Objectives and Measurable Attributes

In addition to specifying fundamental objectives, a decision process recognizes the existence of other, more operational objectives by which the fundamental objectives can be achieved and measured. Although comprehensive and essential to decision making, we determined that the higher-level, fundamental objectives specified by DMS were either too broad (for example, in the case of project feasibility) or possibly lacking controllability (for example, in the case of meeting aquatic resource health objectives) to allow sufficient understanding for analyzing alternatives. We therefore worked with workshop participants to identify lower-level “component objectives” (Keeney, 2007) for each fundamental objective, which served to clarify and define the essential elements of the higher-order objectives, as well as operationalize measurable attributes used for evaluating and comparing catchments. To quantify and evaluate management objectives, planners must specify performance metrics or measurable attributes for each objective at an appropriate level in the objective hierarchy. Measurable attributes are used for predicting the expected performance of any decision alternative in terms relative to the objectives, comparing relative benefits and quantifying tradeoffs among multiple objectives, and evaluating progress towards achieving objectives after a decision is implemented.

Objectives Hierarchy

We structured our component objectives through an “objectives hierarchy” to clarify their relation to fundamental objectives and provide a more comprehensive and transparent foundation for tradeoff analysis (Keeney, 2007). An objectives hierarchy (also called a “means-ends network”) is a tool used to organize and visualize a network of management objectives with the primary goal of providing a logical and mathematically coherent foundation for developing and conducting tradeoff analyses. Objectives are arranged hierarchically such that subordinate (component or means) objectives identified under a higher-level objective are part of, and help define, that higher-level objective (See Lyons and others, 2020, fig. 10.1). Lower-level objectives affect the achievement of objectives at higher levels, and the highest-level objectives represent the fundamental values that ultimately drive decision making. Therefore, it is preferable to measure the performance of any decision alternative at the highest level possible in the hierarchy because of the proximity to the values that we fundamentally care about. However, defining measurable attributes at the highest level of the hierarchy (that is, for fundamental objectives) is commonly impractical, as would be the case, for example, of the objective to maximize aquatic resources health. Instead, expected performance is measured at the level of the component objectives, and then these metrics are aggregated through the hierarchy to evaluate the performance of any proposed decision at the level of individual fundamental objectives. Such an approach is needed to evaluate an overall performance assessment and tradeoffs among fundamental objectives.

To accomplish this assessment, decision makers must weight objectives according to their preferences, reflecting the reality that all objectives are not valued equally (see below in the “Objective Weights” and “Value Functions” sections). At each level of the hierarchy, weights are quantitative statements about the importance of a given objective relative to other objectives. The values of subordinate objectives, themselves weighted relative to other objectives at the same level, are proportionally adjusted by the weight for the associated objective one step higher (or to the left; fig. 2) in the hierarchy. In this manner, criteria measures can be mathematically combined and transferred upward (leftward) through the hierarchy until reaching the relevant fundamental objective, without the risk of “double counting” (that is, biasing one objective because it has a larger number of associated means objectives being measured).

Through an iterative process of elicitation that spanned three face-to-face workshops, an objectives hierarchy for watershed planning was developed (fig. 2). Detailed descriptions of the elements of the objectives hierarchy are presented in subsequent sections of this document. Using these multiple objectives in scoring and prioritizing catchments can be classified as a multicriteria decision analysis (MCDA) problem (Prato and Herath, 2007; Gregory and others, 2012; Kurth and others, 2017). Solutions to MCDA problems affirm that multiple objectives are evaluated simultaneously, and some may be in competition (that is, an alternative doing better on one objective may result in lower performance on another), and that objective attributes are often measured on different scales (Keeney, 2002; Davies and others, 2013).

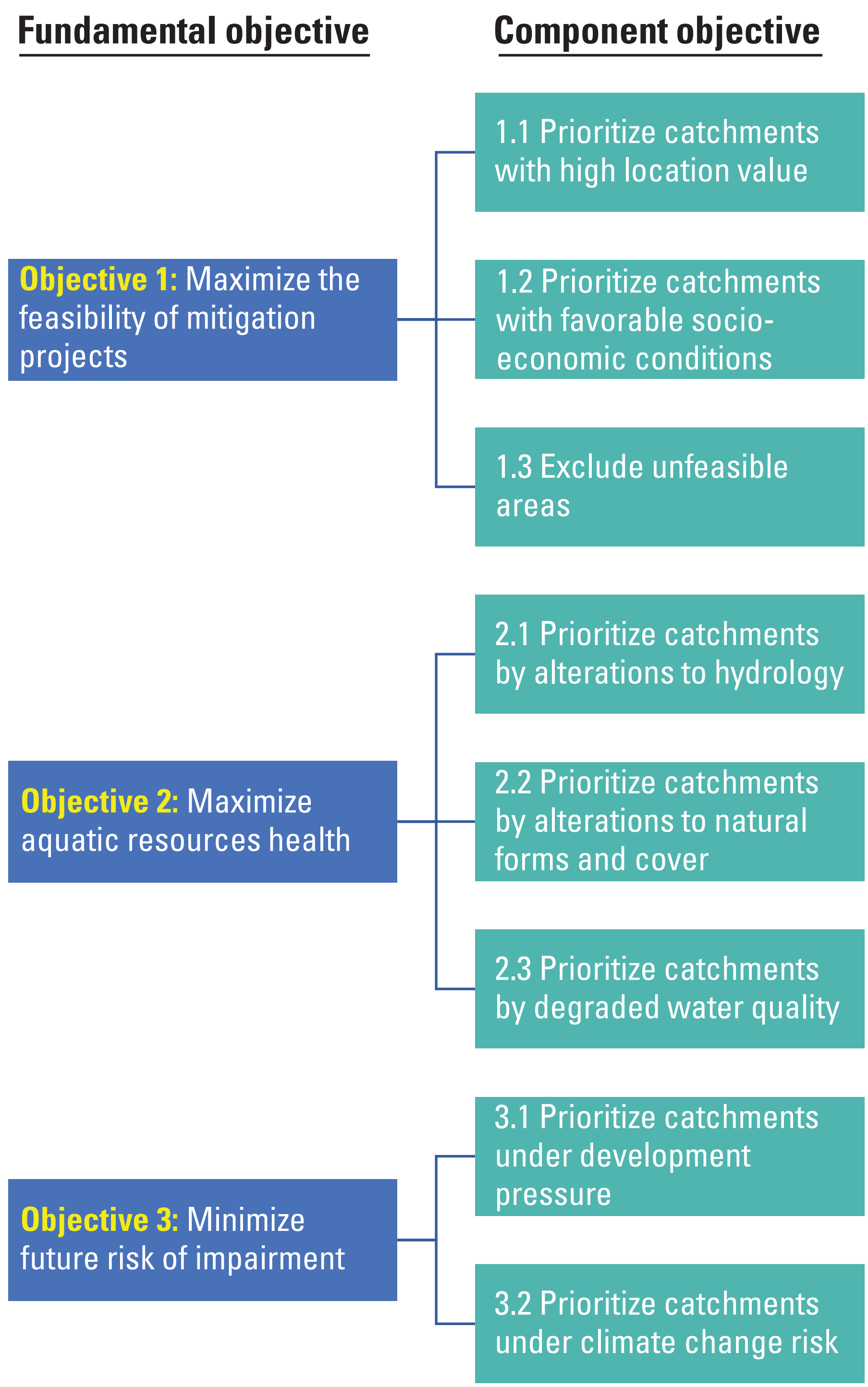

Figure 2. Diagram showing objectives hierarchy for restoration planning at the Division of Mitigation Services of the North Carolina Department of Environmental Quality. Descriptions of measurable attributes associated with each component objective are detailed elsewhere in the report.

Value Functions for Component Objectives and Measurable Attributes

MCDA problems are characterized by the need to account for tradeoffs among objectives when evaluating decision alternatives. Although many methods exist for addressing MCDA problems, we applied multi-attribute value theory (Lyons, 2020) to model tradeoff analyses and rank the expected relative value of individual catchments as function of DMS preferences.

We conceptualized a prioritization scheme that depended on a spatially explicit assemblage of [0–1] scores for each catchment in a given service area (fig. 2). The score would be a number that reflected the total value, V_i, of catchment i after evaluating the predicted outcome of individual objectives (eq. 1). The relative value (benefit) of scoring a catchment higher for projects is a preference-weighted average of the contribution from each objective:

$$V_i = \sum_{j=1}^{n} x_{i,j} \, w_j \qquad (1)$$

where

- V_i is the total value (or the score) of catchment i,
- n is the total number of objectives within a level of the objectives hierarchy,
- x is the performance measure (that is, the outcome of a value function, standardized to a common scale [0,1] over all measures) for objective j in catchment i, and
- w denotes weights or relative preferences for each of the j=1…n objectives.

Because the objectives represent the comprehensive set of values attributed to the decision problem, the weights should sum to 1:

$$\sum_{j=1}^{n} w_j = 1 \qquad (2)$$

The predicted outcome (on its natural scale) for each objective in a given catchment is expressed through a value function to produce a value $x_{i,j}$, which accurately reflects the decision maker's preferences over the range of possible outcomes and standardizes the metric to a [0,1] scale for comparison with all other objectives (eq. 1). Value functions can take a variety of forms, including linear and nonlinear representations, and are standardized by scoring as zero the lowest possible measurable attribute value for the objective (across all catchments), and scoring as one the highest possible attribute value. The linear value function confers the property that any incremental change in predicted outcome is valued equally by stakeholders. More complex value functions can be used to better represent decision-maker preferences, such as to capture risk attitudes (the function of which would then be classified as a "utility") or when benefits are not valued equally across the range of possible outcomes. For example, as we present in a subsequent section, an identified objective for the decision framework was to prioritize watersheds based on increased benefit of reducing the catchment-weighted averaged distance between mitigation projects and intact areas (see subobjective 1.1.2, proximity to projects and intact areas). As such, the marginal benefit of reducing interproject distance (the measurable attribute for this subobjective) from 200 to 190 kilometers (km) is valued differently than reducing this distance from 30 to 20 km. A proposed value function for this objective might take the form depicted in figure 3*A*, in which catchments with average distances of 30 km or less (that is, on the natural scale, x axis) would be considered of high value (that is, expressed as close to 1.0 on the standardized value scale, y axis) and catchments beyond that distance quickly decline in value (that is, close to zero on the value scale, y axis). An alternative form of this value function might reflect a preference by the DMS to have all selected mitigation sites catchments be within 30 km of a protected area (fig. 3*B*). This alternative would be a step function or constraint, the effects of which on the prioritization results can be understood by comparing the two functions specified in figure 3.

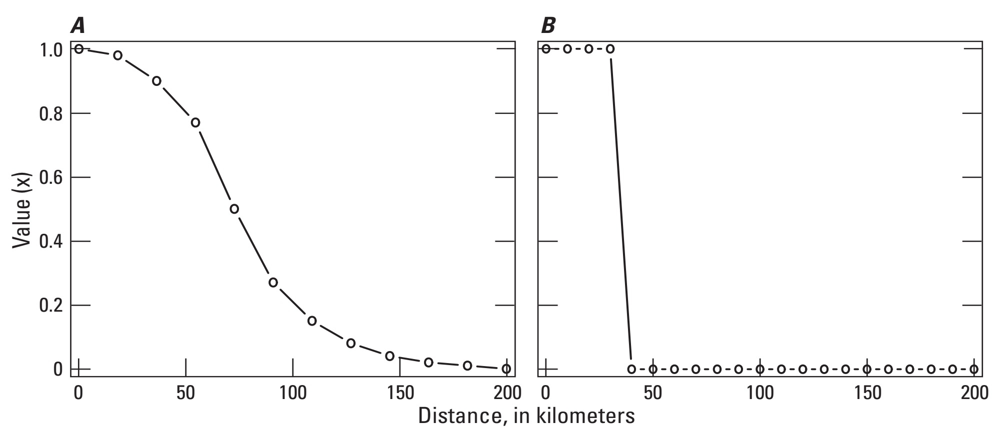

Figure 3. Graphs showing two forms of value functions specifying decision-maker preferences for the outcome for a single objective (distance between intact areas). *A*, relation as a sigmoidal decline in value with increasing distance to nearest mitigation project. *B*, alternative specification that quantifies any site farther than 30 kilometers as having zero value relative to this objective.

Objective Weights

Objective weights are essential for analyzing the tradeoffs inherent in complex, multicriteria problems because the weights represent how a decision maker values each objective. As a subjective component of the decision model, selecting from several established techniques used to elicit accurate objective weights requires some consideration to accurately depict the decision maker's intent and preferences. Ample literature exists on this subject (see Keeney and others, 1990; Goodwin and Wright, 2001, 2004; Monat, 2009 for examples). The first consideration is the choice of objective attribute scale used when determining weights; the second consideration is the method to elicit the weights themselves (Monat, 2009). The selection of an attribute scale and the approach used to determine objective weights must appropriately capture their mathematical relation. Objective weights are not absolutes but depend on the range of possible consequences (for example, when purchasing a new car, price is one common objective of the decision maker. The weight assigned to this objective should reflect the range of car prices under consideration, where lower weight is attributed to this criterion if the price differential is small [for example, $500 over the range of alternatives] relative to a large difference in cost between the least and most expensive options [for example, $5,000]).

The two primary forms of attribute scales are local and global. A local scale establishes the range of attribute values based on the set of alternatives currently available to the decision maker, whereas a global scale establishes a value for the worst and best cases of an attribute based on participants' experience (that is, personal knowledge of the subject), on the imagined worst- and best-case scenarios, or on an aspirational range of what the participants believe could realistically be achieved (Monat, 2009). The use of local attribute scales requires recalculation of objective weights if new alternatives arise that change the range of possible outcomes; in addition to the cognitive and logistical burden of a new elicitation, research has shown that criteria weights are often adjusted insufficiently to correctly account for the new range (Monat, 2009). Assigning global attribute scales has the benefit of being more intuitive, easier to elicit, easier to convey preferences to others, and not subject to recalculating weights as the decision context evolves. Use of either scale requires normalizing attribute values for the actual alternatives to evaluate a decision over multiple objectives measured on different scales. For local scales, the alternative with the best value for the objective is transformed to 1, the worst value is transformed to 0, and intermediate values are mapped to their relative positions between 0 and 1. Alternatively, when using global scales the global best and worst cases are set at 1 and 0, respectively, and the attribute values of the actual decision alternatives are mapped relative to these; these transformed values are then used in the subsequent tradeoff analyses.

Next, an appropriate method for eliciting objective weights, as a function of attribute scales, must be selected. Although there are several methods for determining objective weights, two commonly used approaches include importance weighting and swing weighting (see Keeney and others, 1990; Srivastava and others, 1995; Goodwin and Wright, 2001, 2004). Importance weights are relative values based on the stakeholder preference for a criterion (objective) relative to the other criteria under consideration (Monat, 2009). Swing weights differ in that they reflect preferences based on how important an objective's swing in value is, from worst to best, relative to the value swings for the other decision criteria (Goodwin and Wright, 2001). Research has suggested that applying local attribute scales precludes the use of importance weighting methods, and using global scales precludes eliciting values by swing weighting (Monat, 2009).

Although we used part of one workshop (December 17, 2019) to demonstrate both elicitation methods—importance weighting using global attribute scales and swing weighting using local scales—we present here only the results of the importance weighting approach (table 1). This method is likely the most useful for the DMS going forward, given their need to transfer the decision model to multiple local contexts, in this case the different service areas in the State. If the approach were to implement swing weighting with local (HUC–8) scales, each would have a particular local attribute scale, which would necessitate rescaling objective weights.

Our demonstration focused on determining weights for the three fundamental objectives. Because attributes were not available for objectives at this level, we selected a single component objective (with its attribute) to represent each of the fundamental objectives. For each component objective, we asked participants to identify a global (aspirational or experiential) scale for the range of attribute values. In practice, this could mean, for example, looking at regional or national values for a particular attribute when State-specific values are unavailable. For some component objectives (for example, probability of future land development), the global range was predetermined by the attribute characteristic (for example, a probability scale from 0 to 1). Considering the global range of each criteria attribute, participants were then asked to rank the importance of each objective relative to the other objectives. Finally, each participant gave 100 points to the highest-ranked objective and assigned a relative importance score (0 to 100 points) to the remaining objectives. Ranking before assigning raw scores is a cognitive aid allowing participants to first prioritize objectives and then express their relative distance from one another using a finer-scale metric. Scores were normalized so the weights sum to 1. This procedure could be performed similarly for the set of component objectives related to each fundamental objective and potentially as one approach for developing composite metrics for component objectives evaluated by more than one attribute (see fig. 2).

Table 1. Outcome of example objective weight elicitation using direct-weighting methods.

[Objective hierarchy is shown in figure 2]

Participant number or metric	Importance weighting		
	Objective		
	Feasibility[1]	Aquatic health[2]	Future risk[3]
Global scale			
Worst	2,000	255	0
Best	1	0	1
Rank			
1	3	2	1
2	2	1	3
3	3	1	2
4	3	1	2
5	3	1	2
Raw score			
1	40	99.99	100
2	50	100	30
3	0	100	75
4	10	100	50
5	50	100	70
Weights			
1	0.17	0.42	0.42
2	0.28	0.56	0.17
3	0	0.57	0.43
4	0.06	0.63	0.31
5	0.23	0.45	0.32
Weight summary			
Mean	0.15	0.52	0.33
Low	0	0.42	0.17
High	0.28	0.63	0.43
Standard deviation	0.115	0.086	0.105

[1]Objective 1, maximize the feasibility of mitigation projects. Parcel density selected as representative component objective (attribute: parcel count per catchment)

[2]Objective 2, maximize aquatic resources health. Existing stream-buffer vegetation selected as representative component objective (attribute: normalized difference vegetation index value)

[3]Objective 3, minimize future risk of impairment. Development probability selected as representative component objective (attribute: probability of land conversion)

Objectives Framework for the Division of Mitigation Services

What follows are detailed descriptions of the elements of the objectives hierarchy identified in figure 2, where we also specify candidate attributes that may be used to predict and evaluate performance towards each component objective and, therefore, the achievement of each fundamental objective (table 2). Although we do not describe each measurable attribute in detail, we propose possible data sources currently available for many of these, or we note information gaps. Items numbered parenthetically refer to attributes in table 2. For this study, we limited our analysis to simple value functions (some are illustrated in this report) that were prototyped for several objectives during meetings with DMS staff.

As the component objectives and measurables are described, it is important to recognize that the fundamental objectives are distinct and independent. That independence carries through to the component objectives. Some measurable attributes are similar; however, this potential "double counting" is appropriate because of the higher-level independence in the objectives hierarchy and is accounted for by the allocation and re-scaling of weights.

Objective 1—Maximize the Feasibility of Mitigation Projects

Early in the project, workshop discussions centered on strategic and logistic elements that have historically prevented or enhanced the project implementation process. The DMS identified the need to specify attributes at the catchment level that would promote "good" stream or wetland restoration project proposals in the subsequent phase of mitigation procurement. Via these discussions, "good" restoration projects were defined as those that were technically feasible and provided the greatest possibility of leveraging opportunities that could increase ecosystem function relative to current condition. Some of these factors are often overlooked in similar restoration decision frameworks (Lovette and others, 2018).

1.1. Prioritize Catchments with High Location Value

This component prioritizes catchments that by location provide opportunities that can be capitalized by the implementation of a restoration project.

Table 2. Multi-objective linear additive model hierarchically structured by fundamental objectives, component objectives, and preliminary measurable attributes.

[Only measurable attributes discussed in the text are numbered. Objective hierarchy is shown in figure 2. Abbreviations: NC, North Carolina; DEQ, Department of Environmental Quality; USGS, U.S. Geological Survey; NDVI, normalized difference vegetation index; USDA, U.S. Department of Agriculture; TSS, total suspended solids]

Fundamental objective	Component objective	Measurable attribute	Unit (scale)
Objective 1: Maximize the feasibility of mitigation projects	1.1 Prioritize catchments with high location value	1.1.1 Proximity to existing mitigation projects	Kilometer (0 to 16)
		1.1.2 Proximity to intact areas: position with regard to headwaters, smaller drainage areas, or unimpeded downstream conditions. Average stream order (numerical designations that indicate where in a catchment stream segments lie; headwaters are streams of 1st, 2d, and 3d order; Schwarz, 2019).	Stream order (1 to 6)
	1.2 Prioritize catchments with favorable socio-economic conditions	1.2.1 Land cost. Average land value in catchment.	U.S. dollar
		Active stakeholder engagement. Known community efforts. Data not currently available. Examples include accounting for existing NC DEQ 319 Grant Program or Total Maximum Daily Load plans.	Number of plans/projects
		1.2.2 Parcel density (also a proxy for population density [North Carolina Geographic Information Coordinating Council, 2019]).	Number of parcels per square-kilometer catchment (25 to 920)
	1.3 Exclude unfeasible areas	1.3.1 Topographic constraints. Elevation and slope (U.S. Geological Survey, 2017).	Percentage (0 to 85)
		1.3.2 Catchments that are entirely water. Percentage of total catchment area classified as water (Homer and others, 2015).	Percentage (0 to 100)
Objective 2: Maximize aquatic resources health	2.1 Prioritize catchments by alterations to hydrology	2.1.1. Indicators of streamflow alteration. Directional change of hydrologic metrics relative to natural conditions (Eng and others, 2019).	Categorical (inflated, diminished, indeterminant)
		Channel straightening (that is, loss of sinuosity) and incision (that is, openness). Positive landscape openness can be used as a metric of channel incision (Rowley and others, 2018).	Degrees (86 to 89)
	2.2 Prioritize catchments by alterations to natural forms and cover	2.2.1 Density of ditch drainage. Density of linear channel features classified as canal, ditch, or pipeline within the catchment (Hill and others, 2016).	Kilometer per square kilometer (0 to 22)
		2.2.2 Fragmentation in the hydrologically connected zone (HCZ). Large areas of potentially restorable wetlands (that is, percentage of total catchment area that is non-impervious land and not wetland [Homer and others, 2015] and with hydric soils [Soil Survey Staff, 2019]).	Percentage (0 to 88)
		2.2.3 Loss of aquatic connectivity. Denuded buffers, calculated as the mean NDVI value within a 30-meter buffer of streams and wetlands (USDA, 2020).	Dimensionless index (0 to 148)
	2.3 Prioritize catchments by degraded water quality	2.3.1 Extent of upland sources of diffuse pollution (for example, nitrogen, phosphorous, or TSS loads). Total sediment load associated with agriculture, development, openness, and land use changes, combined (Gurley and others, 2019).	Milligram per year per square kilometer (1 to 446)
		2.3.2 Extent of point-source pollution in the HCZ. Direct disturbances near or within mitigable areas; total direct phosphorus contamination (Gurley and others, 2019).	Kilogram per year per square kilometer (0 to 167,681)

Table 2. Multi-objective linear additive model hierarchically structured by fundamental objectives, component objectives, and preliminary measurable attributes.—Continued

[Only measurable attributes discussed in the text are numbered. Objective hierarchy is shown in figure 2. Abbreviations: NC, North Carolina; DEQ, Department of Environmental Quality; USGS, U.S. Geological Survey; NDVI, normalized difference vegetation index; USDA, U.S. Department of Agriculture; TSS, total suspended solids]

Fundamental objective	Component objective	Measurable attribute	Unit (scale)
Objective 3: Minimize future risk of impairment	3.1 Prioritize catchments under development pressure	3.1.1 Extent of mitigable areas under near-term risk of development. Future development probability as estimated by the Future Urban-Regional Environment Simulation (FUTURES) model under a business-as-usual development scenario (Sanchez and others, 2020a, b)	Probability (0 to 100)
	3.2 Prioritize catchments under climate change risk	3.2.1 Extent of intact, mitigable areas with resiliency capacity. Estimate of site-specific resilience capacity to climate change (for example, the Nature Conservancy Resilience Score; Anderson and others, 2014)	Resilience score (least resilient to most resilient; Likert scale)

1.1.1. Proximity to Existing Mitigation Projects: Catchment Position

Disturbances in the headwaters cascade negative consequences downstream through river networks. For example, smaller streams near urban centers are vulnerable to burial, channelization, and straightening, leading to a modified stream network with lower drainage density, sometimes termed as stream deserts (Elmore and Kaushal, 2008).

Data Sources

The Enhanced NHD, version 2 (Brakebill and others, 2020), provides catchment-level information on stream size and particularly Strahler stream order (1–10). Each stream segment is treated as a node in a tree. Upstream segments are assigned low stream-order numbers; these, in turn, flow into higher order streams downstream (Strahler, 1952). This variable provides a readily available dataset that can be used to identify catchment position.

Value Function

Catchment position scores follow a linear threshold function with the highest values associated with the lowest stream order numbers (1–3) but with a ramp to accommodate a sliding value scale for small streams and various hydrologic configurations (fig. 4).

1.1.2. Proximity to Intact Areas

Projects that are in proximity to each other, to intact areas (see below for definition of "intact"), or to existing protected areas can lead to larger areas and more cost-effective mitigation, thereby amplifying the environmental effect of a single project. The metric derived to meet this objective was to prioritize catchments based on the likelihood that a mitigation project could reduce the average distance between projects or between projects and existing protected areas.

Data Sources

Using existing data from DMS Web Map (https://deq.nc.gov/about/divisions/mitigation-services/dms-planning/dms-web-map) on the location of tier-1 projects, we developed an initial measurable attribute dataset entitled "distance to existing projects." This metric was computed by calculating a raster surface with the Euclidean distance between every location across the services area and the nearest project site; and by estimating the mean Euclidean distance by catchment using zonal statistics.

To refine this measurable attribute, the dataset should more accurately represent the objective. A dataset that quantifies the level of intactness in the state would be useful for this attribute and for others that are part of the framework. The degree of "intactness" can be defined as an estimate of remaining natural cover after accounting for specific measures of disturbance. Several methods have been developed and are available to compute this metric (Carr and others, 2016).

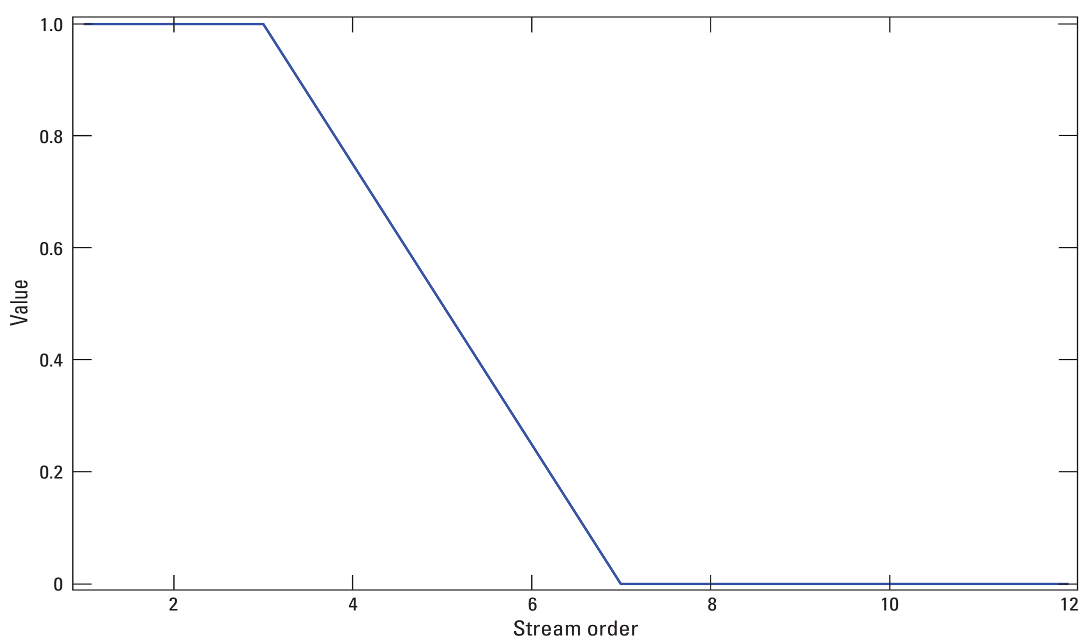

Figure 4. Graph showing piecewise linear function that associates the highest value (1.0) to low stream-order catchments, which are indicative of headwaters, and the value function decreasing to a predefined threshold (with a value of zero at stream-order 7 in this illustration).

Value Function

As discussed in the previous section, various considerations can affect the form of the value function. In discussions with workshop participants, opportunities to prioritize watersheds by the potential to reduce the distance between projects or between projects and intact areas were highly valued. This was even more important if the metric could indicate opportunities for projects to be implemented adjacent to the desired areas. Therefore, we proposed a value function in the form of figure 4, where distances below a predefined threshold would be valued highest and value would decline with increasing distance.

1.2. Prioritize Catchments with Favorable Socio-Economic Factors

This score identifies favorable factors that enhance the feasibility of project implementation and long-term effect. In particular, the DMS favors opportunities that leverage existing public engagement and stakeholder interest, have a history of cooperative and interested landowners, or both. The process of developing a watershed management plan or a total maximum daily load typically involves a substantial stakeholder engagement effort.

Cooperative landowners and affordable land cost also simplify the logistics of developing a restoration project. These considerations are limited to the areas where the DMS has authority to intervene and can be a considerable constraint in project development.

Data Sources

Various datasets can be compiled to develop a single composite metric of socioeconomic factors to estimate project feasibility. Examples include existing catchment or watershed restoration plans, 319 projects, total maximum daily load plans, and records of stakeholder engagement activities. The DMS identified the density of parcels in a catchment (1.2.2) or in the hydrologically connected zone (HCZ) as a proxy measure of project feasibility, including cost effectiveness (1.2.1). Overall, such datasets would likely function as proxy metrics of public interest in the restoration of local waterways. Additionally, the HCZ is a mask developed by U.S. Environmental Protection Agency (2011) that identifies areas contiguous to surface waters that have a high runoff potential.

Value Function

We applied a prototype “socioeconomic factors index” with a linear value function to equally value incremental changes in socioeconomic project feasibility.

1.3. Exclude Unfeasible Areas

A mask can be developed to exclude catchments with characteristics that make mitigation projects unfeasible or of lower priority. These characteristics include topographic constraints (1.3.1) such as (1) areas with high slope or elevation that increase the cost or difficulty of mitigation, (2) catchments that are primarily water bodies (1.3.2), or (3) catchments that lack a minimum threshold of aquatic resources. Although it might initially seem counterintuitive, this mask would also exclude State and Federally owned conservation lands because research suggests that only a minor increase in ecosystem health improvement can be gained by restoration efforts in catchments that are already in good to fair condition (Sheldon and others, 2012); these lands may automatically be ineligible for generating mitigation credits if already classified as protected.

This is an integrated binary mask with only two values, 0 or 1, that include the following considerations: permanently protected areas, topographic constraints set up as slope greater than a predetermined threshold, and catchments that are mostly water. This mask can be updated in the future with new considerations.

Objective 2—Maximize Aquatic Resources Health

Many catchment planning efforts have focused on the goal of achieving aquatic ecosystem uplift by targeting aquatic stressors through mitigation projects and activities. In discussions, a few key values emerged. From a functional uplift perspective, prioritizing stressor-based objectives could mimic the primary effects of development which are (1) disruption of natural hydrology, (2) disruption of natural forms and cover, and (3) effects on water quality.

Recognizing the complexity of ecosystems, the workgroup prioritized objectives and subsequent measurable attributes that are relatively independent and reflective of overlapping functional benefits from single actions (“low hanging fruit”). One example of this is reforestation of denuded riparian buffers, a practice that provides multiple measurable benefits to ecosystems (lowering stream temperature, improving riparian and instream habitat and connection to existing habitat corridors, reducing bank erosion and sedimentation, creating diverse channel form and hydraulics, and dissipating energy via introduction of woody debris). Dense forest cover in the hydrologically active areas substantially enhances ecosystem health (Sheldon and others, 2012). Thus, identifying gaps in riparian buffer is a high priority subobjective. Subobjectives and measurable attributes follow.

2.1. Prioritize Catchments by Alterations to Hydrology

Alterations to stream hydrology, which include changes in magnitude and timing of concentrated flow, are primary effects of anthropogenic disruption such as urban expansion (Walsh and others, 2005; O'Driscoll and others, 2010; Nagy and others, 2011). Hydrological alterations lead to environmental perturbations that propagate through all dependent ecosystem services (habitat and water quality). The workgroup iterated over how to incorporate hydrology into a prioritization framework. Knowing that some changes in hydrology originate with upland disturbance, some discussions focused on relating impervious cover and ditch drainage to hydrologic impairment. Other changes in hydrology result from network or near-stream effects such as flow barriers and changes in geomorphology. A stressor focus for hydrology was additionally confounded by the fact that stressors affect multiple functions of an aquatic system. Given the complexities of cause and effect between disturbances and hydrologic response, the group converged towards identifying symptoms of impairment, without full knowledge of causes of impairments. A prioritization objective based on a measurable level of impairment could lead to identifying impaired catchments that are restorable and actions could lead to multiple benefits. Measurable attributes that operationalize this objective follow.

2.1.1. Indicators of Streamflow Alteration

Many measurable streamflow metrics have been associated with ecological deterioration and quantify how altered a stream is by anthropogenic influence (Eng and others, 2013; McManamay and others, 2014; Mazor and others, 2018; Carlisle and others, 2019). Several were discussed by the workgroup including hydrologic metrics that have been locally recognized as important (Praskievicz and Luo, 2020). Indices that integrate multiple metrics to characterize alteration and disturbance of the streamflow regime are particularly useful in this application. Although most of these efforts are national or regional in scale, the results and methods can be the basis of immediate assessments and refined subsequently.

Data Sources

At national and regional scales, datasets are available that can serve as starting points for immediate assessments. One dataset is the "Geospatial Attributes of Gages for Evaluating Streamflow, version II (called "GAGES II") dataset (Falcone, 2011), which provides classifications for long-term streamgages (and associated stream segment) for the conterminous United States. The assessment is based on streamflow measurements maintained by the USGS and indicators of disturbance. Other more localized data sources may exist and could be leveraged for refinement (Praskievicz and Luo, 2020). In fact, North Carolina has one of the highest densities of streamgage networks in the country, and determining gradients of streamflow alteration is achievable statewide.

Value Function

Catchments are prioritized by the level of impairment to the hydrologic function with highest priority given to the most impaired and lowest priority to the least impaired. This could be done with a simple linear function; however, the value function based on impairment carries the consideration that some systems are irretrievably impaired. Therefore, further analysis could constrain the value function to an interval of "actionable" impairment levels. During workshop discussions, we arrived at a working definition of "actionable" attributes as those that could be ameliorated directly by the DMS or other State controls.

2.2. Prioritize Catchments by Alterations to Natural Forms and Cover

Spatial datasets can be used to identify physical changes in the river-floodplain geometry that fundamentally alter the flow regime and the ecosystem health. Similarly, geographic information system data can provide information on habitat fragmentation, which is the transformation of continuous habitat into several patches that are isolated from each other and are functionally unlike the original.

2.2.1. Density of Ditch Drainage

Artificial drainage presents major ecosystem effects through the development of extensive ditch networks that reduce storage and induce large-scale vegetation changes (Blann and others, 2009). This has been a widespread practice of water table management for agriculture in eastern North Carolina (Lecce and others, 2006). This measurable would quantify the density of features that evidence such modifications in areas that were previously high-water table zones.

Data Sources

A dataset has been developed for the North Carolina DMS using high-resolution digital elevation models (Rowley and others, 2021). The dataset spans agricultural areas in the eastern part of the State. Potentially urban ditch features that are part of stormwater management in cities in the State could be added.

Value Function

The benefit of reducing the extent of artificial drainage is hypothesized to be most beneficial at intermediate stressor levels. Catchments above a deterioration threshold stressor level (for example, 70 percent of catchment is affected by artificial drainage) are of lower priority because it is presumed that the level of effect is unrecoverable. On the other side, catchments below a lower threshold (for example, only 10 percent affected) are similarly of lower priority because of the lack of effect from the existing stressor and the potential high marginal costs of further reduction of effects.

2.2.2. Fragmentation in the Hydrologically Connected Zone

Anthropogenic activities fragment landscapes that are essential habitat for a wide range of aquatic species. Urbanization, agriculture, and water management can disconnect riparian corridors through changes in cover and structural impediments that limit connections between channel and floodplain (Hohl and others, 2014). In North Carolina, a study measuring the response of benthic macroinvertebrate community structure determined that agricultural and developed land cover in riparian areas closely correlated with loss of aquatic ecological integrity (Potter and others, 2004). A measurable attribute for this component objective would be the extent of wetland loss, nonforest cover and hydrologic modifications in the HCZ.

Data Sources

Some relevant datasets are accessible through the U.S. Environmental Protection Agency Recovery Potential Screening tool (U.S. Environmental Protection Agency, 2020); specifically, the riparian U-index is summarized as percent anthropogenic cover within the riparian corridor. In addition, the USGS Hydrologic Alterations Dataset (Rowley and others, 2021) could be used to quantify hydrologic modifications in riparian zones that further the fragmentation. The dataset allows for filtering of in-line and off-line ponds; and for this objective, the off-line ponds would seem best suited to quantify discontinuities within the HCZ.

Value Function

Based on workshop discussions, the value function for this objective is proposed as a concave function where even small amounts of fragmented area are valued highly. Projects that restore (through reforestation or other means) riparian buffers will be considered highly effective projects that propagate multiple habitat and functional benefits such as enhanced species dispersal and temperature regulation. In addition, even at low levels of fragmentation (in other words, close to pristine areas), the ability to protect forested riparian corridors with project easements is valuable. However, in contrast, workshop participants acknowledged that a threshold of forest cover must exist at which the value of the proposed areas is perceived as unfeasible for mitigation and thus excluded from consideration.

2.2.3. Loss of Aquatic Connectivity

Aquatic barriers are structural modifications such as culverts, buried streams, and dams that fragment aquatic habitat and threaten aquatic species such as fish by limiting river network connectivity necessary for fish passage. Possible metrics of this loss include mean NDVI values or the length (in river miles or similar unit) of stream network gained if an impediment were removed. The metric could be further informed by measures of river network quality such as river sinuosity.

Data Sources

The Southeast Aquatic Resources Partnership recently inventoried large- and medium-sized dams and road-related barriers in the Southeast (Southeast Aquatic Resources Partnership, 2020). The analysis includes prioritization metrics based on aquatic network length gained using the NHD. The resolution of this dataset is too coarse for the catchment-scale prioritization analysis given that most of the workshop discussions on this objective were focused on small- and modest-scale barriers such as farm ponds. The USGS has developed a dataset of small ponds (Rowley and others, 2021) for the State, which can serve as the basis of a refined analysis.

Value Function

Discussions focused on small-scale, non-infrastructure barriers and features such as dams and farm ponds. Although these can present negative hydrologic effects in the form of lost connectivity in river networks and in the floodplain, they can also perform a beneficial environmental function, such as sediment and nutrient retention (Berg and others, 2016). Given these considerations, a value could be defined by a convex function where only “significant” gains in network length would be highly valued.

Further data analysis could help characterize thresholds and define “better and significant” gains in network length. As an example, using nested upstream network length from the small ponds dataset for North Carolina (Rowley and others, 2021), data analysis may show that most upstream network gain is modest with median network gained at about 2 km, indicating that these features generally do not impound large stream networks. Conversely, for a small percentage of ponds, hypothetical removal could result in a significant gain in network length (fig. 5).

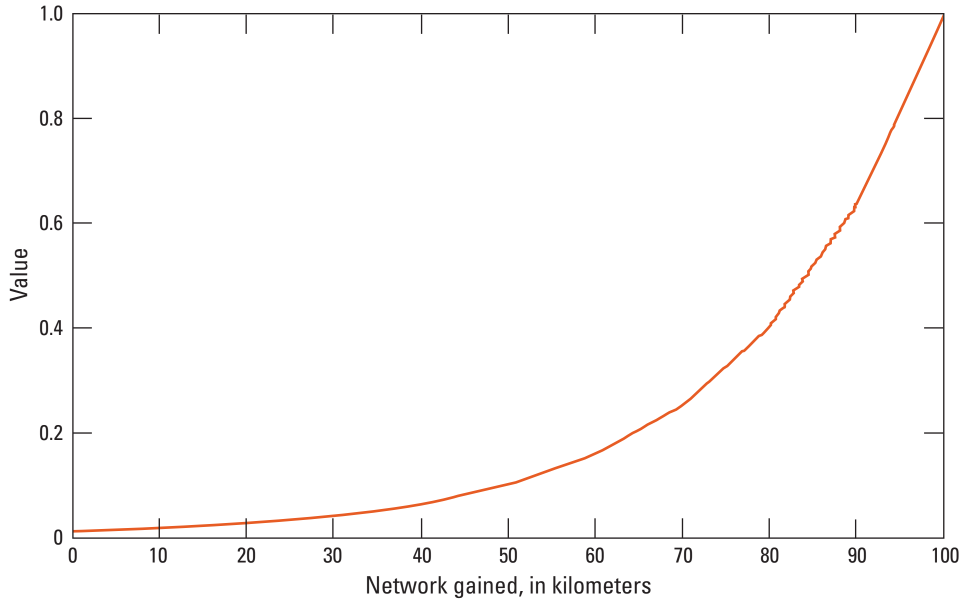

Figure 5. Graph showing hypothetical convex value function for river network gained with small pond removal. Given the logistics and tradeoffs of pond removal, conceivably only pond removals with a high network-gained value (about two standard deviations) would be increasingly valued (greater than 0.5).

2.3. Prioritize by Degraded Water Quality

Development and agriculture in a catchment lead to impairments in stream water quality function through an oversupply of nutrients (nitrogen and phosphorus) and alterations to the sediment flux. Water-quality degradation has been attributed as a main driver of extinction of native freshwater fishes in the southeastern United States. (Warren and others, 2000). Suspended sediment is not only a water-quality stressor that has depleted fish species richness, but also can be a symptom of human-induced structural changes, such as channel incision, that are detrimental to habitat and hydrology (Rowley and others, 2018).

2.3.1. Extent of Upland Sources of Diffuse Pollution

Impairments of water quality can be attributed to diffuse (or nonpoint) pollution sources that at a broad, catchment scale have a substantial effect such as noxious algal blooms and loss of sensitive aquatic species in local and downstream water bodies (Gurley and others, 2019). Over-application of fertilizer in some agricultural and urban regions, storm water runoff, and stream incision are primary sources of water-quality stressors and can be quantified at the catchment level (Gurley and others, 2019). A measurable attribute for this objective would be the proportion of in-stream load of total nitrogen and total phosphorus associated with actionable anthropogenic sources.

Data Sources

The datasets that accompany the North Carolina Water-Quality Model Mapper (U.S. Geological Survey, 2019) could be used to derive information such as the proportion of stream load that is statistically attributed to anthropogenic sources. These sources can be distinguished between actionable at a State-level such as development, agricultural activities, and rapid land change; and non-actionable such as atmospheric deposition or legacy nutrient sources.

Value Function

Although most drivers of water-quality impairment are generated in upland areas and therefore are not directly addressed by mitigation projects, other entities in North Carolina Department of Environmental Quality have policy and regulatory controls that protect water quality. The workgroup designated agricultural sources (such as confined animal operations) as “actionable” sources while excluding background sources such as atmospheric deposition. By focusing only on the actionable sources, the value function could be linearized such that all changes in water-quality improvement are equally valued.

2.3.2. Extent of Point-Source Pollution Sources in the Hydrologically Connected Zone

Impairments of water quality also can be attributed to point source and other direct disturbances or sources of pollution that are near the stream or within mitigable areas. A measurable attribute for this objective would be the proportion (mass of contaminant, in kilograms per square kilometer) of in-stream pollution associated with direct dischargers and direct, near-channel disturbance.

Data Sources

The SPAtially Referenced Regression On Watershed attributes (SPARROW) model output (Gurley and others, 2019) provides measures of stream effect statistically associated with point loads and channel incision. Channel incision would be considered symptomatic of anthropogenic disturbances that lead to instability in stream-floodplain deposition dynamics.

Objective 3—Minimize Future Risk of Impairment

Workshop discussions identified the need for forward-looking planning that capitalized on elements of the compensatory framework; specifically, because part of the credits are received in anticipation of future development, the framework can identify windows of opportunity where restoration planning can effectively mitigate future impairments.

3.1. Prioritize Catchments Under Development Pressure

North Carolina has experienced accelerated urban growth, which is expected to continue into the next several decades (Sanchez and others, 2020a). Areas near urban and suburban centers are under significant development pressure (Sanchez and others, 2020a). Some of these areas include mitigable land that would be considered valuable to aquatic resources and resiliency (Smith and others, 2008; U.S. Environmental Protection Agency, 2011). A measurable attribute for this subobjective is the extent of intact, mitigable area within each catchment that is at a quantifiable risk of near-term development (3.1.1).

Data Sources

This is a data gap where additional analysis is needed, but some resources exist. As part of a previous study, an initial dataset was developed to quantify development pressure based on a 2065 projection of land use (Sanchez and others, 2020b). The dataset has some limitations, specifically that it does not currently mask unfeasible areas and that it requires further refinement of intact areas.

Value Function

Considerations for determining the value function included reviewing the current mitigation process within the DMS. One element discussed was the role that easements have in the current implementation of restoration projects. Given this element of the process, this objective is valued linearly such that any risk of development is considered valuable.

3.2. Climatic Change Risk

This component objective was developed in recognition of the threats to mitigable areas from climatic change effects. These threats include increased frequency of extreme storms and sea-level rise in coastal areas. This objective seeks to prioritize landscape assets that enhance resiliency (Anderson and others, 2014). Floodplains, for example, temporarily increase the storage capacity of a river during a flood, reducing the rate of rising waters to enhance ecosystem resiliency and decrease risk of impairments (Ruckelshaus and others, 2020). The measurable attribute for this objective would be a measure of the extent of intact, mitigable area (HCZ) within each catchment that is predicted to maintain the flooding function (3.2.1).

Data Sources

This is a data gap where additional analysis is needed. Although existing datasets can provide an initial understanding of how changing climate conditions are likely to disproportionately affect less resilient areas, research is needed to better understand the effect of climate change on future flood risk. The Nature Conservancy Resilience Score offers a comprehensive set of estimates of site-specific resilience (that is, species diversity and ecological function) as the effects of climate changes become more pronounced (Anderson and others, 2014). Another recently completed dataset identified options to increase social-ecological resilience in North Carolina (Schaffer-Smith and others, 2020) based on historical imagery of recurring flooding. Datasets that use carbon sequestration as an estimate of resilience capacity have also been developed (Warnell and Olander, 2020).

Value Function

This objective is valued linearly such that any increment of resiliency is considered equally valuable.

Potential Future Enhancements

Engaging in a decision process provides a framework for problem solving but also implies integration of the elements as they are specified. Within the scope of this study a systematic framework for a multicriteria decision making was established for the goals of the DMS. At this phase, some simplifications were used to prototype the decision process, including the use of proxy datasets and simplified value functions.

The problem statement and objectives hierarchy are the most complete component of the framework developed in this study. These elements provide a reference frame for evaluating current operational decisions including the datasets that are used for prioritizing. The measurable attributes and value functions discussed in this report are preliminary and should be revisited and refined. New and (or) improved datasets are usually made available frequently because of advances in geospatial analysis and technologies; and with a clear decision framework, it is possible to determine whether measurables should be updated or not. The framework can evolve with improvements to the measurable datasets such that the scale of the information is resolved, or additional improvements are made to better align a dataset with a means objective. The mathematical form of the postured value functions should be reviewed, including deriving meaningful thresholds and curve fitting data. Statistical analysis of such datasets can also help elucidate improved mathematical forms of individual value functions. During workshop discussions, we used short-hand, rapid concepts such as “actionable” stressors or improvement “thresholds,” and these concepts can be more carefully defined and implemented in subsequent studies and projects.

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