Advances in Multi-Criteria Decision Analysis and Multi-Objective Optimization for Sustainable Water Resources and Sediment Management

By

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DISSERTATION

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To my mom,

who failed in making me a child prodigy

but succeeded in giving me

the confidence to seek opportunity

and the stubbornness to see its completion.

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ABSTRACT

This dissertation makes new advances in multi-criteria decision analysis (MCDA) and MCDA-based multi-objective optimization (MOO) and applies these methods to new areas of sustainable sediment and water resources management. Chapter 1 briefly introduces some central themes of this dissertation. Chapter 2 presents a new method for identifying preference weights in MCDA decision models. Chapter 3 applies existing tools for MCDA to the new topic area of sustainable marine sand resource use. Chapter 4 presents a new version of the Dredged Material Management Decisions (D2M2) software and applies it to optimize dredged sediment placement for multiple objectives.

In the new approach for preference weight identification presented in Chapter 2, a stakeholder or decision maker is observed playing a game (e.g., a serious video game) with a similar context to a real-world decision problem of interest. As the player make choices within the game, a record is kept of each chosen and non-chosen alternative and its performance data. After gameplay is finished, analysis is performed on the choice data from the gameplay log. Two approaches are demonstrated to best fit weight sets to the observed decisions. A brute force, enumeration approach evaluates all possible weight sets in a discretized weight space and an evolutionary optimization approach, with parameters tuned for a more explorative search, generates, evaluates, and evolves random weight sets within the continuous weight space. In an illustrative case study with a simple water management game, both approaches produce similar results showing a weight space of best fit. Tradeoffs between shorter and longer gameplay and analysis time affect the accuracy and completeness of the results. While further work is needed to validate the decision models inferred from gameplay against the decision models used in real life, this approach has promise for avoiding some cognitive biases and increasing the scalability of weight identification in MCDA applications.

Chapter 3 applies MCDA to sustainably manage sand deposits (borrow areas) on the ocean floor that are dredged for fill material for coastal engineering projects such as beach nourishment. Borrow area users and managers have expressed concern that existing approaches are not sufficiently sustainable, e.g., do not adequately promote the long-term viability of borrow areas and balance environmental, social, and economic concerns. To remedy this, an MCDA workshop was held with stakeholders and subject matter experts from state and federal government, industry, and academia. Workshop participants were asked to develop an MCDA criteria hierarchy for evaluating the sustainable use of marine sand borrow areas, suggest metrics and scoring considerations for those criteria, list best management practices for sustainable borrow area use, and provide additional observations about existing challenges and future recommendations. Each of these products fills a gap in the literature for marine sand resource use.

The D2M2 software advanced and applied in Chapter 4 creates MCDA-based MOO models of dredged material placement scenarios. This new version incorporates several features to better specify costs, benefits, and impacts and to support the modeler in developing useful solutions. It is applied in a case study using realistic site and management data for dredging and sediment placement along the Gulf Intracoastal Waterway (GIWW) near Galveston, TX. The site data are optimized in nine scenarios that vary the site network and weighting scheme for seven objectives that include financial cost, environmental impacts, and beneficial uses and effects. Results show tradeoffs between impacts and benefits, identify proposed sites most likely to be useful for system management, and highlight the need for additional placement capacity in the system over the 20-year timeframe, a need that can largely be filled through the creation of proposed beneficial use sites included in the model.

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Chapter 1

Introduction

The chapter introduces some basic concepts related multi-criteria decision analysis (MCDA) and sustainable development, which are foundational to the substantive chapters of this dissertation. It also previews additional topics presented in the following chapters. Beyond this, each chapter contains its own introduction and/or background sections that further introduce concepts and review the literature relevant for that chapter. Chapter contents may also build on topics introduced in preceding chapters.

MULTI-CRITERIA DECISION ANALYSIS

Decision science is a focused and formalized subfield of operations research and management science that deals with human decision making.[1] It is fundamentally concerned with choices, e.g., a decision maker or group of stakeholders selecting or develop a best option or course of action from a set of possible alternatives. It includes *normative* decision theory, which covers how rational actors should make decisions, *prescriptive* decision theory, which gives practical recommendations for good decision making in real-world settings, and *descriptive* (behavioral) decision theory, which reports how humans actually make decisions, including measurement of bias, error, and irrationally. [2,3,4,5]

Multi-attribute utility theory (MAUT) is prominent in decision science research. It often extends the concepts of von Neumann-Morgenstern expected utility theory[6] to multi-attribute problems such that each alternative can be evaluated with respect to multiple objectives or criteria that have different levels of importance to the problem. Other multiple criteria decision analysis (MCDA; also known as multi-criteria decision-making, MCDM) theories, such as multi-attribute value theory (MAVT), are more frequently applied in practice, often making simplifying assumptions about the risk tolerance used in classic MAUT in exchange for greater ease of application.[4] Depending on the form of prescriptive MCDA/MAUT/MAVT model used, criteria importance may be described with weights that quantify the decision maker's relative preferences between criteria and through utility/value functions that describe the desirability of different levels of performance for each criterion with respect to the decision context.[1,7]

Decision science, and behavioral sciences in general, rely heavily on surveys and interviews as research mechanisms.[8,9] For example, prescriptive decision analysts often use structured interviews and surveys to ask decision makers or stakeholders to enumerate relevant criteria, describe utility or value functions, suggest alternatives, and identify tradeoff weights. Surveys and interviews also are used with subject matter experts to elicit probability judgements and to estimate alternative performance.

Although many MCDA model variations exist, the applications in this dissertation use a linear, additive MAVT model of independent criteria, a popular form of MAVT application.[3,4] Here, each alternative, indexed by $\boldsymbol{j}$, available to the decision maker(s) or stakeholders from set of alternatives can be described by data that estimate its performance, $\boldsymbol{v_{i,j}}$, against $\boldsymbol{n}$-many relevant criteria, indexed by $\boldsymbol{i}$. These data are typically developed by subject matter experts and presented to the decision makers(s) or stakeholders by the analyst. Priorities among competing criteria are represented through a decision model that includes quantified tradeoff weights, $\boldsymbol{w_i}$, that capture the relative importance of the criteria to the decision maker(s) or stakeholders and are normalized to sum to one.

Value functions, $\boldsymbol{f_i(v_{i,j})}$, quantify the relative benefit expected from any level of performance for criterion $\boldsymbol{i}$. (These are similar to utility functions in MAUT models but use the term "value" instead of "utility" to note that they assume constant risk preference.) Linear value functions can be described by their endpoints or a slope and intercept and neglect changes in marginal value over the range of performance considered in the alternative evaluation problem. The value functions map performance data from whatever units they are provided in onto a common zero-to-one value scale normalized with respect to the decision maker(s)' or stakeholders' perceptions of benefit across criteria. With an additive value model, the total MAVT value score for each alternative, $\boldsymbol{a_j}$, is calculated as $\boldsymbol{score(a_j) = \sum_{i=1}^{n} w_i f_i(v_{i,j})}$ and represents the total benefit of each alternative summed across all criteria. Under these assumptions, the alternative the decision maker(s) or stakeholders choose, $\boldsymbol{a_{j*}}$, should be the one with the highest total MAVT score, $\boldsymbol{score\left(a_{j*}\right) = Max_j(score\left(a_j\right))}$.

SUSTAINABLE DEVELOPMENT

Modern visions for sustainable development draw from a framework popularized in the classic 1987 report *Our Common Future* from the United Nations World Commission on Environment and Development.[10] One component of this framing of sustainability deals with resource use and consumption, asserting that a renewable resource is used sustainability when its rate of its use does not deplete it but leaves it able to provide value for future generations as well. This deals with equity of resource use over long time horizons. Whenever possible, discussions of sustainability should include a long-term, multi-generational perspective for expected resource management.

Another component of this classic framing of sustainability suggests that sustainable decisions about natural resources use should balance the three broad goals of safeguarding the environment, promoting societal welfare, and supporting economic development or providing economic benefit.[11] This conceptualization of the environmental, social, and economic "three pillars" of sustainability can be applied to both renewable and finite resource use and is predominantly concerned with equity across sectors in the present.

MCDA can be applied to help evaluate the sustainability of proposed plans or projects, for example by including criteria that that estimate intergenerational resource availability and/or reflect the three pillars. Several recent publications review MCDA applications to sustainability in different sectors. Kuman et al. (2017) review applications of MCDA to sustainable renewable energy development.[12] Stojčić et al. (2019) review applications of MCDA to sustainability engineering, including construction and infrastructure, supply chains, transport and logistics, energy, and other engineering disciplines.[13] Pérez-Gladish et al. (2021) present a special issue of the International Journal of Sustainable Development and World Ecology that focuses on recent developments in MCDA for economic development, social cohesion, and environmental sustainability.[14] Within business management, Chowdhury and Paul (2020) review uses of MCDA in studies of corporate sustainability.[15] These and other works establish a well-grounded basis for using MCDA to incorporate sustainability considerations in the design, evaluation, and selection of project alternatives. Nevertheless, opportunities remain to apply MCDA to new types of sustainability problems, including in water resources and sediment management.

OTHER TOPICS IN THIS DISSERTATION

Building on the topics presented above, Chapter 2 presents topics related to video gaming and game analytics. It reimagines traditional MCDA and its decision makers and stakeholders in the context of game play, as players making choices in a virtual environment. It combines concepts from MCDA and game analytics to develop a new topic of decision model inference from gameplay analysis. It also introduces optimization topics for MCDA inference, following a handful of other works, and recasts MCDA modeling as an error-minimization optimization problem. This approach is applied to a text-based video game for sustainable water management that includes criteria for financial cost, economic growth, agricultural production, urban housing, and environmental preservation.

Chapter 3 continues to focus on MCDA and sustainability but switches topic areas. It introduces the topics of dredging, beach nourishment and coastal engineering projects, physical and environmental processes related to marine sand deposits, MCDA workshops, and best management practices. It integrates these topics by using an MCDA workshop to develop a generalized MCDA model and list of best practices for sustainably managing marine sand deposits.

Chapter 4 builds on the discussion of sustainable dredging in Chapter 3 but shifts to the topic of navigational dredging (for maintaining the navigability of waterways for marine transportation). It uses a different type of optimization from the type presented in Chapter 2, where the objective is to minimize or maximize an aggregate MCDA score. It applies this in a case study to sustainable manage dredged sediment under MCDA criteria for financial cost, environmental impacts, and beneficial uses of sediment.

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Chapter 2

Inferring Preference Weights for Multi-Criteria Decision Models Through Analysis of Gameplay Choices

ABSTRACT

Video games, both recreational and serious, are ubiquitous in modern society. Game analytics, the systematic analysis of game environmental and player data to draw meaningful insights, provides powerful tools for game designers and developers to create more engaging and profitable games. Multi-criteria decision analysis, a formalized domain of decision science, develops and applies rational decision models to help users structure objectives, identify preferences, and integrate complex information to evaluate alternative choices and make efficient, value-maximizing decisions. Decision analysis is regularly used in diverse fields such as environmental management, healthcare, oil and gas production, military and government operations, etc. to help decision makers and stakeholders identify and select better alternatives, with substantial financial payoffs and other benefits. An opportunity exists to integrate game analytics and decision analysis for observational research on human decisions in gaming environments. Prior demonstrations of decision model inference in non-gaming environments provide a foundation for this effort, as do existing examples of other types of inference-making and behavioral studies in gaming environments, where game-based approaches are shown to capture many of the same benefits and outcomes as physical observational studies. Observational studies in non-gaming (i.e., real world) environments often involve data collection via surveys, interviews, and physical observation experiments. These have time, cost, and logistic constraints on scalability and produce data that faces fundamental limits in accuracy, completeness, frequency, resolution, integrity, etc. In contrast, because a game's state is fully knowable, gameplay data is limited only by data storage, computing power, and the analyst creativity. While they are expensive to create, once created, gaming environments are scalable and can be applied broadly. They also enable analysts to observe decisions made in extreme scenarios that would be difficult to replicate in physical observational studies. The level of customization, adaptability, and repeatability available when crafting game-based observational study environments also may present opportunities to reduce study susceptibility to some cognitive biases and errors when compared to non-gaming environments. When applied to infer parameters of decision models, these benefits combine and offer promise of real-world improvements for decision analysis.

This chapter: 1) introduces the concept of inferring preference weights for multi-criteria decision models from analysis of observed player choices in gaming environments, 2) presents a simple, proof-of-concept game related to water management, 3) demonstrates application of two decision-model inference methods (brute force enumeration and evolutionary optimization) to game-play logs generated by playing the water management game, 4) presents and discusses Pareto-efficient and near-Pareto-efficient result sets of inferred weights from each method, which are largely successful in capturing the weights used to generate the gameplay data, and 5) summarizes further work that can advance decision-model inference from gameplay observation.

Keywords: multi-criteria decision analysis, game analytics, preference weight inference, inverse problems, parameter estimation

INTRODUCTION

Video games are ubiquitous in modern society. About one third of the world's population, including half of all US adults and nearly all US teens engage in some type of video game play.[1,2,3] Although most games are recreational, "serious games"[4] are an important subset used for training and education by schools, businesses, governments, and the military. In 2020, an estimated 2.7 billion gamers will have been $159.3 billion on video gaming (and over $200 billion by 2023).[1] For serious games, the global market is expected to reach $28.8 billion annually by 2025.[5] In addition to growing sophistication and graphical realism, virtual and augmented reality in computer, console, and mobile gaming is poised to accelerate game use.[6] The current and anticipated prevalence of gaming in daily life presents new opportunities to use gameplay data and observations of player choices in gaming environments to gain insights about how people make decisions under a wide range of conditions, with repeated trials that would otherwise be difficult or costly to replicate or observe.

Video games allow players to experience exotic environments and equipment (e.g., exploring a remote jungle, piloting a commercial airliner). To interact in these settings, players use their decision-making skills and mental abilities (e.g., problem solving, wit, intuition, attention to detail). Research suggests that the human mind generally engages in decision-making in digital environments as if they were real,[7,8,9] though some details of these interactions (e.g., risk taking behavior) have been observed in different circumstances either to be consistent or somewhat differ in digital vs real settings.[10,11] Nevertheless, with appropriate analysis, observation of in-game behavior may provide insights into the player's thinking, potentially with less expense, time, and expertise requirements than traditional behavioral studies, depending on game development effort and the scale of application.

Game analytics, the systematic analysis of game environmental and player data to draw out insights, can help game designers and developers create more engaging, bug-free, beneficial, and profitable games. Their use of game analytics has grown, especially in the recreational video game industry, to improve player experience and game profitability.[12] This emerging discipline seeks to record and analyze a player's gameplay logs to draw insights about a game's mechanics. This helps game designers, developers, and producers create better games by testing whether existing or proposed games work as intended, identifying glitches and optimizing player experience to increase the game's appeal.

The events tracked in commercial game analytics are typically higher order, such as the number of players globally, the average time spent per player, and the level of interaction per player. Yet, since nearly all events and variables related to a player's avatar and the game environment can be tracked from the spatio-temporal environmental state data recorded from within the gameplay environment, commercial game analytics do occasionally delve into minutiae about specific in-game actions.[13] In principle, there is little difference in the analyses of gameplay data verses data collected in the real world other than the greater precision available in virtual settings, and many behavioral analysis techniques and tools developed for other disciplines can be applied to gameplay data.[14] Current developments in game analytics are primarily led by the major global software firms and game-development studios. As such, game analytics is developing apart from behavioral research and has rarely shown interest in using observations of in-game play to infer player traits or characteristics beyond the moment in the game. However, when applied to broader research questions, an opportunity exists to integrate game analytics and observational research of human decision making within gaming environments, an area not yet explored.

Decision science is a separate field of study and application disconnected from game analytics. Decision science, and behavioral sciences in general, rely heavily on surveys and interviews as research mechanisms.[15,16] Structured interviews and surveys are used, for example, to ask decision makers or stakeholders to enumerate relevant criteria, describe utility or value functions, suggest alternatives, and identify tradeoff weights, and to ask subject matter experts to provide probability judgements and estimate alternative performance. This is problematic because survey and interview mechanisms are subject to many well-known cognitive biases and types of error that skew outcomes,[17,18,19] somewhat impairing the aim of decision science to help decision makers add rationality and transparency to their decisions. Due to this, in part, psychological research notes that surveys may poorly predict actual behavior.[20,21] Survey results can also be heavily influenced by the choice of elicitation method.[22] Montibeller and von Winterfeldt[23,24] summarize and discuss how 26 particular cognitive and motivational biases affect all phases of decision analyses. These biases and errors are sometimes exploited by corporations and policy makers to create substantial changes in outcome from subtle shifts in language or framing,[25,26] which can also be an unintentional danger for decision analysts. Many errors and biases that accompany traditional elicitation techniques can be reduced, [23,24,27,28,29] but only with substantial difficulty, effort, skill, and care in study design and application. Without elimination of bias and error, the data elicited via surveys and interviews may not reflect what analysts believe they do and may fall short of expectations when used to predict future decision making.

Surveys and interviews also have logistical drawbacks. They may be cognitively demanding for the respondents[30] and not efficient to scale over large groups due to the required analysts' time involvement, administration and processing costs, and implementation effort. As a partial solution, a few researchers and practitioners have implemented MCDA surveys via online questionnaires.[e.g.,31,32,33,34,35] While this addresses some of the scalability concerns of traditional decision science surveys, the lack of a interaction with a decision analysts who can answer process questions is anticipated to degrade the accuracy of the results.[36] Aubert and Lienert[37] use online MCDA surveys with questions asked by gamified digital avatars instead of human analysts and incorporate feedback about response consistency. These advances may overcome some of the disadvantages from the loss of interaction with the analysts, but remain subject other biases and cognitive effects that are similar to in-person surveys. Developing novel methods to parameterize decision models that avoid triggering even some cognitive and motivational biases could be a major step forward, especially if implemented through an approach that is more scalable and less logistically burdensome than traditional approaches.

As a potential improvement over surveys and interviews, knowledge of behavior and decisions in the past can help predict future outcomes in similar situations.[38,39] Many scientific disciplines use this principal in physical observational studies,[40] e.g., to measure different types of cognitive effects. Direct observation is valuable for opening new frontiers unavailable through traditional elicitation, but also requires greater effort than surveys and interviews and has limited scalability due to high cost, time, and logistic constraints. Data produced from physical studies also faces fundamental limits in accuracy, completeness, frequency, resolution, integrity, etc. of the recorded data beyond which further improvements are infeasible or physically impossible. Advancing this approach, some behavioral and cognitive research observes human behavior in video games and virtual environments.[41,42] Because a game environment's state is fully knowable, analysis of gameplay environmental data is limited only by data storage, computing power, and the analyst creativity. Behavioral observation studies in virtual environments leverage the same relative consistency between past and future behavior as is leveraged in physical behavioral observation, and captures many of the same benefits, but with vastly improved scalability and with fewer time, cost, and logistic constraints to implement the analysis. Developing a game is costly, but existing virtual environments can likely be extended at more modest cost. Applying data mining techniques to data from gameplay observation also may support identification of patterns in decision making that would otherwise evade the analyst.

However, using past decision making to predict future decisions require additional analysis steps not needed with traditional interviews and elicitations. This is because decision model inference from observed choice behavior is an inverse problem.[43] In traditional forward modeling, the initial conditions are known, the relevant equations and parameters are available, and calculations must be performed to get the results. The analysis process in inverse modeling in reversed such that it starts with observation of outcomes and ends with inference of model parameters. Inverse modeling (or probabilistic inversion) was popularized in the geosciences, where the physical equations are well understood (e.g., from physics and engineering), physical results can be observed (e.g., contaminant plume size, electromagnetic-induction waveform), and the initial conditions and model parameters are unknown (e.g., plume source location, mineral-deposit size), and several methods and tools for probabilistic inversion exist.[44] Unlike most forward modeling, inverse problems are typically ill posed and lack a unique solution, since several potential combinations of model parameters and initial conditions could lead to the same observed result. This requires error-minimizing optimization and often results in a collection of likely parameter sets instead of a single parameter set.[45] The application of inverse modeling to infer decision-model parameters is expected to have similar strengths and weaknesses as its application in other disciplines. For example, these methods will have uncertainty in the resulting weight sets that decreases with more decision observations per player.

A few prior efforts have used decision model inference in non-gaming settings, which provides encouragement about decision model inference for in-game observations. For example, Neslo & Cooke[46] combine probabilistic inversion with discrete choice models and random utility theory to enable out-of-sample validation for stakeholder preference models, with a health-care application. Nelso et al.[47] use a simpler procedure to apply probabilistic inversion to rank-order data to derive stakeholder preference weights for multi-criteria decision models. Kraan & Bedford[48] use probabilistic inversion to transform expert judgements about output uncertainties into input uncertainties in the context of management-science models for decision making. Though not explicitly referring to MCDA, Riordan et al.[49] use Bayesian inverse planning to quantify preferences between alternative planning priorities for unmanned aerial systems. Though also not connected to MCDA, economic concepts of revealed preference pursue similar types of meaning from interpreted analysis of consumer choice data. While these approaches provide proof of concept, they have not yet gained broad popularity in the decision science community, likely due in part to the impracticality of making a sufficiently large number of decision observations to adequately parameterize the inferred decision models. Applying these approaches to gaming environments seems promising because in-game observations can be more scalable and efficient. As with other studies, knowing what to measure is important to improve analysis efficiency and accuracy.

Outside of decision science, several other efforts have applied gameplay log analysis to infer potential real-world usefulness. Smith and Vogt[50] present ongoing development of the Operation Overmatch game by the U.S. Army Early Synthetic Prototyping project, where soldiers choose and configure futuristic vehicles and weaponry to use in small team engagements against other human players. The soldiers' use of different capabilities and their mission success are tracked and mined from gameplay data to learn which capabilities might be most useful in realistic settings, to inform decisions about which technologies to advance towards physical production. Seater[51] and Keena[52] similarly use gameplay analysis to compare variants of unmanned aerial systems and robotic ground vehicles. They use the successes that player have accomplishing their missions using different technology variants to learn which variants might perform better in the real-world. Castronova[53] observes locations where commerce centers develop in massively multiplayer recreational gaming worlds to infer macro-level economic effects from coordination game theory in online role-playing games.

Some disciplines use gameplay data to learn about other aspects of human thinking. The fields of learning analytics[54,55] and educational data mining[56,57] study knowledge acquisition in various pedagogical settings, including some virtual environments and serious games. [58] Analyses of game-log data is used to assess what and how much has been learned by a student or trainee, often in comparison with other test and control groups taught the same material through video, print media, or human interaction instead of through a virtual classroom or educational game. These approaches show that gameplay log analysis is viable for learning about an individual's real-world thinking, and provide a departure point for broader gameplay log analytics for decision science in non-pedagogical settings.

Beyond learning analytics and educational data mining, Gonzalez and colleagues measured various cognitive effects using games where players seek to optimally operate control-system dashboards and manage simulations for resource allocation and accumulation and disbursement of different supply stocks in dynamic systems.[59,60,61] Holmgård et al.[62] identify and assess different decision-making styles based on observation of in-game player behavior, aiming to create more "believable" computer-controlled characters in recreational games. Godoy[63] uses virtual environments to assess players' real-world risk-taking propensity in sexual health, to identify promising risk-communication interventions. Tlili et al.[64] use an education video game to model player personality in terms of introversion or extroversion. Seok and DaCosta[65] look at the intersection of personality and gaming to identify the extent to which five broad personality characteristics are loosely predictive of a college student's frequency of video game use. While none of these studies infer parameters in decision models, they support the concept that observation of virtual behavior can be significantly linked to an individual's real-world cognitive processes and characteristics.

Building on this diverse past work, this chapter proposes that MCDA models can be successfully parameterized from observation of choices made in virtual environments, integrating aspects of game analytics and decision science. This concept is supported by the success of past efforts to infer decision models from physical observation, use game analytics to infer real-world technology performance, and use game analytics to study other aspects of human thinking and cognitive effects. With effort, virtual environments (especially first-person, immersive environments) developed with modern gaming platforms can have more realism than is possible in interview or survey questions or most physical settings for observational behavioral studies. If this proposed approach can overcome some biases and errors inherent in survey and interview elicitation, increase accurate decision-model parameterization, enable the analysis of results to be automated, reduce the need for intensive researcher involvement, and/or provide for a more scalable approach, then it holds promise for advancing decision analysis research and practice.

In the following text, this chapter presents analytic methods based on these concepts, uses a simple game to generate gameplay data in an illustrative example, performs weight inference from the gameplay observations, presents and discusses the results, and summarize conclusions, limitations, and next steps to further the concept of decision model inference from observed gameplay choices.

METHODS

This section summarizes: 1) a simple water-management game for generating observations of player decisions, 2) a method for evaluating candidate weight sets, 3) a brute-force, enumeration analysis approaches for inferring MCDA weight from gameplay data, and 4) an evolutionary optimization analysis approaches for inferring MCDA weight from gameplay data.

Illustrative water-management decision game

A simple, text-based water management game provides gameplay data to illustrate the concept of decision-model inference. In this game, the player plays as the executive director of a water agency. Due to population growth, agricultural expansions, and climate variability, the agency's service area constantly faces potential water shortages and other impacts. The player must decide how to invest the agency's funds to develop water projects that will create the best water-resources future for their region across a range of objectives. They must balance their time between raising funding and implementing water projects that best implement their vision for the region, given annual choices between several alternatives available for consideration (Figure 2.1).

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Congratulations! You have been promoted to Executive Director of a California water agency. This is a
challenging responsibility and one for which you have been preparing for years. Due to population
growth, agricultural expansions, and climate variability, your service area is constantly facing
potential water shortages and impacts. The board of directors needs your help to decide how to invest
your agency's funds. Your goal is to develop successful water projects that will create the best water-
resources future for your region across a range of objectives. To do this successfully, you will need to
balance your time in different years across choices to implement water projects vs to grow your agency's
financial balance. You only have 15 years remaining before retirement to make your legacy. How will you
invest that time?

In time periods when you choose to implement a water project instead of secure additional funding, your
staff will present you with data for 4 available alternatives to choose between in terms of:
  *Total project cost ($K),
  *Number of urban homes for which a secure water supply is provided (# homes),
  *Increase in local GPD from improved industrial water supply (% GDP),
  *Acres of agricultural land retained or added to production (# acres),
  *Acres of environmental habitat added or restored to healthy ecological function (# acres).

Based on these data, how will you spend your time and which alternatives will you choose? Press Enter
when you are ready to start managing your region's water resources!
```

Figure 2.1. *Screenshot of the introduction to the text-based water management game.*

The player plays for a fixed number of rounds set by the analyst prior to gameplay. In each round, the player can choose to either gain a known funding amount, already selected by random draw, or to invest their currently available funds in one of several, yet unknown, random project alternatives. If they choose to invest in a project, performance data ($\boldsymbol{v_{ij}}$) for several project alternatives ($\boldsymbol{a_j}$) is randomly drawn from distributions internal to the game. The player then selects the alternative that they feel best advances their overall water-resources vision for their region. The number of alternative and criteria presented to the user per round is chosen by the analyst prior to gameplay. The order in which a player is presented with data for different criteria shifts randomly between rounds to reduce potential bias related to criteria order. After making a choice, data for both the preferred alternative and all non-preferred alternatives are saved in the gameplay log for later analysis. If the player chooses to raise funding instead of implement a water-resources project, the identified funding is added to their total balance available for future investment in water-resources projects (Figure 2.2).

```
*** Year 1 ***
Your current available budget is: $400K.
Would you like to spend this year:
 1) improving your budget by pursuing an investment opportunity to gain $40K?
 2) implementing a project that increases capacity for a desalinization plant to provide fresh water?
 Enter 1 or 2 (or Q to quit):

2
Here are the available project alternatives - which is best for your region?
   Max        Max              Max          Min        Max
   Ind(%GDP)  Urban(#homes)  Env(#acres)  Cost($K)  Ag(#acres)
A          8             35           10        55        100
B          1             10           50       175          0
C         10             15           25       185          5
D          5             35           95        75          5
 Please press A, B, C, or D to mark your choice and then press the Enter key to continue (or just press
Q to quit):

D
Congratulations, your choice will be implemented!
```

Figure 2.2. *Screenshot of gameplay interaction in text-based water management game.*

In the version of the game used in this example, the player is presented with four project alternatives per round. Each alternative is presented to the player with level-of-performance data for five criteria ($\boldsymbol{n = 5}$), that include: total project cost ($K), number of urban homes for which a secure water supply is provided (# homes), increase in local contributions to gross domestic product from improved industrial water supply (% GDP), acres of agricultural land retained or added to production (# acres), and acres of environmental habitat added or restored to healthy ecological function (# acres). Data for the alternatives are randomly drawn, with uniform distributions (Table 2.1) used to provide greater variability in gameplay experience within the bounds of interest. The player starts the game with an initial budget of $400K and can earn between $5K and $135K (randomly drawn from a uniform distribution) per round spent pursuing an investment opportunity instead of implementing a project. Players with prior familiarity with the criteria in question will be better positioned to make consistent choices throughout the game, needing less exploratory play to gain familiarity with the criteria.

Table 2.1. *Ranges for uniform distributions from which alternative data are drawn.*

Criteria	**Min**	**Max**
Cost ($K)	20	250
Urban (# homes)	0	50
Industry (% GDP)	0	12
Agriculture (# acres)	0	100
Environment (# acres)	0	100

Gameplay data used for demonstration of decision-model inference was generated in 7 gameplay trials. Two trials were played in games with 15 rounds for potential decisions and 5 trials were played in games with 40 rounds for potential decisions. Five trials were played based on pre-determined, rigid decision rules and 2 were played by the author based on the author's experienced preferences (Table 2.2). The distributions from which funding amounts and alternative performance values are drawn were consistent across the trials.

Table 2.2. *Summary of the seven gameplay trials, including the decision rules consistently applied by the player in each round, the number of rounds played, and number of project-selection decisions made. (In each round, the player can choose between four available project alternatives or can invest in growing their financial resources; the number of rounds in which they made a project-selection decision is shown in the "# Decisions" column.) In the first five trials, the player played with a fixed-preference decision rule to provide benchmarks for assessing the results of the decision-model inference. In the last two trials, the author played with his actual preferences and judgments.*

Trial ID	Decision Rule Applied for the Duration of Each Trial	# Rounds	# Decisions
Env8	Always earn money instead of doing a project if the payoff is >= $75K. For projects, always choose the alternative that has the **highest Environmental score**. For ties, choose the alternative with the higher Agriculture score.	15	8
Env26	Always earn money instead of doing a project if the payoff is >= $75K. For projects, always choose the alternative that has the **highest Environmental score**. For ties, choose the alternative with the higher Agriculture score.	40	26
Cost6	Always earn money instead of doing a project if the payoff is >= $75K. For projects, always choose the alternative that has the **lowest Cost score**. For ties, choose the alternative with the higher Agriculture score.	15	6
Cost26	Always earn money instead of doing a project if the payoff is >= $75K. For projects, always choose the alternative that has the **lowest Cost score**. For ties, choose the alternative with the higher Agriculture score.	40	26
Urb&Ind21	Always earn money instead of doing a project if the payoff is >= $75K. For projects, **alternate between** choosing the option that has the **highest Urban score** and the option that has the **highest Industry score**. For ties in Urban score, choose the alternative with the highest Industry score, and vice versa for ties in Industry score. (If both Urban and Industry sores tie, next choose the alternative with the lowest Cost score, and if that ties next choose the alternative with the highest Environmental score.)	40	21
Auth20	The author playing with the **author's preferences**.	40	20
Auth22	The author playing with the **author's preferences**.	40	22

Evaluation of candidate weight sets

The objective of the decision-model inference analysis in this chapter is to identify many candidate weight sets, apply them to the observed decision problems, compare their performance, and identify those that best reproduce the outcomes from the player's gameplay log. Each candidate weight set is used in a linear-additive multi-attribute value theory (MAVT, see introduction) formulation of MCDA model with decision and environmental data from the game environment, and compared with the actual choice observations to measure its predictive accuracy. The "best" inferred weight sets are those that maximize prediction success and minimize prediction error. Regardless of what method is used to generate the candidate weight sets, their evaluation with respect to the observed decisions and gameplay data is the same.

Let a candidate weight set, $\boldsymbol{W_k}$, be defined to contain one weight per criterion $\{\boldsymbol{w_{i=1,k}}, \dots, \boldsymbol{w_{i=n,k}}\}$. Let it be called a viable weight set if three conditions are met: $\sum_{i=1}^{n} \boldsymbol{w_{i,k}} = \mathbf{1}$, $\boldsymbol{w_{i,k}} \geq \mathbf{0}\ \forall \boldsymbol{i}$, and $\boldsymbol{w_{i,k}} \leq \mathbf{1}\ \forall \boldsymbol{i}$. Among the alternatives, indexed by $\boldsymbol{j}$, in each observed decision in the gameplay data, indexed by $\boldsymbol{h}$ (which vary in number as listed in Table 2.2), the alternative selected by the player is identified as $\boldsymbol{a_{j*,h}}$. The gameplay record contains level-of-performance data ($\boldsymbol{v_{i,j,h}}$) for each criterion, for each alternative, for each decision observed in that gameplay trial. Value functions, $\boldsymbol{f_i}(\,)$, linearly normalize the performance scores based on the minimum and maximum values of the distributions from which they were drawn (Table 2.1), distributions selected to be reasonable for use with linear marginal preferences. The MAVT equation is applied to all alternatives in each observed decision event, $\boldsymbol{score_k}(\boldsymbol{a_{j,h}}) = \sum_{i=1}^{n} \boldsymbol{w_{i,k}} \boldsymbol{f_i}(\boldsymbol{v_{i,j,h}})$, revealing how each weight set scores the alternatives. These scores are ranked from highest (most preferable) to lowest for each decision. Any difference in rank for the player's actual selected alternative between the MAVT model and the gameplay record (where it is ranked first by implication) is identified as the error of $\boldsymbol{W_k}$ for that decision: $\boldsymbol{error_{k,h}} = \left|\mathbf{1} - \boldsymbol{rank}(\boldsymbol{score_k}(\boldsymbol{a_{j*,h}}))\right|$. The sum of squared error across all decisions in a gameplay trial, $\boldsymbol{SSE_k} = \sum_{h} \boldsymbol{error_{k,h}}^{\mathbf{2}}$, is finally used to compare the effectiveness of $\boldsymbol{W_k}$ in reproducing the player's decision outcomes in that trial. (Note, squared error is used instead of absolute error to more heavily penalized greater differences in rank.)

Brute force, enumeration approach for generating candidate weight sets

One way to generate and use candidate weight sets in decision-model inference is through a "brute force" approach that enumerates an evenly spaced grid of viable weight sets. Here, the analyst first chooses the number, $\boldsymbol{m}$, of evenly-spaced weights to enumerate per criterion, discretizing the continuous zero-to-one weight continuum. (These weights differ incrementally by $\mathbf{1}/\boldsymbol{m}$; for example, using $\boldsymbol{m} = \mathbf{20}$ produces weight increments of 0.05.) The choice of $\boldsymbol{m}$ involves tradeoffs between model runtime and number of weight sets evaluated. Once generated, all non-viable weight sets are discarded. The remaining viable weight sets roughly cover all possible player weighting preferences, with greater or lesser granularity depending on the size of $\boldsymbol{m}$. After all non-viable, enumerated weight sets are discarded, the number of remaining viable weight sets is equal to $(\boldsymbol{m} + \boldsymbol{n} - \mathbf{1})\ \boldsymbol{Choose}\ (\boldsymbol{n} - \mathbf{1})$, a combination of the number of criteria in the model and the density of enumerated weights. For the gameplay trial data summarized in Table 2.2, the brute force, enumeration approach of decision-model inference is applied twice, once with $\boldsymbol{m} = \mathbf{20}$, producing 10,626 viable candidate weight sets, and once with $\boldsymbol{m} = \mathbf{50}$, producing 316,251 viable candidate weight sets (Table 2.3).

Table 2.3. *Candidate weight sets generated in two brute force, enumeration runs per gameplay trial. These are used to compare results generated with lessor or greater granularity and computational effort.*

ID	Number of increments in weight continuum	Distance between each weight value tested	Number of viable weight sets (i.e., that sum to one)
B20	20	0.05	255,024
B50	50	0.02	316,251

These groups of viable candidate weight sets are evaluated by applying the MAVT equation as described above (producing between 796,950 applications of the MAVT equation for a trial with $\boldsymbol{m = 20}$ and 6 observed decisions and 32,890,104 applications for a trial with $\boldsymbol{m = 50}$ and 26 observed decisions).The candidate weight set(s) with the lowest sum of squared error across all decisions in the trial, $\boldsymbol{W_{k\_best}}$, where $\boldsymbol{SSE_{k\_best} = Min_k(SSE_k)}$, form a Pareto-efficient frontier of weight sets that best reproduce the players observed decisions and, by extension, best represent the player's preferences as expressed within the context of that gameplay trail. These Pareto-efficient sets are summarized and plotted in the results section to show the range of inferred weights for each criterion, which can potentially to inform future decision analysis applications in related decision contexts.

Because the sums of squared error for all candidate weight sets are available, sets of near-Pareto-efficient weights are also identified, having the next-lowest sums of squared error after those in the Pareto sets. Consideration of near-Pareto weights may be useful to analysts, stakeholders, and decision makers seeking to broaden the analyses conclusions, e.g., due to concerns about: the effect of MAVT's simplifying assumptions, the effect of cognitive biases inherent in human decision making, having too few observations in the decision record to confidently justify exclusion of non-Pareto results, or having Pareto sets with narrower-than-anticipated ranges of inferred weights.

Evolutionary optimization approach for generating candidate weight sets

Another way to generate candidate weight sets for decision-model inference is through an "evolutionary optimization" approach that iteratively tests and refines weight sets to gradually develop weight sets that better reproduce the player's decision record. Evolutionary optimization algorithms[66] take their name and conceptual foundations from evolutionary biology, where each generation of individuals compete to combine and pass on a portion of their genes to the next generation, perhaps with mutations. In evolutionary optimization, candidate parameter sets are created and evaluated across many generations. Those that perform best with respect to the evaluation function pass on some combination of their values to candidate elements in the next generation, perhaps with modification. Different evolutionary algorithms draw from this type of biological inspiration to create optimization approaches well suited to various types of problems.

The decision-model inference approach described here implements the Differential Evolution[67,68] algorithm (as available in the SciPy package version 1.1.0 for the Python 3 programming language) with a "best/1/bin" search strategy. Differential Evolution seeks to find the global minimum of a multivariate function (i.e., weight sets having the lowest sum of squared error from the MAVT model across all observed decisions in a gameplay trial) through stochastic search rather than gradient descent. Various parameters control the optimization including: a differential weight (aka mutation constant), $\boldsymbol{d}$, that is randomly sampled from a uniform distribution once per generation, where larger values increase the search radius but delay convergence; a crossover probability (aka recombination constant), $\boldsymbol{c}$, where larger values allow greater numbers of mutants to progress into the next generation but risk reducing population stability; and the population size, where larger values generate better candidate weigh sets per generation but require more computational effort to evaluate each generation.

The initial generation, $\boldsymbol{g = 1}$, of candidate weight sets is populated via Latin Hypercube sampling of the weight parameter space. These candidate weight sets are evaluated with the MAVT equation, as described above, and the best-performing weight set in that generation is identified, $\boldsymbol{W_{k\_best,g}}$. Candidate weight sets for subsequent generations are produced as follows. First, a mutant weight set is generated by taking the difference between two randomly selected weight sets from the current generation, multiplying that difference by the differential weight, and adding it to the best weight set (hence the "best" in best/1/bin) from the current generation, $\boldsymbol{W_{k\_mutant,g} = W_{k\_best,g} + d_g * (W_{k=rand1,g} - W_{k=rand2,g})}$. Then, a combined weight set, $\boldsymbol{W_{k\_combined,g}}$, is constructed by taking random draws, $\boldsymbol{rand_{i,k}}$, from a binomial (hence the "bin" in best/1/bin) distribution in [0,1) for each criterion in each weight set and comparing those values to the crossover probability. If the random value is less than the crossover probability, the mutant weight for that criterion is included in the combined weight set. Otherwise, the existing weight for that criterion in that weight set of the current generation continues into the combined weight set. At least one random weight from the mutant weight set is guaranteed to be included in the combined weight set,

$\boldsymbol{w_{i,k\_combined,g} = \begin{cases} w_{i,k\_mutant,g}, & if\ ((rand_{i,k} < c)\ \ OR\ \ (rand_i = i)) \\ w_{i,k,g}, & otherwise \end{cases}}$, where $\boldsymbol{rand_i}$ is a randomly generated index of $\boldsymbol{i}$ in the range [1, $\boldsymbol{n}$]. Next, the combined weight set is evaluated with the MAVT equation. If it has a lower sum of squared error than the weight set in the current generation, it becomes the candidate weight set in the next generation, otherwise the weight set in the current generation continues into the next generation, $\boldsymbol{W_{k,g+1} = \begin{cases} W_{k\_combined,g}, & if\ SSE_{k\_combined,g} < SSE_k \\ W_{k,g}, & otherwise \end{cases}}$.

For each gameplay trial in Table 2.2 the Differential Evolution optimization is run four times with different values for the optimization-control parameters (Table 2.4), enabling a comparison of results generated with quicker run times testing fewer numbers of candidate weight sets versus longer run times testing greater numbers of candidate weight sets. To ensure comparability, the results of all optimization runs shown here are generated using the same initial random seed. All remaining Differential Evolution parameters are left at default values for the SciPy optimization package, namely, the maximum number of generations is set to 1,000, the relative tolerance for convergence is set to 0.01, the absolute tolerance for convergence is set to 0, and results polishing after convergence is used. The sums of squared error for all candidate weight sets evaluated in each optimization run are tracked, allowing both Pareto-efficient and near-Pareto sets to be identified for each run.

Table 2.4. *Combinations of optimization-control parameters are varied across four optimization runs per gameplay trial to compare results generated with lessor or greater computational effort (in order of increasing effort).*

ID	Distribution for differential weight, $\boldsymbol{d}$ (aka mutation constant)	Crossover possibility, $\boldsymbol{c}$ (aka recombination rate)	Population size per generation
O15	Uniform[0.5, 1.0)	0.7	15

O20	Uniform[0.5, 1.5)	0.6	20
O25	Uniform[0.5, 1.9)	0.5	25
O35	Uniform[1.0, 1.9)	0.2	35

RESULTS AND DISCUSSION

Comparison of computational effort and outcomes across analysis types and gameplay trials

All analyses were run on a mid-level laptop PC from a recent model year using a Python 3 integrated development environment (IDE). No code-efficiency optimization was applied beyond that provided by the IDE.

The number of candidate weight sets evaluated by the brute force, enumeration analyses was 10,626 for each B20 analysis run and 316,251 for each B50 analysis run. The number of candidate weigh sets evaluated by the evolutionary optimization analyses ranged from a minimum of 240 (for 16 generations with an O15 analysis run) to a maximum of 350,000 (for 1,000 generations with an O35 analysis run) (Table 2.5; analysis parameterizations defined in Tables 2.3 and 2.4).

Runtime for the brute force, enumeration analyses across all gameplay trials ranged from a minimum of 34.8 seconds (with an B20 analysis parameterization) to a maximum of 54 minutes and 16.8 seconds (with an B50 optimization parameterization). The runtimes for the evolutionary optimization analyses across all gameplay trials ranged from a minimum of 2.0 seconds (with an O15 optimization parameterization) to a maximum of 14 minutes and 40.8 seconds (with an O35 optimization parameterization) (Table 2.5).

Table 2.5. *Comparison of computational effort, sum of squared error, and number of results in Pareto sets across analysis parameterizations and gameplay trials for both brute force enumeration and evolutionary optimization analysis types. Results are presented in six columns for different analysis parameterizations and seven sets of rows for different gameplay trials.*

Analysis	**Brute force, enumer.**		**Evolutionary optimization**			
Parametrization:	**B20**	**B50**	**O15**	**O20**	**O25**	**O35**
Env8 trial						
# Candidate weight sets	10,626	316,251	345	680	1,375	7,490
# Generations	-	-	23	34	55	214
Runtime	35.0s	46m 41.3s	2.0s	3.0s	5.1s	37.1s
SSE of Pareto set	0	0	0	0	0	0
# In Pareto set	444	12,467	411	782	1,300	10,807
SSE of near-Pareto set	1	1	1	1	1	1
# In near-Pareto set	572	16,525	481	851	1,747	8,837
Env26 trial						
# Candidate weight sets	10,626	316,251	1,470	6,640	10,425	35,000
# Generations	-	-	98	332	417	1,000
Runtime	48.0s	54m 16.8s	27.4s	2m 16.0s	3m 46.8s	14m 40.8s
SSE of Pareto set	0	0	10	10	10	10

# In Pareto set	1	1	303	1,404	1,369	1,806
SSE of near-Pareto set	2	2	11	11	11	11
# In near-Pareto set	4	17	833	3,914	6,884	18,383
Cost6 trial						
# Candidate weight sets	10,626	316,251	360	460	850	3,500
# Generations	-	-	24	23	34	100
Runtime	34.8s	46m 15.1s	4.1s	2.4s	4.4s	21.1s
SSE of Pareto set	0	0	0	0	0	0
# In Pareto set	514	14,045	552	432	826	4,437
SSE of near-Pareto set	1	1	1	1	1	1
# In near-Pareto set	230	6,253	158	211	315	1,824
Cost26 trial						
# Candidate weight sets	10,626	316,251	330	1,540	1,925	24,815
# Generations	-	-	22	77	77	709
Runtime	48.0s	53m 30.7s	5.4s	23.0s	29.4s	8m 40.5s
SSE of Pareto set	0	0	0	0	0	0
# In Pareto set	12	374	378	1,377	1,153	19,099
SSE of near-Pareto set	1	1	1	1	1	1
# In near-Pareto set	44	1,167	278	1,447	1,186	23,584
Urb&Ind21 trial						
# Candidate weight sets	10,626	316,251	1,020	1,060	12,925	35,000
# Generations	-	-	68	53	517	1000
Runtime	43.6s	51m 34.5s	8.4s	8.9s	2m 23.1s	12m 5.8s
SSE of Pareto set	8	8	8	9	8	8
# In Pareto set	1	2	634	598	3,287	2,470
SSE of near-Pareto set	9	9	9	10	9	9
# In near-Pareto set	5	98	1,391	275	13,328	24,786
Auth20 trial						
# Candidate weight sets	10,626	316,251	240	880	1,375	35,000
# Generations	-	-	16	44	55	1,000
Runtime	54.3s	51m 8.1s	3.5s	13.9s	17.4s	12m 36.2s
SSE of Pareto set	1	1	1	1	1	1
# In Pareto set	13	401	379	550	1,179	30,947
SSE of near-Pareto set	2	2	2	2	2	2
# In near-Pareto set	47	1,671	183	683	1,287	23,123
Auth22 trial						
# Candidate weight sets	10,626	316,251	375	1,140	1,400	32,970
# Generations	-	-	25	57	56	942
Runtime	57.1s	52m 11.4s	6.6s	16.4s	23.1s	9m 0.7s
SSE of Pareto set	0	0	0	0	0	0
# In Pareto set	6	155	334	503	944	26,786
SSE of near-Pareto set	1	1	1	1	1	1
# In near-Pareto set	24	731	372	649	1,359	33,329

Comparison of inferred weights across gameplay trials for the same analysis parameterizations

The results include 42 Pareto-efficient sets from applying each of 6 analysis parameterizations to 7 gameplay trials. Each Pareto set contains many inferred weight sets that have weights for the 5 criteria used in the game. These data are summarized on 42 parallel axis plots (some of which are shown on Figure 2.3, all of which are shown on Figures 2.6, 2.8, 2.10, 2.12, 2.14, 2.16, 2.18). Each Pareto set may have many inferred weight sets as members (Table 2.5), which are each represented by a line on the plot. Inferred weights for individual criteria in a weight set can be read from the vertical axis wherever a line crosses a criterion's tick mark on the horizontal axis. (Line segments between criteria marks have no numerical meaning but are useful for differentiating lines from each other and for showing which individual weights belong together in a weight set.) The range and distribution of inferred weights for a criterion, across all Pareto weight sets, is shown from all lines over a criterion's tick mark. Approximate line density can be judged based on line darkness, since the lines have partial transparency and thus overlapping lines appear darker than individual lines, and based on the broader or narrower spread of lines across the plot. Another version of these plots includes both the Pareto and near-Pareto sets on the same axis (some of which are shown on Figures 2.4-2.5, all of which are shown on Figures 2.7, 2.9, 2.11, 2.13, 2.15, 2.17, 2.19), showing how much broader the range of inferred weights would be for the small increase in error in the near-Pareto set.

One way to explore the results is to compare weights across gameplay trials, some of which shared a decision rule, for one analysis parameterization, e.g., the B50 or O35 analysis parameterizations that explore greatest numbers of candidate weight sets.

In the O35 analysis results, the Env8 trial includes 8 observed decisions from the player, compared with 26 decision observations in the Env 26 gameplay trial (Figure 2.3). In both cases, the analysis correctly identifies that the player made decisions using a weight scheme that heavily weights the environment and placed little weight on other criteria. Though the observed decisions in the Env8 and Env26 trials were both generated with the same fixed decision rule, which always choose the alternative with the best environmental score, the greater number of observed decisions in the Env26 trial allowed the analysis to identify a narrower range of inferred weights and come closer to identifying the actual decision rule used. When pairing these results with the runtime data (Table 2.5), we see that the Env8 analysis ran to completion instead of timing out, finished quicker, and has fewer weight sets in its Pareto set than the Env26 analysis, which ran until it timed out at 1,000 generations and has a larger Pareto set. The median and maximum inferred weight for the environment criterion in the Env8 trial are 0.53 and 0.89, respectively, versus 0.84 and 0.94 in the Env26 trial (Tables 2.6 & 2.7).

The Cost6 and Cost26 results for the O35 analysis (Figure 2.3 & Table 2.5) show a similar pattern as the Env8 and Env26 trials, with the fewer observations in the Cost6 data leading to a quicker runtime, smaller Pareto set, and wider range of inferred weights than in the Cost26 gameplay trial. In both the Cost6 and Cost26 trials, the results correctly identify that the player made decisions using a weight scheme that placed a high weight on cost and little weight on other criteria. While the narrowing of inferred weight range between the Cost6 and Cost26 trials is not as pronounced as between the Env8 and Env26 trials, potentially related to differences in the random alternatives available for selection in each trial, since a similarly fixed decision rule was applied, the Cost26 trial still comes closer than the Cost6 trial to identifying the decision rule used. The median and maximum inferred weight for the cost criterion in the Cost6 trial are 0.57 and 0.90, respectively, versus 0.72 and 0.98 in the Cost26 trial (Tables 2.8 & 2.9).

The Urb&Ind21 gameplay trial (Figure 2.3) explores weight inference using a fixed decision rule that divides weight evenly between two criteria. (A trial with the same decision rule and a smaller number of observations was not included in the gameplay due to the anticipated high uncertainty in its results, with a more complex decision rule and so few observations.) The inferred weights in this trial correctly identify that the player made decisions with weights that highly preferred the urban and industrial criteria and had little preference for the other criteria, with median urban and industrial weights of 0.48 and 0.46, respectively (Table 2.10). This trial infers a narrow range of weights for all criteria, with an average difference between minimum and maximum values of just 0.04.

Whereas the Env8, Env26, Cost6, Cost26, and Urb&Ind21 trials were generated with a fixed decision rule and explore differences in the range of inferred weights with fewer or more decision observations, the observations in the Auth20 and Auth22 trials (in Figure 2.3) were generated using the hidden decision processes of an actual human, include a similar number of observations, explore variation and consistency in inferred weights between gameplay sessions, but lack a fixed, external decision rule for accessing accuracy. Though the Auth22 trial ran to completion and the Auth20 trial timed out, both explored candidate weight sets over a similar number of generations and have Pareto sets of roughly similar size. The results of both Auth20 and Auth22 trials for the O35 analysis parameterization identify that the player made decisions using a decision process that favored cost, urban, and environmental criteria over industrial and agricultural criteria. The Auth22 trial shows a narrow range of inferred weights for criteria and more pronounced preferences between the more-preferred and less-preferred groups of criteria, though it is not known if that is due differences in the alternatives shown, to a strengthening in player preference as a result of the gameplay experience, or to other inconsistencies in human decision making. Median weights for cost, urban, and environmental criteria in the Auth20 trial were 0.27, 0.27, and 0.21, respectively, and were 0.30, 0.41, and 0.19, respectively, in the Auth22 trial (Tables 2.11 & 2.12).

When the near-Pareto sets are underlaid on these plots (Figure 2.4, blue lines), the overall patterns remain as described above. For most criteria in most trials, the inferred weight range is widened only slightly by inclusion of a near-Pareto set with the next-lowest sum of squared error. In a few cases, including the near-Pareto set substantially widened the weight range, such as for the cost criterion in the Cost6 trial and all criteria in the Env26 trial. There does not seem to be any correlation between the width of weight range for criteria in the Pareto set and the width of range added by the near-Pareto set.

Consideration of near-Pareto sets may nevertheless be useful to some analysts, stakeholder, and decision makers. For some, seeing that the near-Pareto set adds little width to the weight ranges identified by the original Pareto can be interpreted as evidence in support of the weight inference in the original Pareto set (i.e., because sensitivity analysis to relax the optimization did not substantially change the results). For others, using the Pareto and near-Pareto together may increase confidence that appropriate weight ranges were captured, counteracting potential concerns about the influence of modeling artifacts or cognitive biases and errors on the results. If desired, the analyses could allow even greater error in the near-Pareto sets if that helped to respond to particular needs and concerns.

The results above (Figures 2.3 & 2.4) were all produced by an evolutionary optimization analysis. It is useful to compare these results with those produced by brute force, enumeration analyses, e.g., the B50 analysis parameterization (Figure 2.5). As with the O35 parameterization, the B50 results from gameplay trials with greater numbers of decision observations have narrower ranges of inferred weights, and the shape of inferred weights in the Pareto sets correspond to the actual decision rules used reasonably well. One small but noticeable difference between similar trials in the B50 versus O35 parameterizations is that the B50 results for the urban criterion weight ranges for the Auth20 and Auth22 trials match each other more closely when their near-Pareto sets are included.

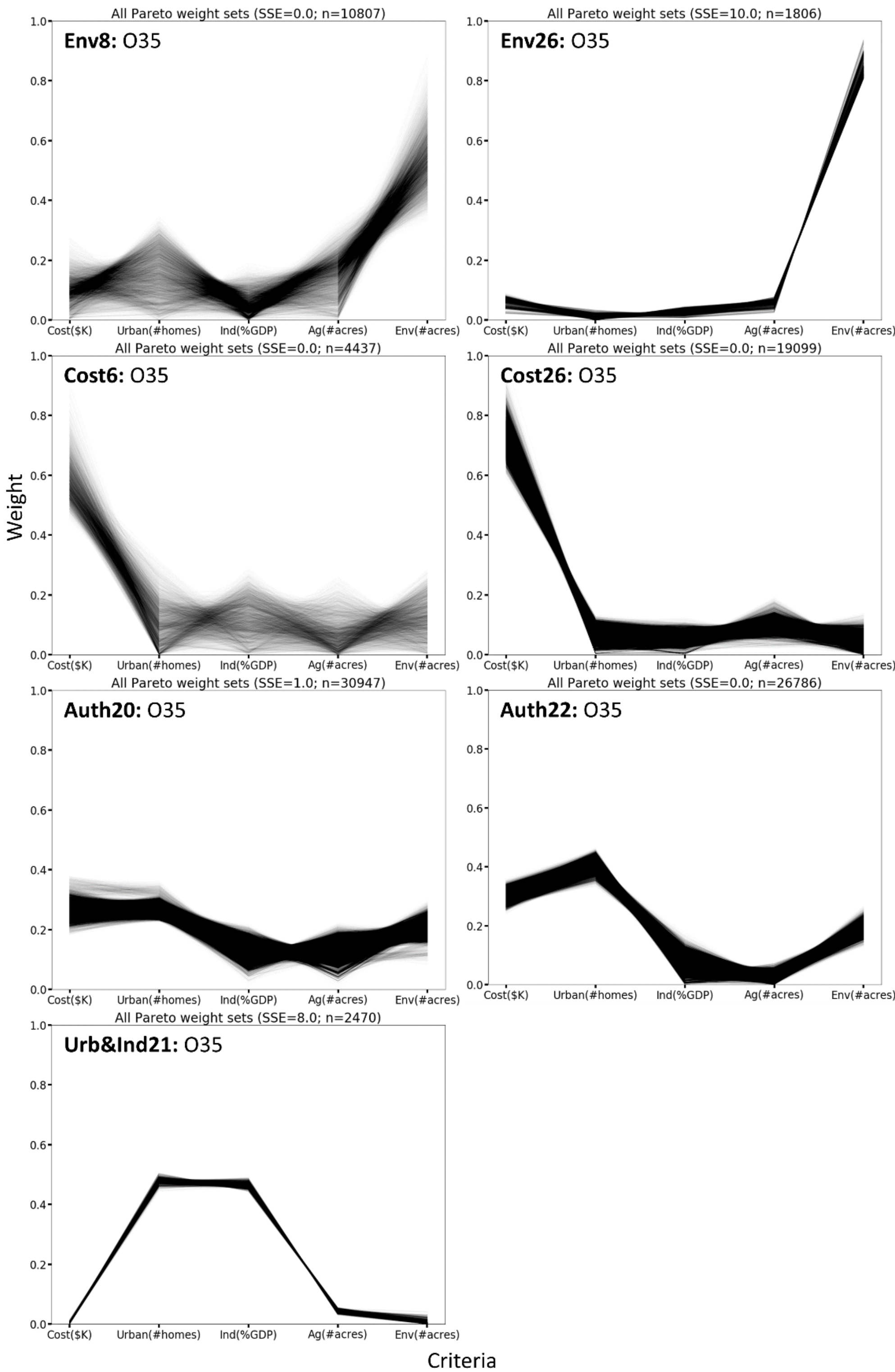

Figure 2.3. *Parallel axis plots show Pareto results for the "O35" optimizations. Subplots for seven game-play trials are identified by bold labels at the upper-left of each. Within subplots, each line represents one weight set in the Pareto results. Values for individual criteria weights are read off the vertical axis where lines cross criteria tick marks on the horizontal axis. Higher weight values represent greater preference.*

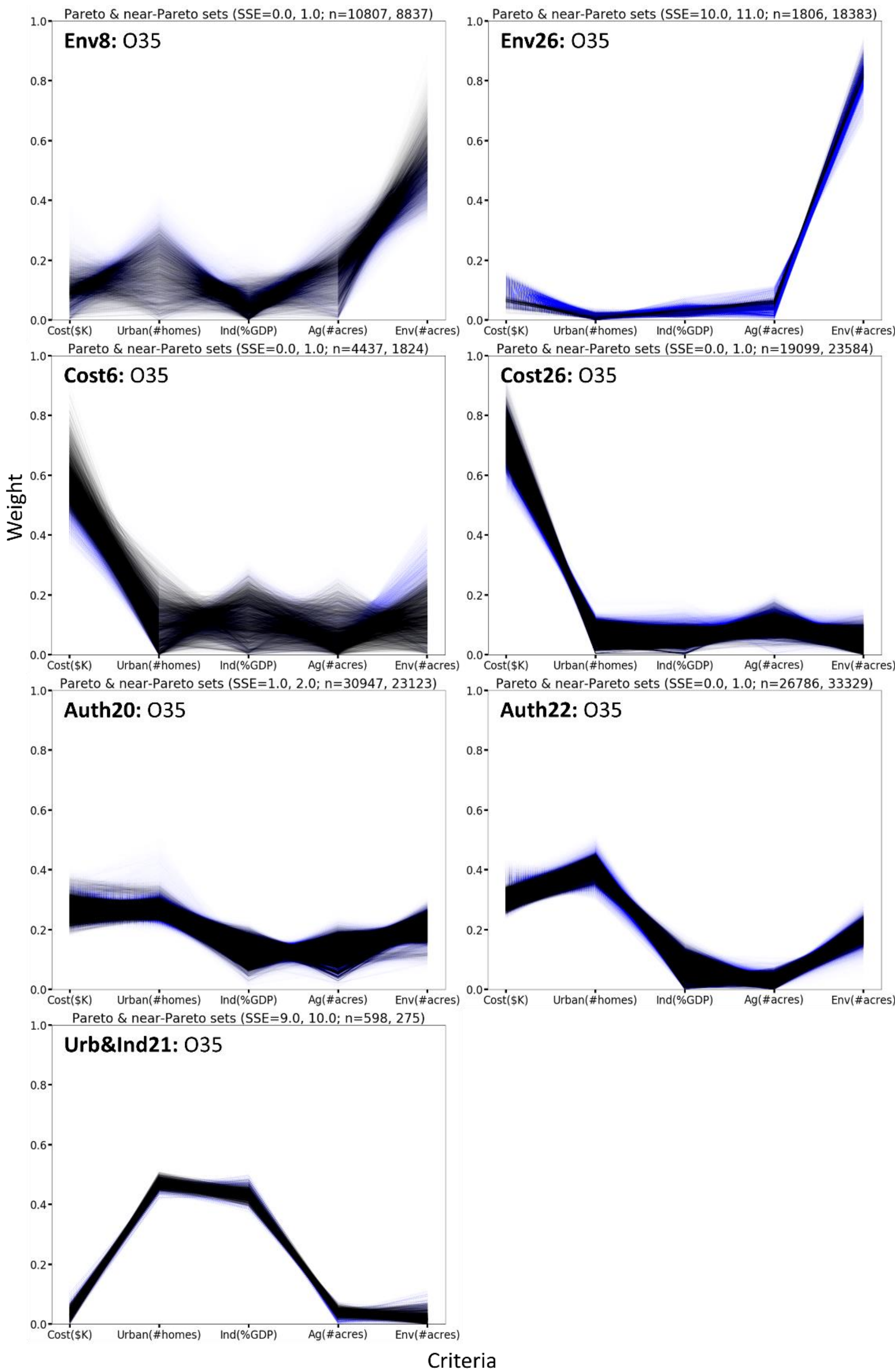

***Figure 2.4**. Parallel axis plots show Pareto (black lines) and near-Pareto (blue lines) results for the "O35" optimization runs. Subplots for seven game-play trials are identified by bold labels at the upper-left of each. Within subplots, each line represents one weight set in the results. Values for individual criteria weights are read off the vertical axis where lines cross criteria tick marks on the horizontal axis.*

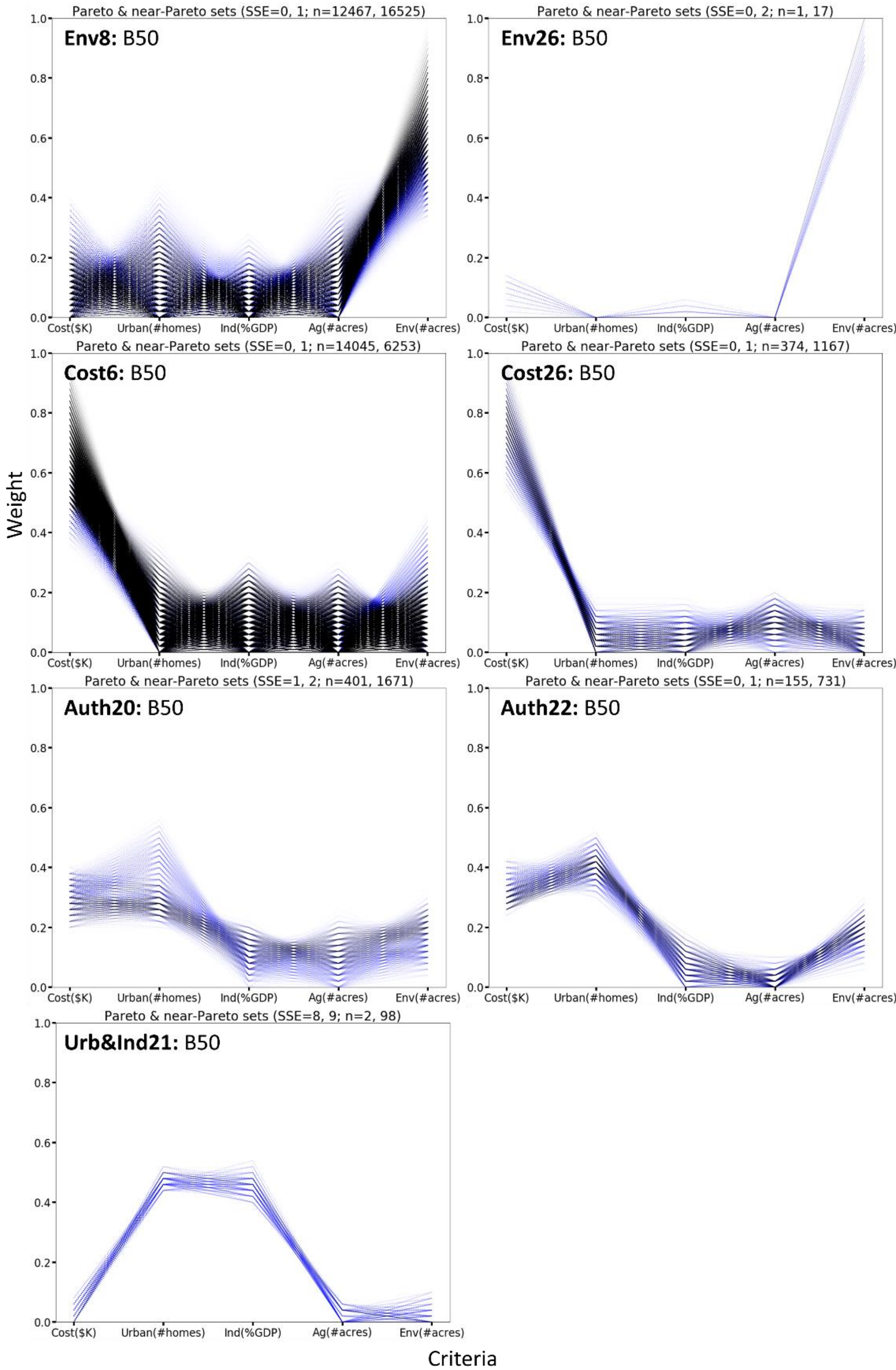

Figure 2.5. *Parallel axis plots show Pareto (black lines) and near-Pareto (blue lines) results for the "B50" brute force, enumeration analyses. Subplots for seven game-play trials are identified by bold labels at the upper-left of each. Within subplots, each line represents a weight set in the results. Values for individual criteria weights are read off the vertical axis where lines cross criteria tick marks on the horizontal axis.*

Comparison of inferred weights for the same gameplay trial across analysis parameterizations

In the subsections below, one for each gameplay trial, tables of results show the minimum, median, and maximum weight values found by each analysis parameterization for each criterion (Tables 2.6-2.12). The distributions of weights for criteria in the Pareto sets are also shown in histograms that plot weights across 10 bins (Appendix B Figures 2.B1-2.B7). Parallel axis plots show the Pareto sets for each gameplay trial by each analysis parameterization (Figures 2.6, 2.8, 2.10, 2.12, 2.14, 2.16, 2.18), or overlay the Pareto and near-Pareto sets on the same plots (Figures 2.7, 2.9, 2.11, 2.13, 2.15, 2.17, 2.19).

In most cases, similar overall conclusions can be drawn from analyzing the same gameplay trial data with different analysis parameterizations. In cases where they differ, it is due to differing strengths and weaknesses of the different analysis approaches. One reason for differences in the results is that the evolutionary optimization analyses only generate and evaluate real-number weights and do not find solutions with exact 0 and 1 weight values, as are included in the gridded weights of the brute force, enumeration analyses. In many situations this may be irrelevant, but it does lead to differences in results for the gameplay trials played with fixed decision rules that uses 1 and 0 weights for all criteria.

A second reason for differences in the results is that the brute force, enumeration analyses are limited to a fixed grid increment and don't explore weights in between, leaving larger gaps between the candidate weight sets explored than do the evolutionary optimization analyses. For this reason, they generally evaluated a smaller number of candidate solutions and had fewer weight sets (sometimes with two or three orders of magnitude fewer) in their Pareto sets than did the evolutionary optimization parameterizations.

A third reason for differences in the results is that in some cases the brute force, enumeration analysis parameterizations found Pareto sets with a smaller sum of squared error than was found by the corresponding evolutionary optimization analysis parameterizations. For example, in the Env26 trial, the Pareto set from the O35 analysis had a higher sum of squared error than the Pareto set of the B50 analysis and is thus closer to the near-Pareto set of the B50 analysis than to the B50 Pareto set.

Env8 trial

The Env8 gameplay trial was played with a fixed decision rule that always favored the environmental criterion. (In case of ties, it also included a provision to secondarily favor the alternative with the better agriculture score, but no ties were encountered.) Gameplay resulted in eight observed decisions made by the player using this decision rule. All six analysis parameterizations successfully inferred a high weight for the environmental criterion and little weight for the other criteria (Table 2.6, Figure 2.6).

Of the four criteria with low inferred weight, the urban criterion consistently had highest maximum value. This doesn't reflect the decision rule used, but can be explained as a artifact of the random alternatives presented in this trial, since the alternative with the highest environmental score also happened to have the highest urban score in three of the eight observed decisions. This highlights a danger of the analysis being misled when using too few observations, something that is less likely to occur in gameplay trials with greater numbers of observed decisions.

For the Env8 trial, the B50 analysis took 80 times longer to run than the B20 analysis and produced a Pareto set with 28 times more weight sets (Tables 2.5 & 2.6). The consequences of this extra computational effort are inferred weight ranges that are an average of 0.02 wider with median weights that differ by an average of 0.01, in Pareto sets with the same sum of squared error. Whether the extra computational effort for this difference in results is worthwhile depends on the use case, preferences, and needs of the analysts, stakeholders, and decision makers.

The minimum, median, and maximum inferred weights were not exactly the same across the four evolutionary optimization analyses but were generally close in value, differing from each other by an average of 0.03. The O15 results most often had a smaller inferred weight range than the O20, O25, and O35 results and had median urban and environmental weight values that differed most substantially from the others.

There were also a few differences between the results from the evolutionary optimization analyses and brute force, enumeration analyses, namely with the B20 and B50 results having slightly lower urban and industry criteria median weights, a moderately higher environmental median weight, and a wider inferred range for the environmental criterion. Other inferred weights were similar between the evolutionary optimization and brute force, enumeration types of analysis.

Inclusion of the near-Pareto results (Figure 2.7) widened the inferred ranges only slightly, and not necessarily symmetrically (i.e., in some cases widening the range more on the upper end than the lower end, or vice versa.) Overall, the conclusions that can be drawn about the relative importance of the criteria are similar with or without consideration of the near-Pareto results.

Table 2.6. *Criterion weights inferred for the "Env8" gameplay trial via six parameterizations (in columns) of the evolutionary optimization and brute force, enumeration analyses. Data show the range of [minimum, median, maximum] criterion weights from all weight sets in the Pareto-efficient set. (See Table 2.2 for a summary of the decision rule used to produce the choice outcomes in this trial.)*

Env8 trial	**Brute force enumeration**		**Evolutionary optimization**			
	B20	**B50**	**O15**	**O20**	**O25**	**O35**
Cost	[.00,**.10**,.25]	[.00,**.10**,.28]	[.01,**.09**,.20]	[.00,**.10**,.23]	[.00,**.13**,.26]	[.00,**.10**,.27]
Urban	[.00,**.10**,.35]	[.00,**.08**,.36]	[.01,**.23**,.34]	[.00,**.12**,.35]	[.00,**.13**,.32]	[.00,**.16**,.35]
Industry	[.00,**.05**,.20]	[.00,**.06**,.20]	[.00,**.05**,.15]	[.00,**.07**,.16]	[.00,**.08**,.19]	[.00,**.05**,.19]
Agriculture	[.00,**.10**,.30]	[.00,**.10**,.34]	[.01,**.16**,.29]	[.00,**.19**,.33]	[.00,**.13**,.31]	[.00,**.16**,.32]
Environ.	[.40,**.65,**1.0]	[.34,**.62,**1.0]	[.34,**.46**,.72]	[.36,**.52**,.84]	[.35,**.53**,.87]	[.33,**.53**,.89]

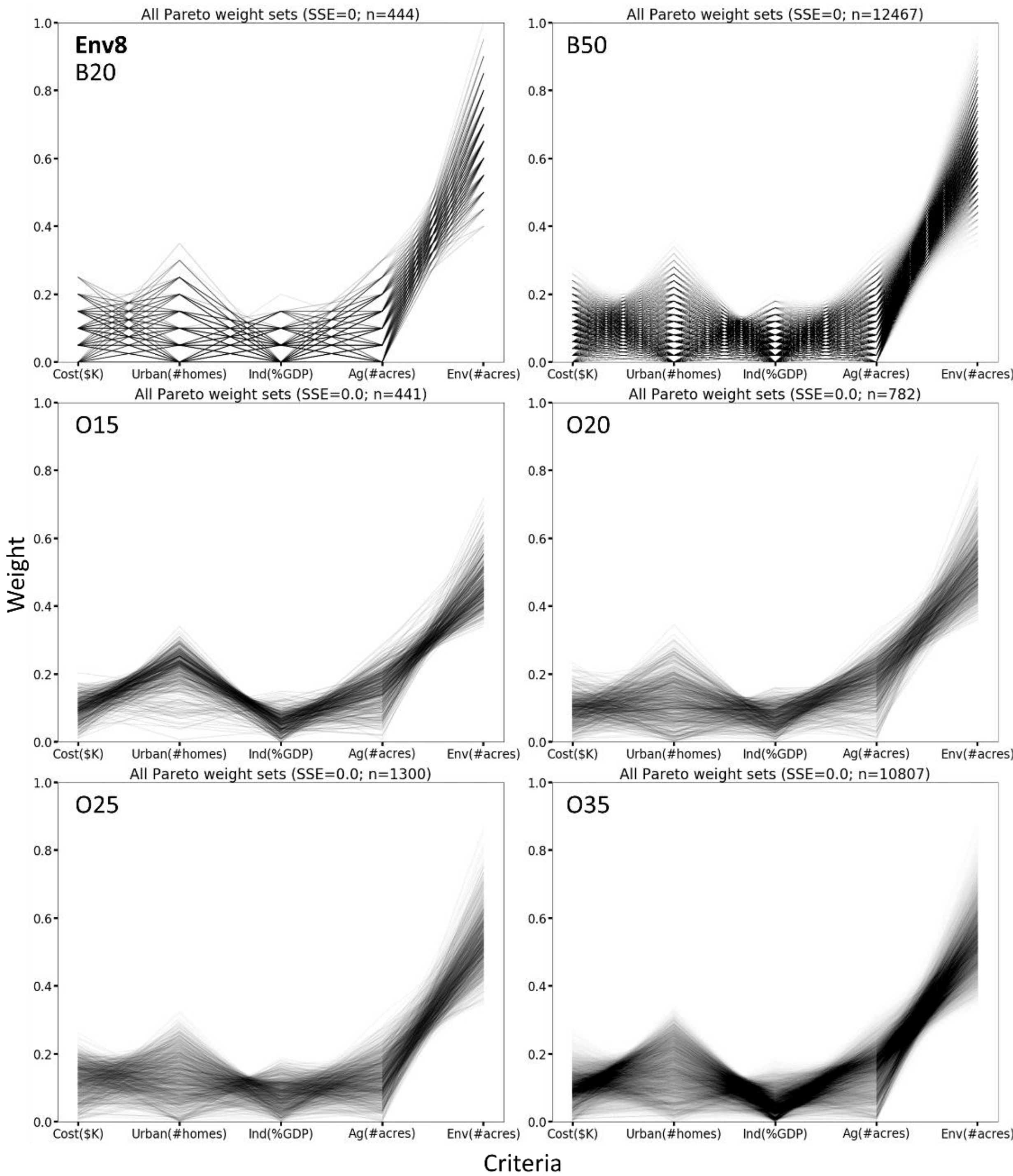

Figure 2.6. *Six Parallel axis plots show Pareto results for the "Env8" gameplay trial from runs of each analysis parameterization (as identified at upper-left of each and as defined in Tables 2.3 & 2.4). Within subplots, each line represents one weight set in the Pareto results. Values for individual criteria weights are read off the vertical axis where lines cross criteria tick marks on the horizontal axis. Higher weight values represent greater preference.*

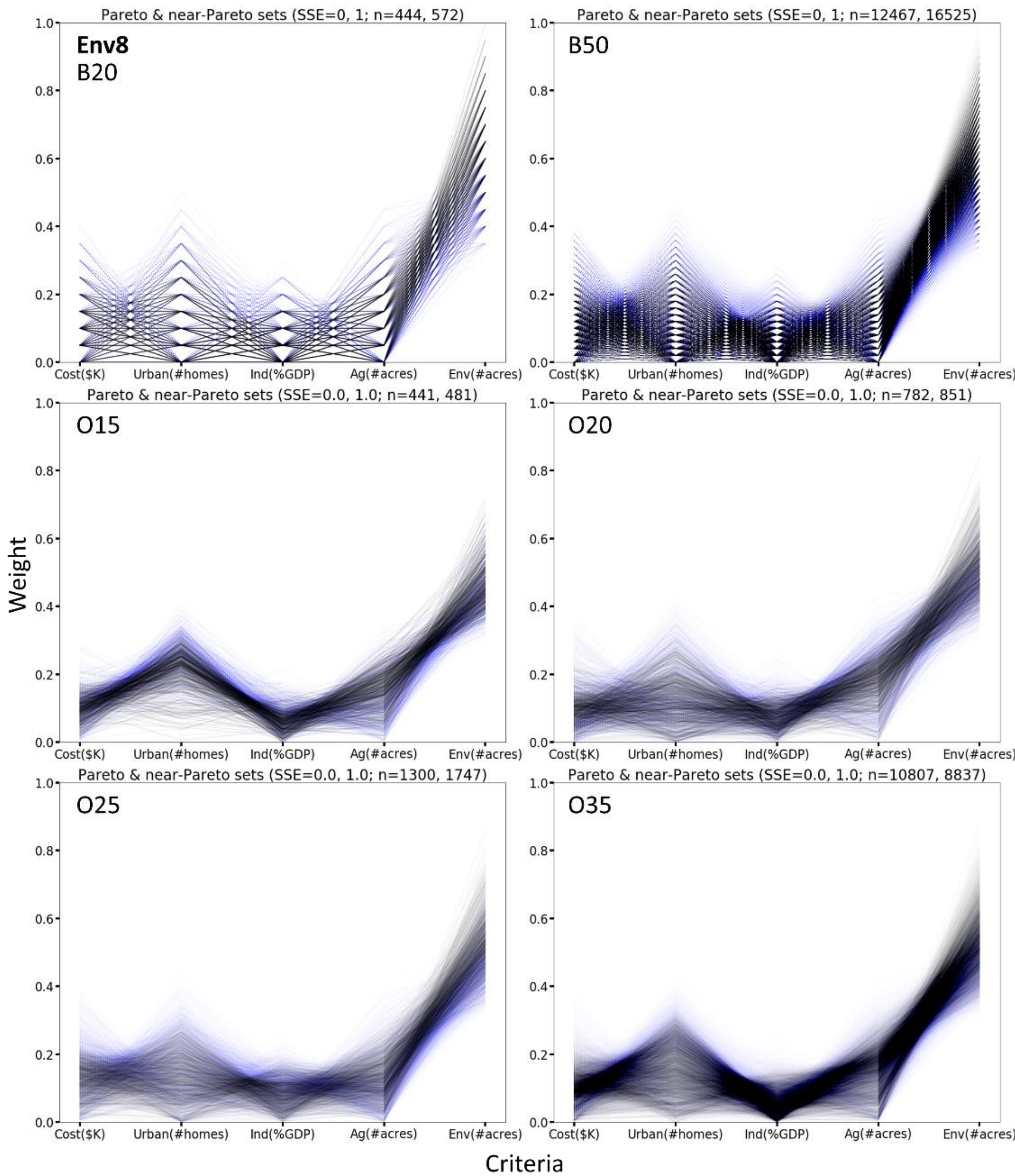

Figure 2.7. *Six Parallel axis plots show Pareto (black lines) and near-Pareto (blue lines) result sets for the "Env8" gameplay trial from runs of each analysis parameterization (as identified at upper-left of each and as defined in Tables 2.3 & 2.4). Within subplots, each line represents one weight set in the results. Values for individual criteria weights in a weight set are read off the vertical axis where the line crosses criteria tick marks on the horizontal axis. Higher weight values represent greater preference.*

Env26 trial

The Env26 gameplay trial includes 26 observed decisions made by the player following the same decision rule as in the Env8 trial. In this trial, there were five cases where the alternatives with the highest environmental scores tied and the agricultural criterion was used as a tie breaker. All six analysis parameterizations successfully identify that a high weight had been placed on the environmental criterion and low weight on the other criteria (Table 2.7, Figure 2.8). The weight ranges that resulted from the analyses are also much narrower than for the Env8 trial. For most of the analyses, the agriculture criterion ranked in second place or tied for second place, reflecting its secondary preference as a tiebreaker. As an artifact of the particular alternatives presented, the inferred weights for the cost criteria are also higher than those of the other criteria with low weight.

For this trial, the B20 and B50 analyses produced the exact same minimum, median, and maximum inferred weights, which match the actual decision rule used. In this case at least, 26 decision observations were more than enough to identify the fixed decision rule using these analysis parameterizations. The sum of squared error was 0 for the Pareto sets from the brute force, enumeration analyses, compared to 10 for the Pareto sets from the evolutionary optimization analyses. Given this difference, the near-Pareto sets (Figure 2.9) for the B20 and B50 analyses, with a next-lowest sum of squared error of 2, most closely match the Pareto sets from the O15, O20, O25, and O35 analyses. For most of the analyses, inclusion of the near-Pareto sets lowered the inferred range for the environment and agriculture criteria and raised it for the others, especially for the cost criterion.

The minimum, median, and maximum inferred weights from the O15, O20, O25, and O35 analyses often, but not always matched each other and were generally within 0.01 or 0.02 of each other when they did not exactly match. These results do not quite reproduce the decision rule with its 0 and 1 weights, but come close to it and lead to conclusions compatible with it. Of the evolutionary optimization analyses, the O35 analyses most often had the widest weight range, which is desirable for a given level of error since it represents more thorough identification of solution weight sets at that error level.

Table 2.7. *Criterion weights inferred for the "Env26" gameplay trial via six parameterizations (in columns) of the evolutionary optimization and brute force, enumeration analyses. Data show the range of [minimum, median, maximum] criterion weights from all weight sets in the Pareto-efficient set. (See Table 2.2 for a summary of the decision rule used to produce the choice outcomes in this trial.)*

Env26 trial	**Brute force enumeration**		**Evolutionary optimization**			
	B20	**B50**	**O15**	**O20**	**O25**	**O35**
Cost	[.00,.**00**,.00]	[.00,.**00**,.00]	[.03,**.06**,.07]	[.04,**.06**,.08]	[.02,**.07**,.09]	[.02,**.06**,.09]
Urban	[.00,.**00**,.00]	[.00,.**00**,.00]	[.01,**.01**,.04]	[.00,**.02**,.04]	[.00,**.01**,.03]	[.00,**.01**,.03]
Industry	[.00,.**00**,.00]	[.00,.**00**,.00]	[.01,**.01**,.03]	[.01,**.02**,.04]	[.01,**.03**,.05]	[.01,**.03**,.05]
Agriculture	[.00,.**00**,.00]	[.00,.**00**,.00]	[.03,**.07**,.08]	[.04,**.07**,.08]	[.03,**.06**,.08]	[.02,**.06**,.08]
Environ.	[1.0,**1.0**,1.0]	[1.0,**1.0**,1.0]	[.81,**.84**,.92]	[.81,**.83**,.89]	[.80,**.82**,.94]	[.80,**.84**,.94]

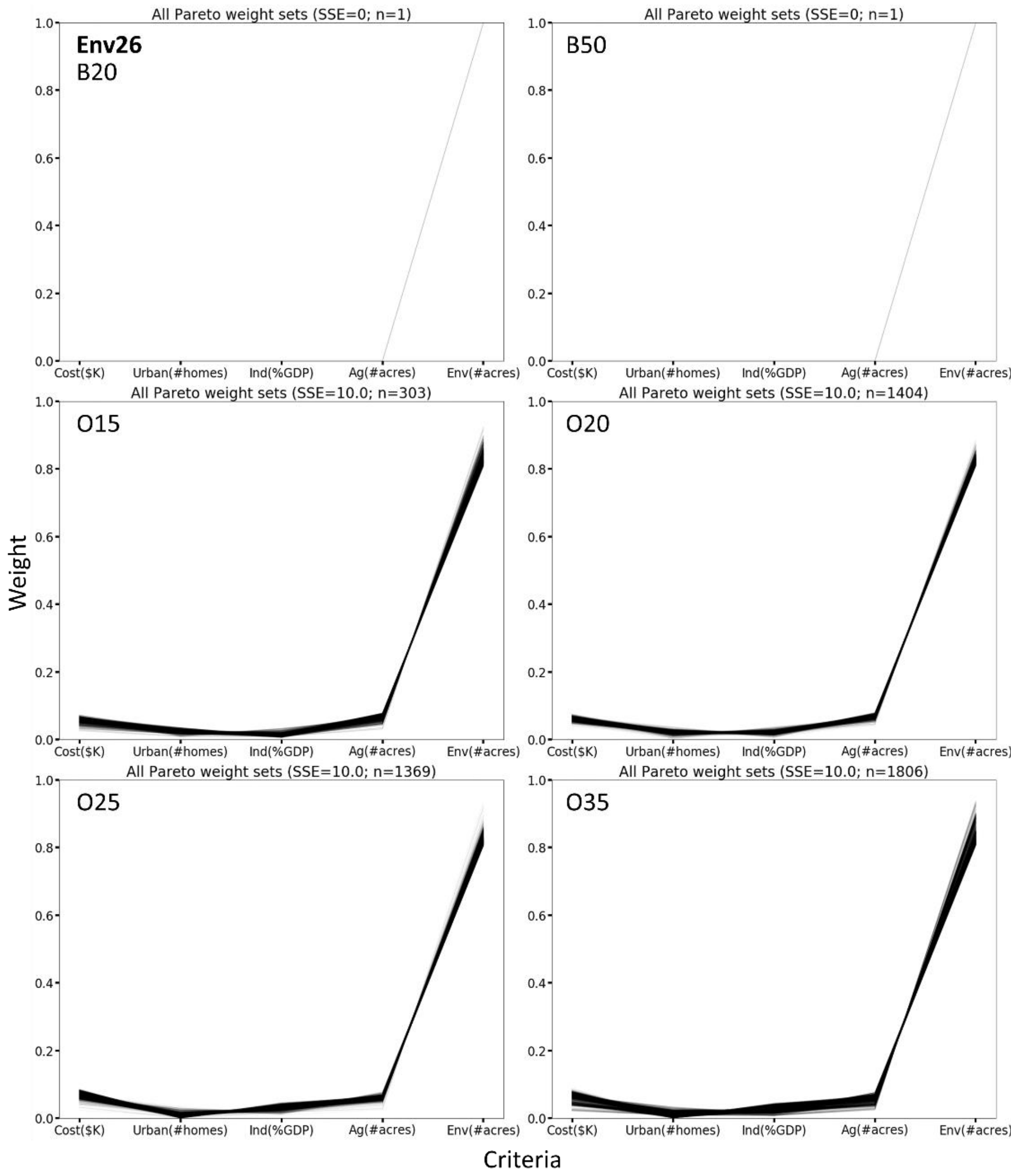

Figure 2.8. *Six Parallel axis plots show Pareto results for the "Env26" gameplay trial from runs of each analysis parameterization (as identified at upper-left of each and as defined in Tables 2.3 & 2.4). Within subplots, each line represents one weight set in the Pareto results. Values for individual criteria weights are read off the vertical axis where lines cross criteria tick marks on the horizontal axis. Higher weight values represent greater preference.*

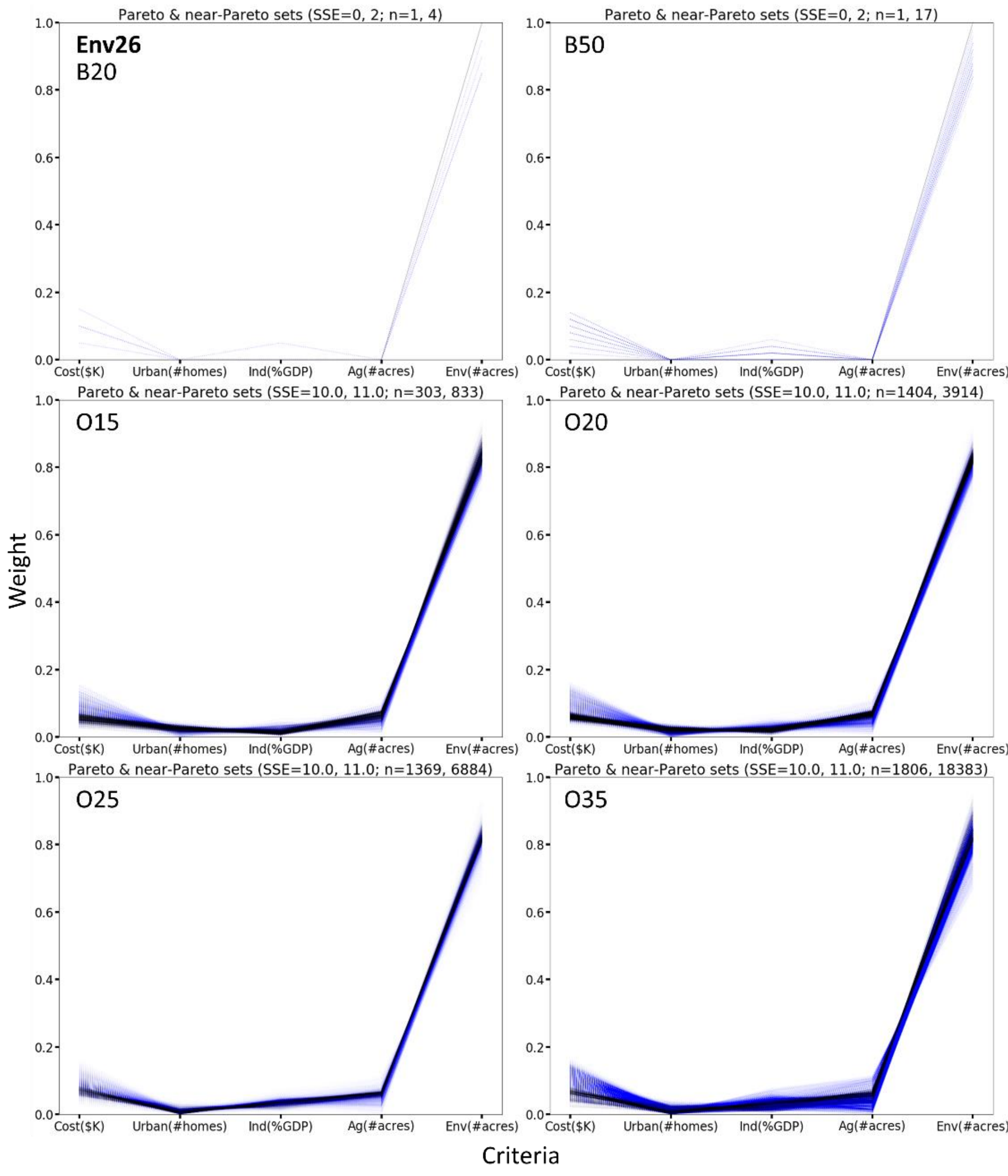

Figure 2.9. *Six Parallel axis plots show Pareto (black lines) and near-Pareto (blue lines) result sets for the "Env26" gameplay trial from runs of each analysis parameterization (as identified at upper-left of each and as defined in Tables 2.3 & 2.4). Within subplots, each line represents one weight set in the results. Values for individual criteria weights in a weight set are read off the vertical axis where the line crosses criteria tick marks on the horizontal axis. Higher weight values represent greater preference.*

Cost6 trial

The Cost6 gameplay trial was played with a fixed decision rule to always favor the alternative with the lowest cost. (The decision rule also included a provision in case of ties to secondarily favor the alternative with the better agriculture score, but no ties were encountered.) Even with only six observed decisions in the gameplay data, all of the analyses were able to successfully infer a high weight for the cost criterion and low weight for all other criteria (Table 2.8, Figure 2.10), the quickest analysis doing so within about two seconds.

The ranges in the Pareto sets were all very wide, from about 0.0 to 0.25 or 0.30 on the low end and about 0.45 or 0.50 to 0.90 or 1.0 on the high end. All analyses had a sum of squared error of 0, so had the potential to find the same Pareto sets. Yet, only the B20 and B50 trials reached maximum values of 1.0. This is an example of one comparative strength of the brute force, enumeration approach that can include exact 0 and 1 weight values. The evolutionary optimization approaches, however, were able to get results that were close and with quicker runtime. The runtime for the O15, O20, and O25 analyses ranged from 2 to 4 seconds. This is an order of magnitude quicker than the runtimes of the O35 and B20 analyses of 21 and 25 seconds, respectively, and vastly quicker than the 46-minute runtime of the B50 analysis.

Aside from reaching maximum values of only 0.84 to 0.94 instead of 1.0 for the cost criterion, the remaining minimum, median, and maximum weights were fairly close across the analyses, given the wide weight ranges inferred. Similarly, inclusion of the near-Pareto set (with sum of squared error of 1, Figure 2.11) added lower inferred weights for the cost criterion and higher inferred weights for environmental criterion, but did little to change the weight ranges for the other criteria.

Table 2.8. *Criterion weights inferred for the "Cost6" gameplay trial via six parameterizations (in columns) of the evolutionary optimization and brute force, enumeration analyses. Data show the range of [minimum, median, maximum] criterion weights from all weight sets in the Pareto-efficient set. (See Table 2.2 for a summary of the decision rule used to produce the choice outcomes in this trial.)*

Cost6 trial	**Brute force enumeration**		**Evolutionary optimization**			
	B20	**B50**	**O15**	**O20**	**O25**	**O35**
Cost	[.50,**.65**,1.0]	[.46,**.62**,1.0]	[.47,**.63**,.94]	[.46,**.58**,.84]	[.46,**.57**,.92]	[.45,**.57**,.90]
Urban	[.00,**.10**,.35]	[.00,**.08**,.34]	[.00,**.04**,.28]	[.00,**.08**,.27]	[.00,**.12**,.30]	[.00,**.10**,.31]
Industry	[.00,**.10**,.30]	[.00,**.08**,.30]	[.00,**.17**,.29]	[.00,**.08**,.25]	[.00,**.15**,.27]	[.00,**.12**,.29]
Agriculture	[.00,**.05**,.25]	[.00,**.06**,.26]	[.00,**.04**,.23]	[.00,**.09**,.24]	[.00,**.07**,.22]	[.00,**.06**,.26]
Environ.	[.00,**.10**,.30]	[.00,**.08**,.34]	[.00,**.07**,.25]	[.00,**.13**,.26]	[.00,**.08**,.28]	[.00,**.12**,.28]

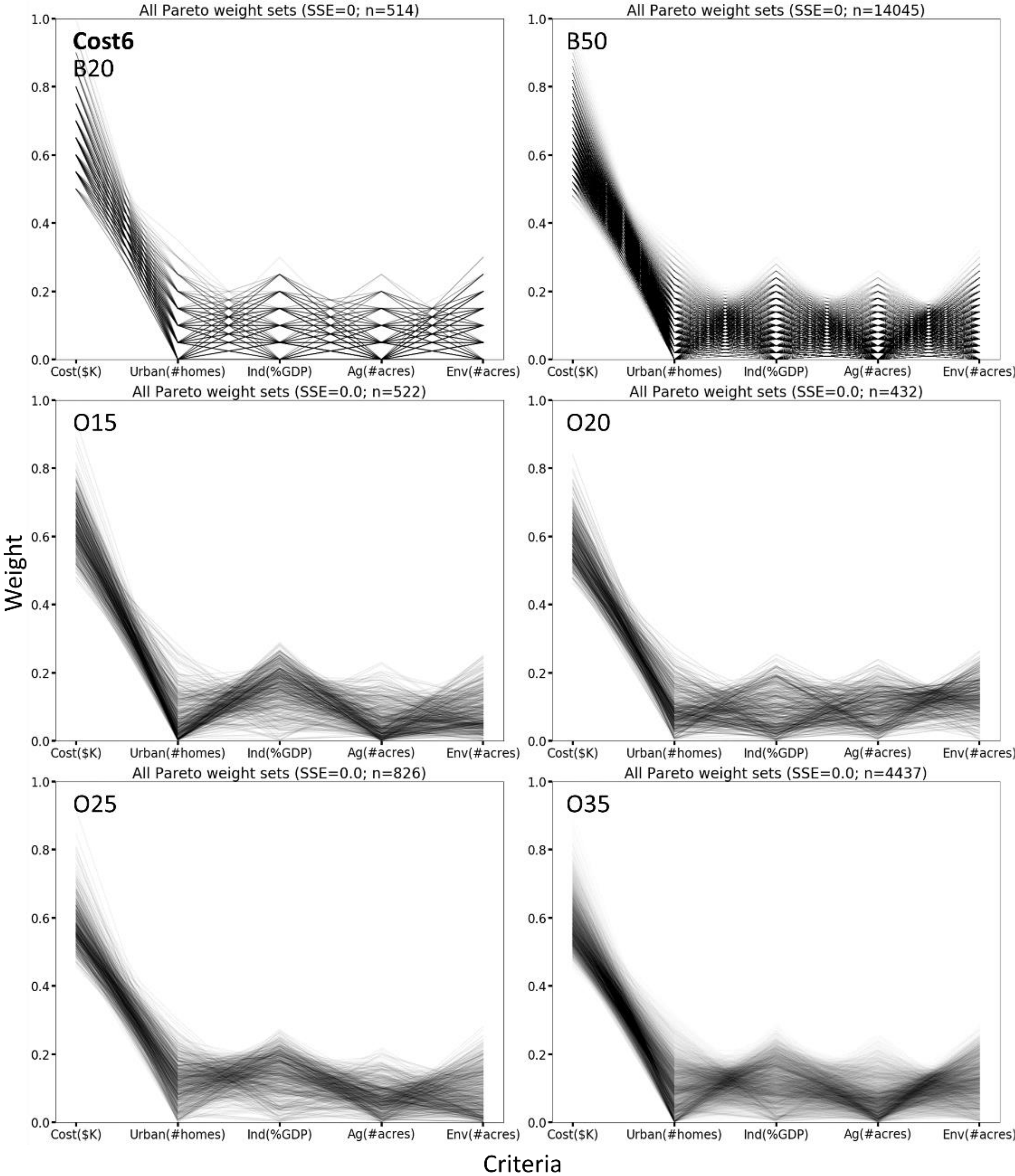

Figure 2.10. *Six Parallel axis plots show Pareto results for the "Cost6" gameplay trial from runs of each analysis parameterization (as identified at upper-left of each and as defined in Tables 2.3 & 2.4). Within subplots, each line represents one weight set in the Pareto results. Values for individual criteria weights are read off the vertical axis where lines cross criteria tick marks on the horizontal axis. Higher weight values represent greater preference.*

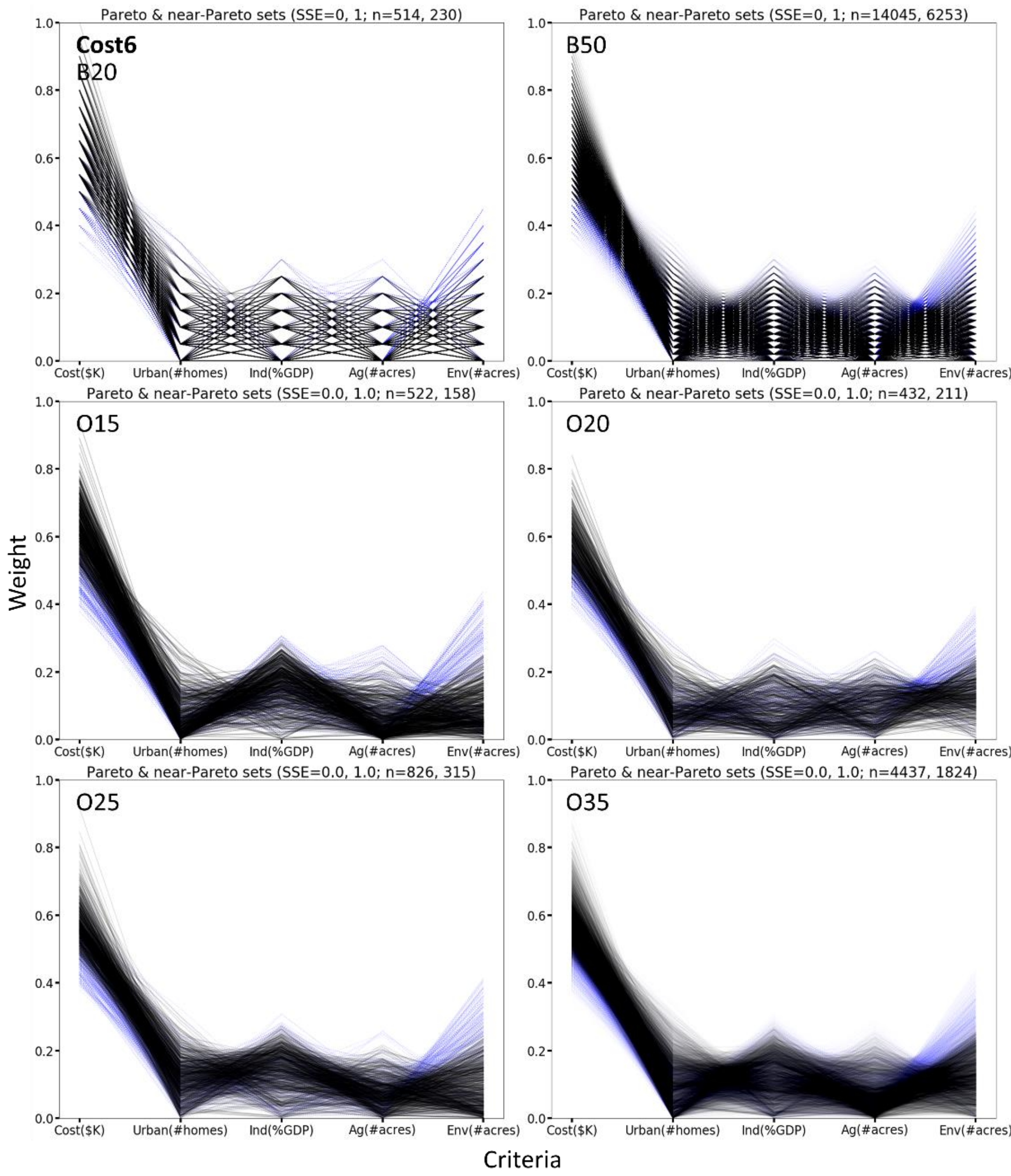

Figure 2.11. *Six Parallel axis plots show Pareto (black lines) and near-Pareto (blue lines) result sets for the "Cost6" gameplay trial from runs of each analysis parameterization (as identified at upper-left of each and as defined in Tables 2.3 & 2.4). Within subplots, each line represents one weight set in the results. Values for individual criteria weights in a weight set are read off the vertical axis where the line crosses criteria tick marks on the horizontal axis. Higher weight values represent greater preference.*

Cost26 trial

The Cost26 trial was played with the same decision rule as the Cost6 trial. All six analyses successfully identified that the player put a high weight on the cost criterion and little weight on the other criteria (Table 2.9, Figure 2.12). There were four ties in this trial where the agricultural criterion was used as a tie breaker and, as a result, all six analyses inferred a higher weight for agriculture than for the other low-weight criteria. It is encouraging for the viability of this approach for weight inference that even such a slight secondary preference for the agriculture criterion shows up so clearly in the results.

The Pareto sets for all six analyses have a sum of squared error of zero, so had the potential to find the same weight sets. Only the brute force, enumeration analyses found a maximum inferred cost weight of 1. The evolutionary optimization analyses found maximum inferred cost weights of between 0.86 and 0.98. The B20 analysis found a minimum value for the cost criterion that was higher than those found by the other analysis (0.70 instead of 0.59 to 0.64) and maximum values for the other criteria that were lower than those found by the other analysis, essentially inferring a more pronounced weight distribution because its course grid size missed identifying viable weight sets at the lower and upper bounds of the Pareto space. The weight ranges inferred by the other analyses were fairly similar to each other.

While the weight ranges in the Cost26 trial are narrower than in the Cost6 trial, they are wider than the corresponding weight ranges in the Env26 trial, presumably due to differences in the random alternatives shown and the degree of information gained by each selection decision between them.

Including the near-Pareto sets (Figure 2.13) broadened the estimated weight ranges for all criteria, added lower weight values for cost and agriculture and higher values for all non-cost criteria.

Table 2.9. *Criterion weights inferred for the "Cost26" gameplay trial via six parameterizations (in columns) of the evolutionary optimization and brute force, enumeration analyses. Data show the range of [minimum, median, maximum] criterion weights from all weight sets in the Pareto-efficient set. (See Table 2.2 for a summary of the decision rule used to produce the choice outcomes in this trial.) Note, the median values of 0.03 (0.025 before rounding) for the Urban and Industry weights inferred in the B20 parameterization represent averages of the two middle weights for those criteria in the Pareto sets.*

Cost26	**Brute force enumeration**		**Evolutionary optimization**			
trial	**B20**	**B50**	**O15**	**O20**	**O25**	**O35**
Cost	[.70,**.85**,1.0]	[.62,**.78**,1.0]	[.63,**.72**,.86]	[.62,**.73**,.90]	[.64,**.78**,.95]	[.59,**.72**,.98]
Urban	[.00,**.03**,.05]	[.00,**.04**,.12]	[.00,**.05**,.11]	[.00,**.06**,.13]	[.00,**.04**,.12]	[.00,**.07**,.12]
Industry	[.00,**.03**,.05]	[.00,**.04**,.12]	[.01,**.06**,.10]	[.00,**.06**,.11]	[.00,**.04**,.11]	[.00,**.06**,.12]
Agriculture	[.00,**.10**,.15]	[.00,**.10**,.18]	[.04,**.09**,.15]	[.03,**.08**,.19]	[.02,**.10**,.19]	[.01,**.10**,.19]
Environ.	[.00,**.00**,.10]	[.00,**.04**,.12]	[.00,**.08**,.13]	[.00,**.08**,.13]	[.00,**.03**,.12]	[.00,**.05**,.14]

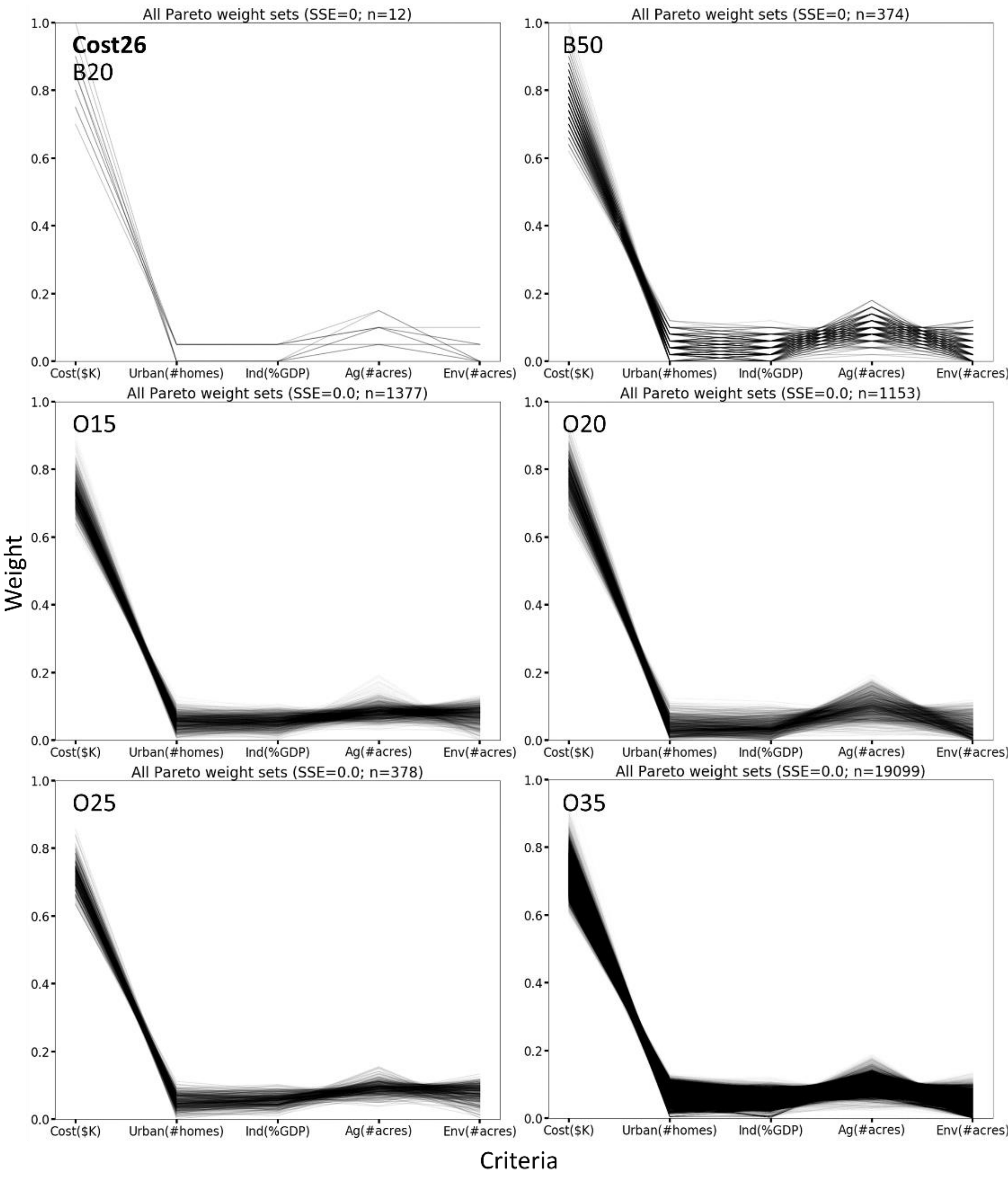

Figure 2.12. *Six Parallel axis plots show Pareto results for the "Cost26" gameplay trial from runs of each analysis parameterization (as identified at upper-left of each and as defined in Tables 2.3 & 2.4). Within subplots, each line represents one weight set in the Pareto results. Values for individual criteria weights are read off the vertical axis where lines cross criteria tick marks on the horizontal axis. Higher weight values represent greater preference.*

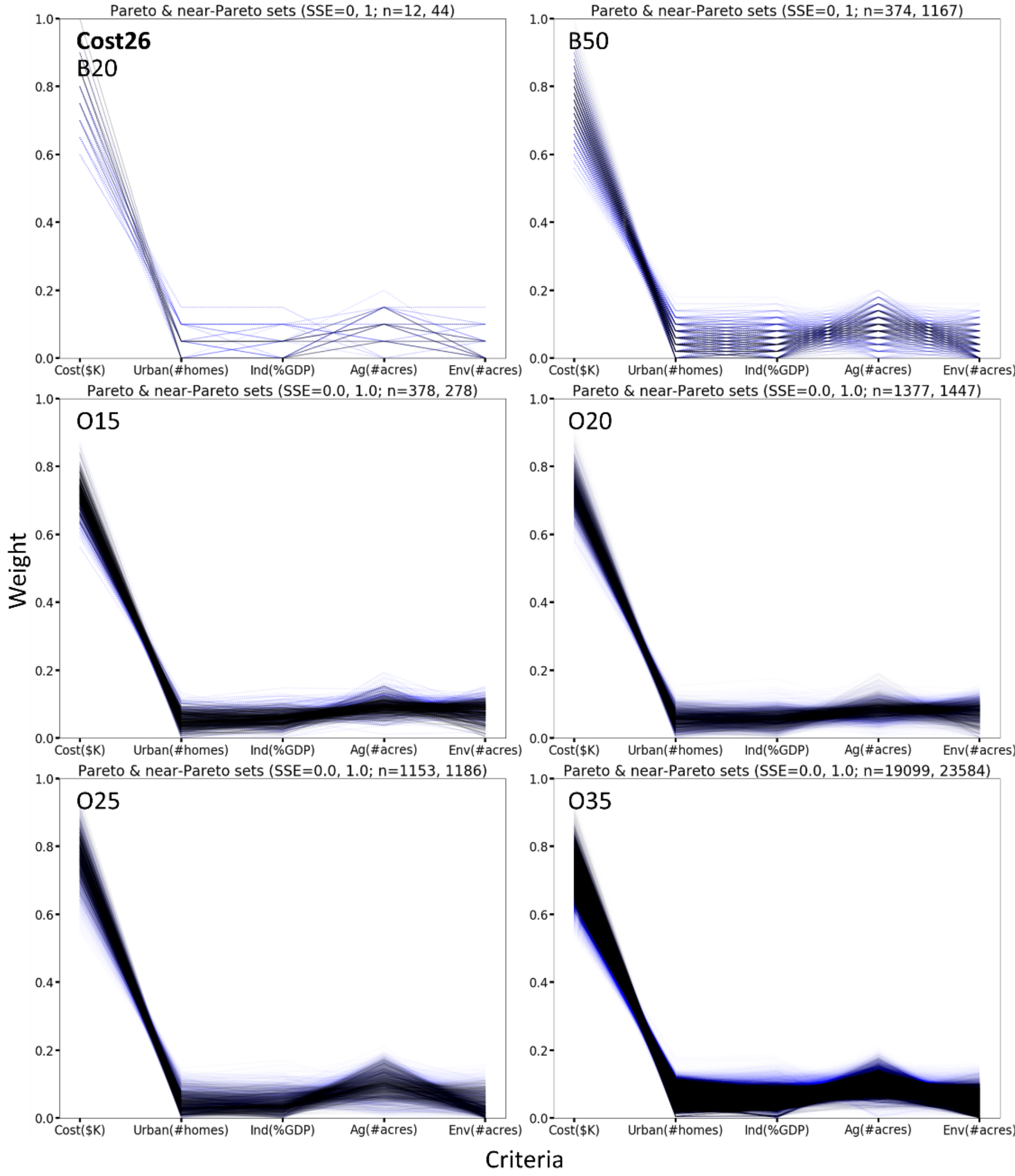

Figure 2.13. *Six Parallel axis plots show Pareto (black lines) and near-Pareto (blue lines) result sets for the "Cost26" gameplay trial from runs of each analysis parameterization (as identified at upper-left of each and as defined in Tables 2.3 & 2.4). Within subplots, each line represents one weight set in the results. Values for individual criteria weights in a weight set are read off the vertical axis where the line crosses criteria tick marks on the horizontal axis. Higher weight values represent greater preference.*

Urb&Ind21 trial

Unlike the gameplay trials discussed above, the Urb&Ind21 trial uses a decision rule that divides priority evenly between two criteria. Gameplay generated by following this decision rule resulted in 21 observed decisions where the player iteratively selected the alternative with the highest urban or industrial criterion score. All six analyses successfully identified high and approximately equal weights for the urban and industrial criteria and low weights for all remaining criteria (Table 2.10, Figure 2.14).

In this gameplay trial, all but one of the analyses had the same sum of squared error (the O20 sum of squared error was one higher than the others). Due to the gridded weight spacing used by the brute force, enumeration analyses, the B20 analysis found a Pareto set with only one element and the B50 analysis found a Pareto set with only two elements. In contrast, all of the evolutionary optimization analyses found Pareto sets with many elements (between 634 and 3287) and wider ranges of inferred weights. The weight ranges found by the O15, O25, and O35 analyses are consistent with each other, with most inferred values being identical or within 0.01 and all inferred values being within 0.02 of each other, despite the 14 times longer runtime of the O35 than the O15 analysis (Tables 2.5 & 2.10).

Inclusion of the near-Pareto sets (Figure 2.15) broadens the inferred weight ranges somewhat. Because the O20 analysis found a Pareto set with a higher sum of squared error than the others, the results in its Pareto set look most similar to the near-Pareto sets from the other analyses. The weight ranges widened by inclusion of near-Pareto sets are not symmetrical for some criteria in this trial. In particular, the near-Pareto sets predominantly add higher inferred weights for cost and environment criteria but lower inferred weighs for the industry criterion. Inclusion of the near-Pareto sets does not substantially change the conclusions about relative criteria importance that can be drawn from the results.

Table 2.10. *Criterion weights inferred for the "Urb&Ind21" gameplay trial via six parameterizations (in columns) of the evolutionary optimization and brute force, enumeration analyses. Data show the range of [minimum, median, maximum] criterion weights from all weight sets in the Pareto-efficient set. (See Table 2.2 for a summary of the decision rule used to produce the choice outcomes in this trial.)*

Urb&Ind21	**Brute force enumeration**		**Evolutionary optimization**			
trial	**B20**	**B50**	**O15**	**O20**	**O25**	**O35**
Cost	[.00,**.00**,.00]	[.00,**.00**,.00]	[.00,**.00**,.01]	[.00,**.03**,.08]	[.00,**.00**,.02]	[.00,**.00**,.02]
Urban	[.50,**.50**,.50]	[.48,**.49**,.50]	[.45,**.47**,.50]	[.43,**.47**,.51]	[.45,**.48**,.51]	[.45,**.48**,.51]
Industry	[.45,**.45**,.45]	[.46,**.47**,.48]	[.45,**.47**,.49]	[.39,**.43**,.48]	[.44,**.46**,.49]	[.44,**.46**,.49]
Agriculture	[.05,**.05**,.05]	[.04,**.04**,.04]	[.03,**.04**,.05]	[.01,**.04**,.07]	[.03,**.05**,.06]	[.03,**.05**,.06]
Environ.	[.00,**.00**,.00]	[.00,**.00**,.00]	[.00,**.01**,.03]	[.00,**.02**,.08]	[.00,**.01**,.04]	[.00,**.00**,.04]

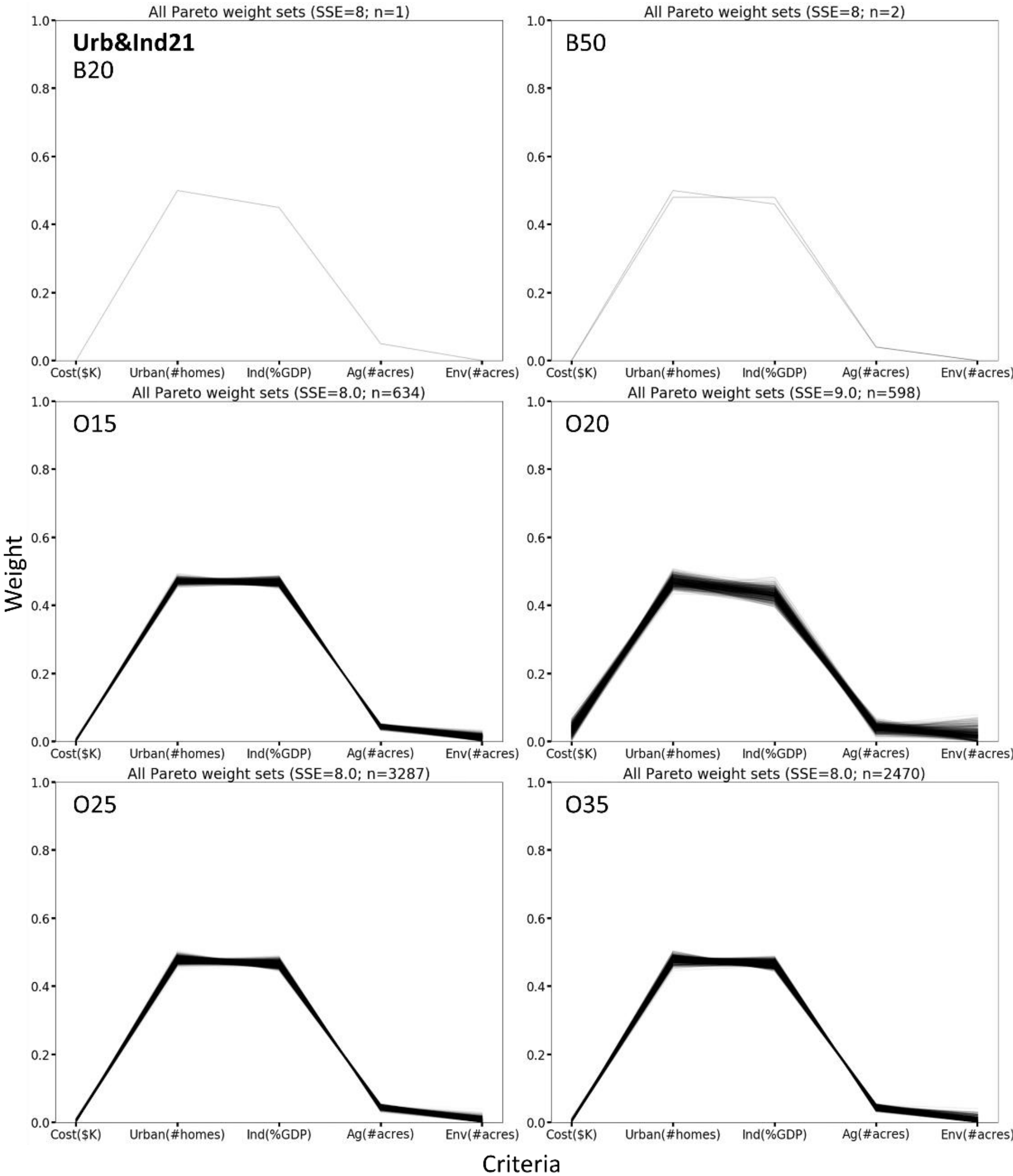

Figure 2.14. *Six Parallel axis plots show Pareto results for the "Urb&Ind21" gameplay trial from runs of each analysis parameterization (as identified at upper-left of each and as defined in Tables 2.3 & 2.4). Within subplots, each line represents one weight set in the Pareto results. Values for individual criteria weights are read off the vertical axis where lines cross criteria tick marks on the horizontal axis. Higher weight values represent greater preference.*

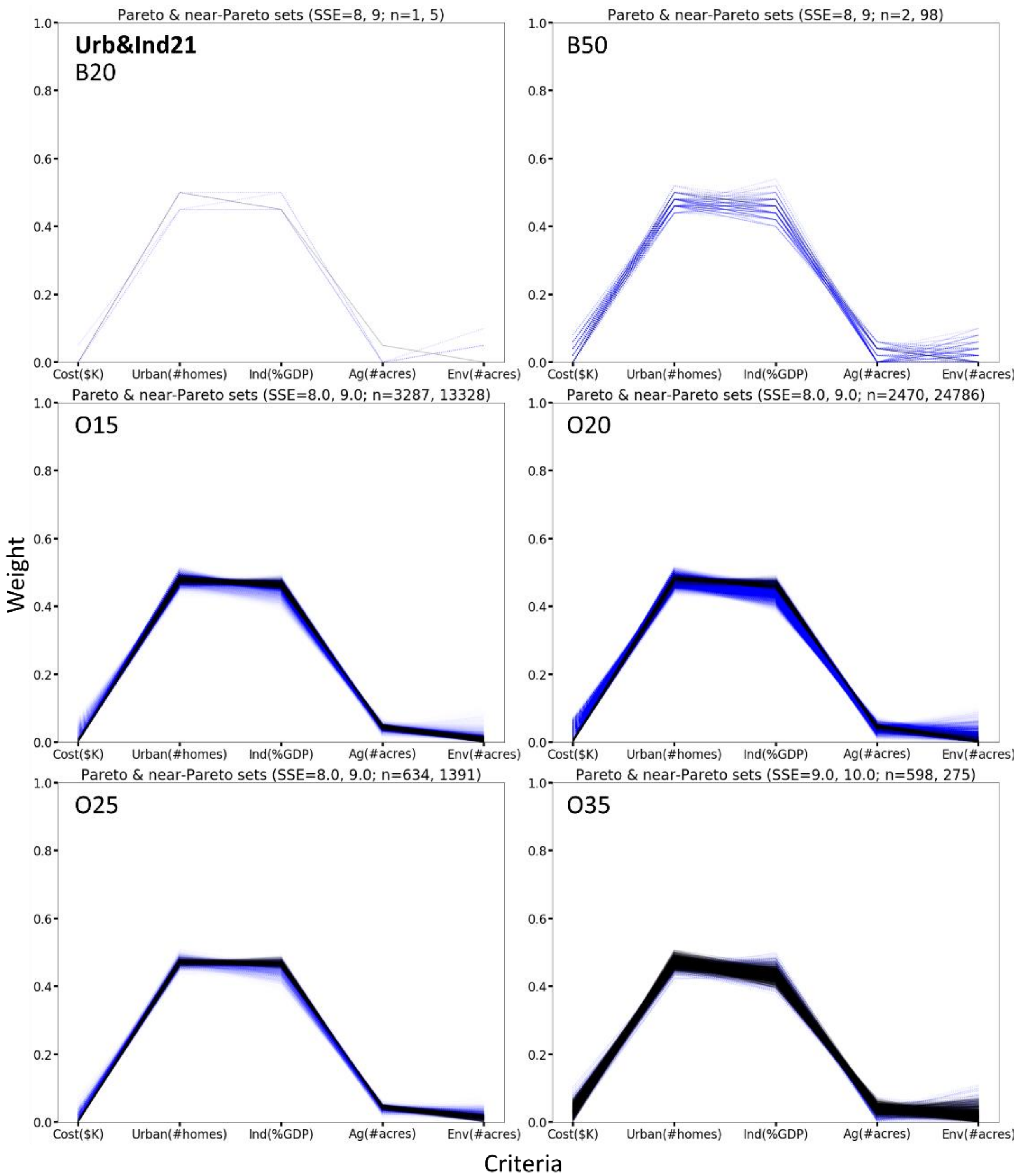

Figure 2.15. *Six Parallel axis plots show Pareto (black lines) and near-Pareto (blue lines) result sets for the "Urb&Ind21" gameplay trial from runs of each analysis parameterization (as identified at upper-left of each and as defined in Tables 2.3 & 2.4). Within subplots, each line represents one weight set in the results. Values for individual criteria weights in a weight set are read off the vertical axis where the line crosses criteria tick marks on the horizontal axis. Higher weight values represent greater preference.*

Auth20 trial

In the Auth20 gameplay trial, the author played without using an explicit decision rule. Instead, the author played used his own preferences, as experienced during the moment of gameplay, to choose between each set of alternatives presented. Before gameplay for this trial started, it was unknown what the results would show. Gameplay for this trial resulted in 20 observed decisions.

The Pareto sets from all six analysis parameterizations (Table 2.11, Figure 2.16) show the highest inferred weights for the urban and cost criteria, a medium weight for the environment criterion, and lower (but non-zero) weights for the industry and agriculture criteria. These trends are not surprising to the author, who played with cost consciousness and a strong concern for residential water supply. The differences in weight are identifiable but less pronounced than in previous trials that followed fixed decision rules placing full weight on one or two criteria and none on others. In this trial, the differences between highest, middling, and lowest inferred criteria weights are similar across analyses, with weights in each of these tiers differing by about 0.08 from the tier(s) adjacent to it.

The ranges of inferred weights are similar throughout the Pareto sets, generally having a spread of about 0.2 for most criteria and analysis parameterizations, except for the urban criterion, which has a narrower range of about 0.12. As might be expected, these inferred weight ranges are wider than in trials with a similar number of observations that followed a fixed decision rule, resulting in substantially greater uncertainty than was present in the results of the Env26 and Urb&Ind21 trials and slightly more than the Cost26 trial.

All Pareto sets had a sum of squared error of 1, so theoretically had accesses to the same potential population of efficient weight sets. With greater numbers of candidate weights explored, the B50 and O35 trials resulted in wider ranges of inferred weights and had Pareto sets with more individuals than did trials with quicker runtimes but less exploration.

Inclusion of the near-Pareto sets (with a sum of squared error of 2) somewhat widens the inferred weight ranges for most criteria and substantially increases the upper bound weight estimate for the urban criterion. In the brute force, enumeration analyses, the near-Pareto results included lower bound inferred weights with a value of 0 for the agriculture and industry criteria, but without substantial change to their median inferred weights.

Table 2.11. *Criterion weights inferred for the "Auth20" gameplay trial via six parameterizations (in columns) of the evolutionary optimization and brute force, enumeration analyses. Data show the range of [minimum, median, maximum] criterion weights from all weight sets in the Pareto-efficient set. (See Table 2.2 for a summary of the decision rule used to produce the choice outcomes in this trial.)*

Auth20	**Brute force enumeration**		**Evolutionary optimization**			
trial	**B20**	**B50**	**O15**	**O20**	**O25**	**O35**
Cost	[.20,.**30**,.35]	[.20,**.28**,.38]	[.19,**.24**,.32]	[.19,**.27**,.38]	[.19,**.27**,.37]	[.18,**.27**,.38]
Urban	[.25,**.30**,.35]	[.24,**.28**,.36]	[.23,**.27**,.34]	[.23,**.28**,.35]	[.23,**.28**,.36]	[.23,**.27**,.36]
Industry	[.05,**.10**,.15]	[.02,**.12**,.20]	[.05,**.14**,.21]	[.03,**.14**,.21]	[.03,**.14**,.21]	[.02,**.13**,.21]
Agriculture	[.05,**.10**,.20]	[.02,**.12**,.22]	[.03,**.13**,.20]	[.02,**.11**,.20]	[.01,**.10**,.21]	[.01,**.13**,.22]
Environ.	[.10,**.20**,.25]	[.08,**.20**,.28]	[.12,**.22**,.28]	[.09,**.20**,.28]	[.09,**.20**,.29]	[.08,**.21**,.30]

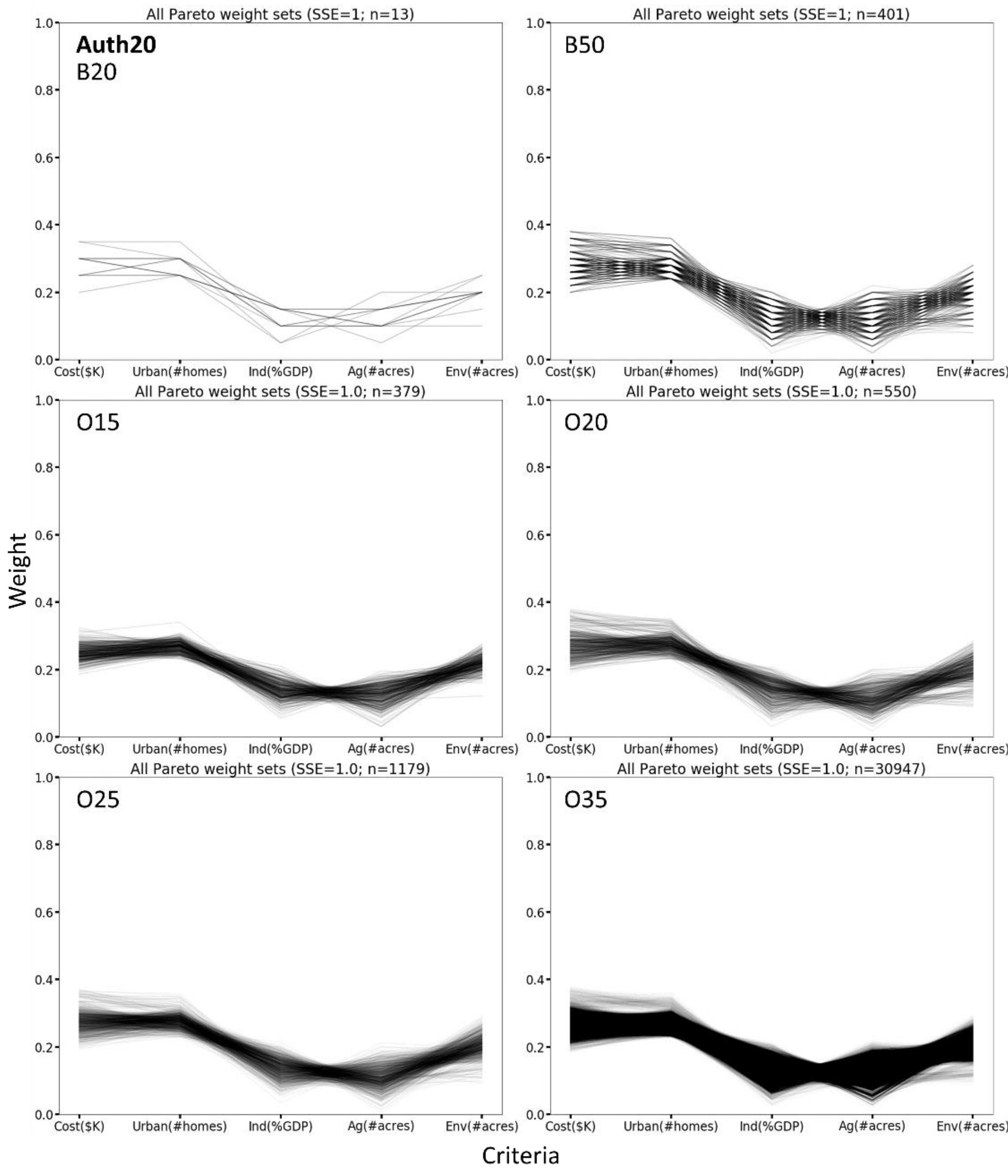

Figure 2.16. *Six Parallel axis plots show Pareto results for the "Auth20" gameplay trial from runs of each analysis parameterization (as identified at upper-left of each and as defined in Tables 2.3 & 2.4). Within subplots, each line represents one weight set in the Pareto results. Values for individual criteria weights are read off the vertical axis where lines cross criteria tick marks on the horizontal axis. Higher weight values represent greater preference.*

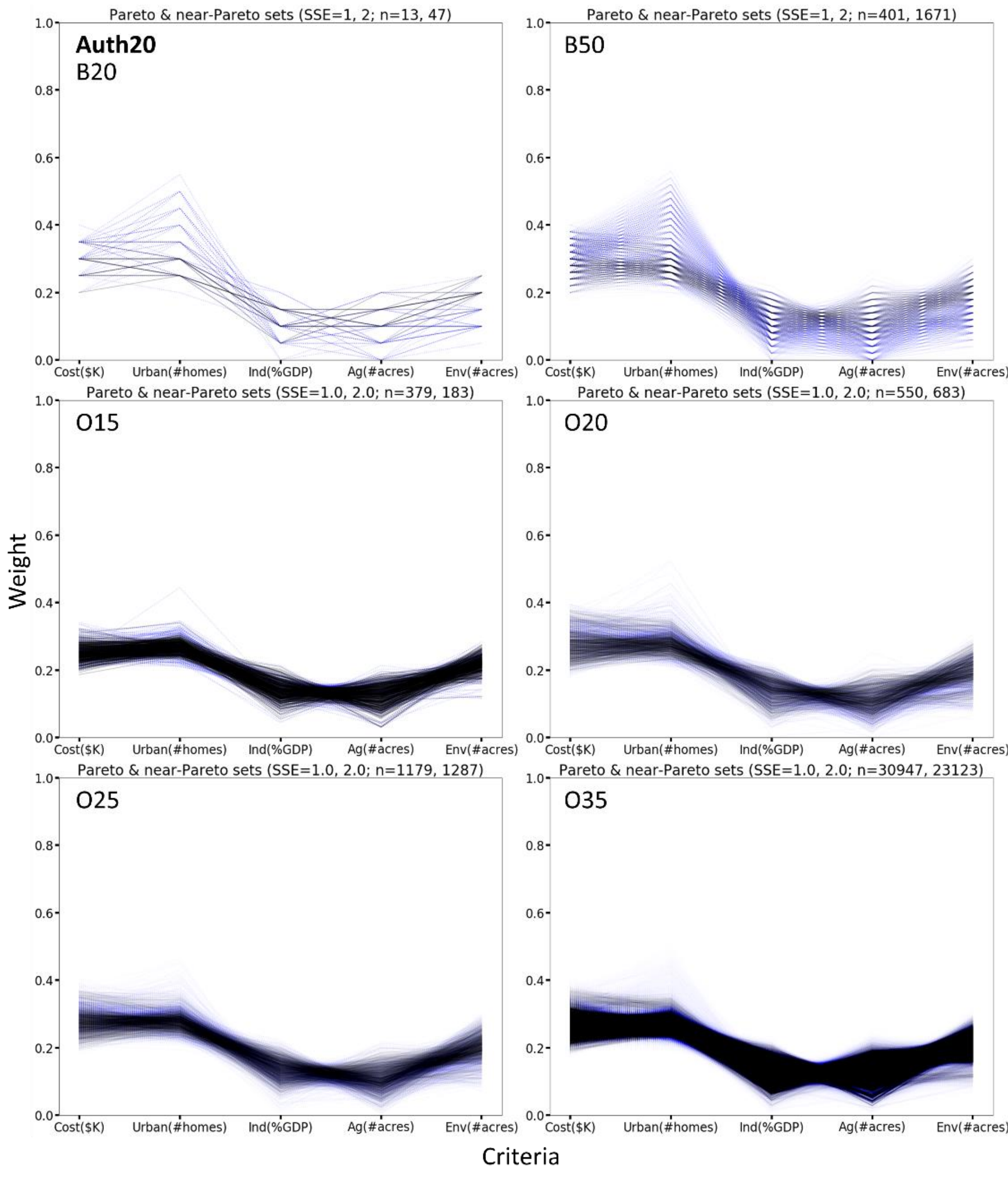

Figure 2.17. *Six Parallel axis plots show Pareto (black lines) and near-Pareto (blue lines) result sets for the "Auth20" gameplay trial from runs of each analysis parameterization (as identified at upper-left of each and as defined in Tables 2.3 & 2.4). Within subplots, each line represents one weight set in the results. Values for individual criteria weights in a weight set are read off the vertical axis where the line crosses criteria tick marks on the horizontal axis. Higher weight values represent greater preference.*

Auth22 trial

The Auth22 gameplay trial was played using the same approach as the Auth20 trial, with the author selecting alternatives based on his subjective preferences as experienced during gameplay instead of based on a fixed decision rule. Gameplay for this trial included 22 observed decisions.

The overall conclusions to be drawn from this trial (Table 2.12, Figure 2.18) in terms of the inferred rank order of criteria preference are similar to those drawn from the Auth20 trial. However, the results from this trial are more pronounced than in the Auth20 trial, having inferred weights with greater differences between them and narrower ranges, though it is unknown whether this is due to a shift in the expression of preferences, to random differences in the alternatives shown, or to inconsistencies in human decision making between trials. The Pareto sets from all six analyses rank the median weights in order from highest to lowest as: urban, cost, environment, industry, agriculture.

All Pareto sets have a sum of squared error of 0, so potentially had the ability to discover the same efficient weight sets. As has been typical, the Pareto sets from analyses with greater exploration (i.e., B50 and O35) have wider weight ranges than analyses that ran more quickly had less exploration, but only marginally so. For this trial, the inferred weight ranges across Pareto sets were quite close, with an average difference of only 0.01 between minimum, median, and maximum inferred weights for the same criteria. One noticeable difference between Pareto sets is that only B50, O25, and O35 Pareto sets have a lower bound for the industry criterion of 0.00 (as a rounded real number in the O25 and O35 results). The lower bound for the agriculture criterion is 0.00 in all Pareto sets.

Inclusion of the near-Pareto sets (Figure 2.19) widens the inferred criteria ranges slightly but does not substantially change the shape of the plots or the conclusions to be drawn.

Table 2.12. *Criterion weights inferred for the "Auth22" gameplay trial via six parameterizations (in columns) of the evolutionary optimization and brute force, enumeration analyses. Data show the range of [minimum, median, maximum] criterion weights from all weight sets in the Pareto-efficient set. (See Table 2.2 for a summary of the decision rule used to produce the choice outcomes in this trial.)*

Auth22	**Brute force, enumeration**		**Evolutionary optimization**			
trial	**B20**	**B50**	**O15**	**O20**	**O25**	**O35**
Cost	[.25,**.30**,.30]	[.26,**.30**,.34]	[.25,**.28**,.35]	[.25,**.28**,.34]	[.25,**.29**,.35]	[.24,**.30**,.36]
Urban	[.40,**.40**,.45]	[.34,**.42**,.46]	[.35,**.40**,.45]	[.34,**.40**,.45]	[.34,**.40**,.45]	[.33,**.41**,.46]
Industry	[.05,**.08**,.15]	[.00,**.08**,.18]	[.02,**.08**,.14]	[.01,**.09**,.16]	[.00,**.08**,.16]	[.00,**.07**,.18]
Agriculture	[.00,**.00**,.05]	[.00,**.02**,.06]	[.00,**.03**,.06]	[.00,**.02**,.06]	[.00,**.03**,.06]	[.00,**.03**,.07]
Environ.	[.15,**.20**,.25]	[.14,**.20**,.26]	[.14,**.20**,.24]	[.14,**.20**,.25]	[.13,**.19**,.26]	[.13,**.19**,.27]

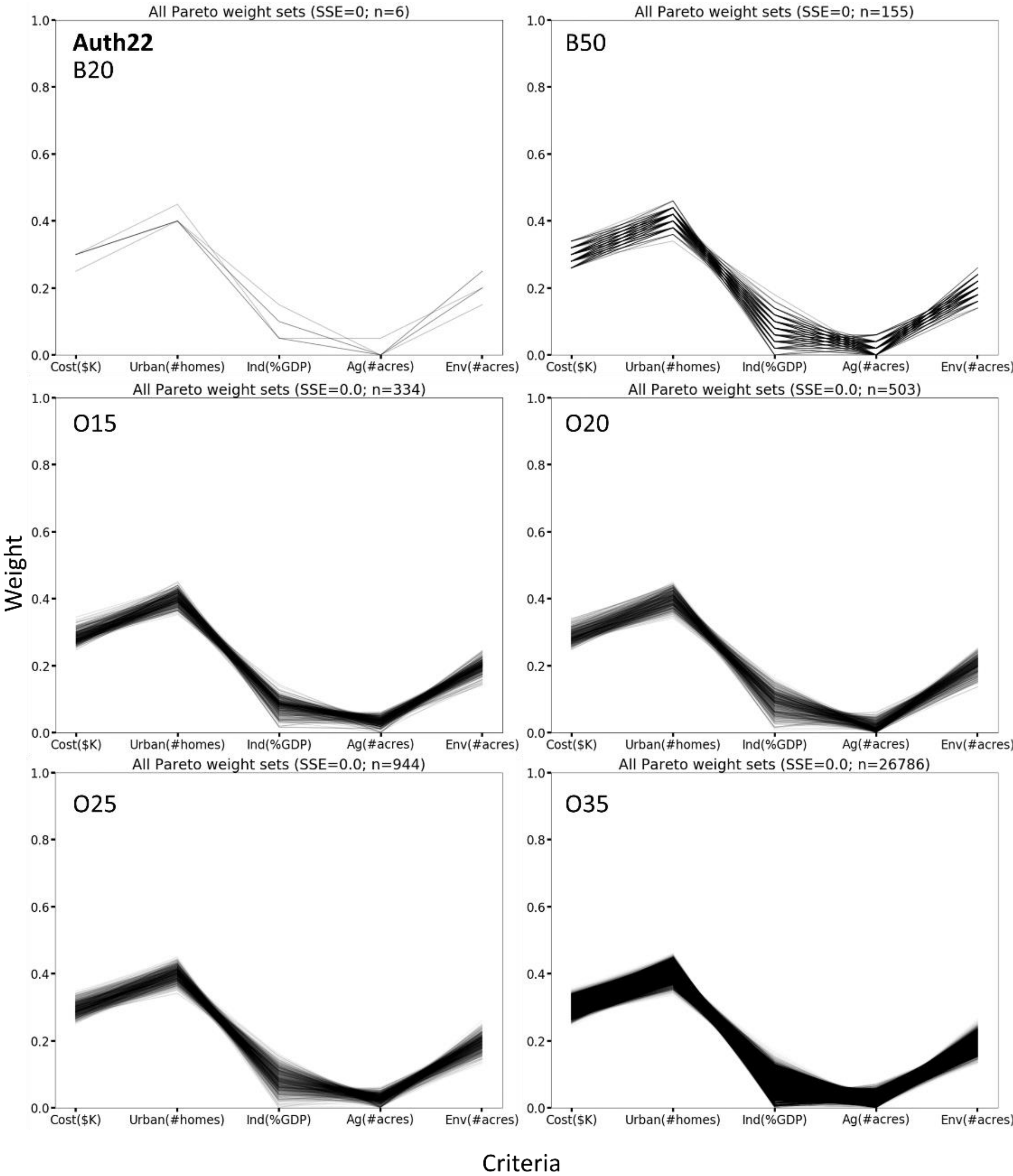

Figure 2.18. *Six Parallel axis plots show Pareto results for the "Auth22" gameplay trial from runs of each analysis parameterization (as identified at upper-left of each and as defined in Tables 2.3 & 2.4). Within subplots, each line represents one weight set in the Pareto results. Values for individual criteria weights are read off the vertical axis where lines cross criteria tick marks on the horizontal axis. Higher weight values represent greater preference.*

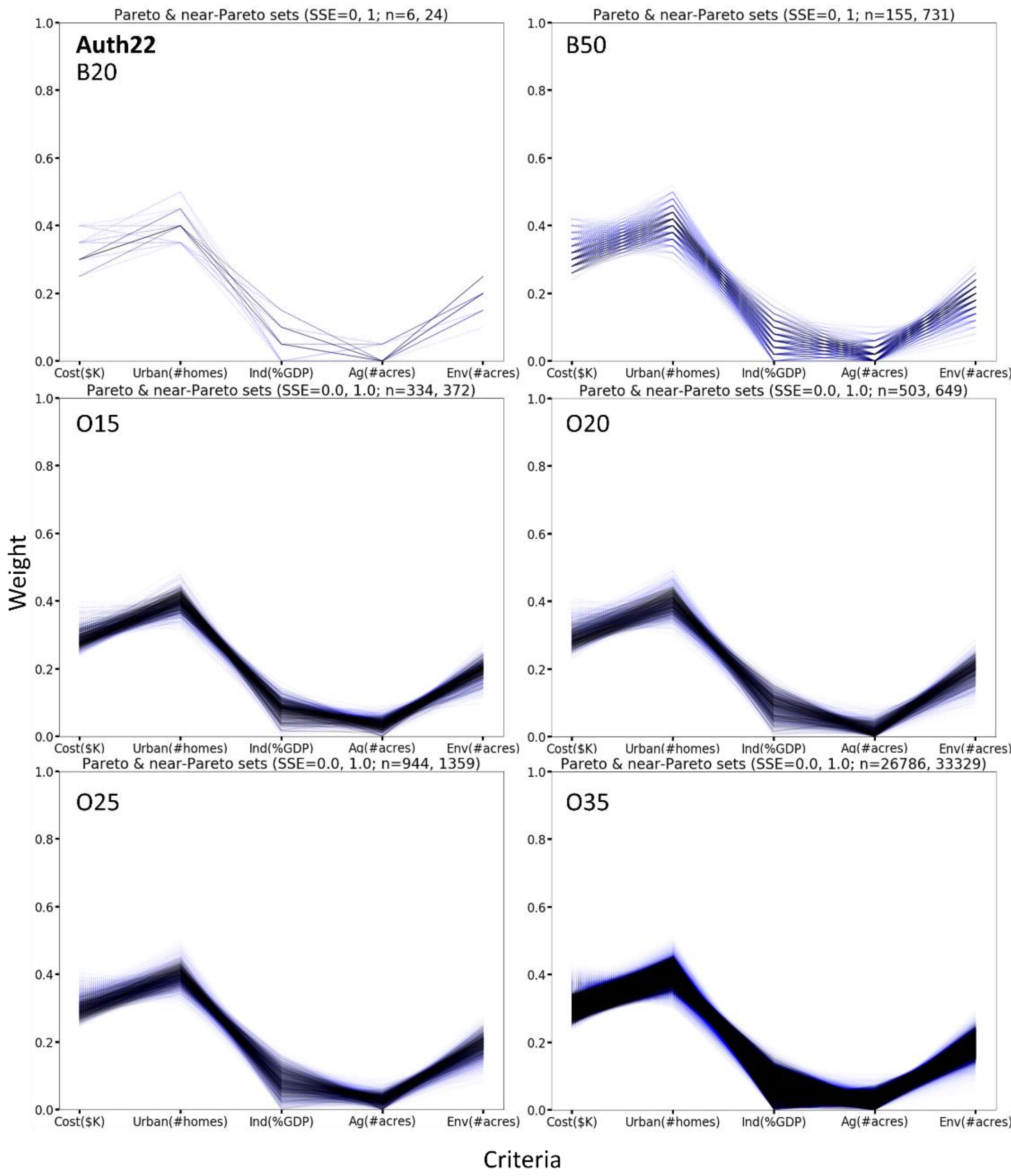

Figure 2.19. *Six Parallel axis plots show Pareto (black lines) and near-Pareto (blue lines) result sets for the "Auth22" gameplay trial from runs of each analysis parameterization (as identified at upper-left of each and as defined in Tables 2.3 & 2.4). Within subplots, each line represents one weight set in the results. Values for individual criteria weights in a weight set are read off the vertical axis where the line crosses criteria tick marks on the horizontal axis. Higher weight values represent greater preference.*

Additional discussion

Pareto sets are described by the ranges between their minimum and maximum and by their median inferred criteria weights. The weight ranges are important because they identify the bounds for preferences that could have produced the observed outcomes; they show what is possible. The medians are important when point estimates for the criteria weights are needed. In the brute force, enumeration analyses, these values cannot be skewed by random elements of the analysis because they have no random component and repeated analyses will always produce the same results with the same grid size. Also, since the analyses use a gridded weight space to explore candidate weight sets, every region of the weight space gets identical potential gets included in the analysis and is able to influence the inferred median and range weight values.

In contrast, the random exploration of the evolutionary optimization analyses could be unbalanced in its exploration of candidate weight sets. Because repeated analyses might not produce identical results if they use different random seeds, the reliability or representativeness of range and median estimates can be questioned. However, the results from the seven gameplay trials analyzed in this chapter show strong agreement between the ranges and medians inferred from the evolutionary optimization analyses with those from the brute force, enumeration analyses (Tables 2.6-2.12). In some cases, this similarity even extends to small details of the inferred weight distributions. For instance, the plots of Pareto sets (Figures 2.3-2.19) often show similar areas of lightness and darkness across analyses, identifying areas with lesser and greater density of candidate weights. In one example, the Pareto sets in the Auth20 gameplay trial (Figure 2.16) consistently show lighter lines on the upper portions of inferred weights for the urban criterion, indicating that some but relatively fewer weight sets in the Pareto sets have high urban weights—a trend observed across all brute force, enumeration and evolutionary optimization analyses.

The most complete analysis would produce Pareto sets with the widest possible ranges of inferred criteria weights for Pareto sets with the lowest possible sums of squared error. In this chapter, the six analysis parameterizations applied to the seven gameplay trials produced inferred weight ranges of different widths for the same criteria and sometimes found Pareto sets with different sums of squared error in the same trial, though differences in sum of squared error across Pareto sets were infrequent. Except in two cases, all analyses found Pareto sets with the same sum of squared error: In the Env26 trial, both of the brute force, enumeration analyses found Pareto sets with a sum of squared error of 0 but the evolutionary optimization analysis parameterizations found Pareto sets with a sum of squared error of 10. In this case, the brute force, enumeration analyses found identical Pareto sets having only 1 member with weights of 1 for environment and 0 for all other criteria, exact integer values that the evolutionary optimization analyses were not able to find. (Interestingly, the Env26 trial also provides the only example where the sum of squared error in the near-Pareto set (of 2) differs by more than 1 from the sum of squared error in the Pareto set (of 0)). The other exception is in the Urb&Ind21 trial, where all analyses found Pareto sets with a sum of squared error of 8 except for the O20 analysis that found a Pareto set with a sum of squared error of 9 despite running to completion.

The differences in inferred criteria ranges are more common and show consistent trends between analysis types and parameterizations. In comparing the results (Tables 2.6-2.12), the analysis parameterizations with the greatest degrees of exploration (B50 and O35) most often identified the widest inferred criteria weight ranges compared to other Pareto sets with the same sum of squared error. For the 5 criteria in each of the 7 gameplay trials, the inferred weight ranges from the B50 analysis are wider than those from the B20 trial in 24 cases, are equal to those from the B20 trial in 10 cases, and is less than that from the B20 trial in 1 case.

In the evolutionary optimization results, for the 5 criteria in each of the 7 gameplay trials, the inferred weight ranges from the O35 analysis are wider than the others 17 times, the ranges from the O35 and O25 analyses tie for widest an additional 12 times, the ranges from the O35 and the O20 or O15 analyses tie for widest an additional 1 time each, the ranges from the O20 analysis are widest 3 times, and the range from the O15 analysis is widest 1 time. (Note results from the O20 analysis in the Urb&Ind21 trial are excluded from these comparisons because it's Pareto set does not have the same sum of squared error as the others from that trial).

The inferred weight ranges can also be compared between the brute force, enumeration and evolutionary optimization analyses for the 5 criteria in each of the 6 gameplay trials that have the same sums of squared error in their Pareto sets. (The Env26 trial is excluded from these comparisons because its Pareto sets do not have the same sum of squared error between analysis types). The inferred weight ranges from the evolutionary optimization methods have wider (more comprehensive for the same sum of squared error) ranges than the brute force, enumeration analysis for 19 of the 20 weight estimates in gameplay trials having more than 20 observed decisions, and have an equal weight range with the brute force, optimization approach 1 time. Conversely, in 9 of the 10 weight estimates in gameplay trials having 8 or fewer observed decisions, the brute force enumeration inferred weights have a wider (more comprehensive) range than those of the evolutionary optimization analyses and 1 time have an equal range. This interesting result suggest that different analysis types may generally be better or worse for inferring broader ranges of possible weights with data from gameplay trials have more or fewer observed decisions.

There are tradeoffs between analysis speed and result completeness and accuracy. The analysis parameterizations that engage in less exploration found results more quickly (Table 2.5) but found results with narrower ranges of inferred weights than other Pareto sets with the same sum of squared error (Tables 2.6-2.12). However, the conclusions that can be drawn from these less complete results in terms of the rank order of criteria preference and their approximate ranges and mean weights are generally the similar with those from analysis with greater exploration (Tables 2.6-2.12, Figures 2.6-2.19). So, tradeoffs between speed and completeness/accuracy should depend on the needs, preferences, and intended uses of the analyst, stakeholders, and decision makers in each particular case.

In cases where decisions are needed in near real time, e.g., if results from analysis of initial gameplay will shape the form of later gameplay or to inform automated decisions made immediately after the conclusion of the game, the quickest running analyses may be most appropriate. Alternatively, for cases where the weight-inference analysis will be incorporated as part of a much longer decision process that spans weeks, months, or years, e.g., for infrastructure investment or natural resources management decisions, the longer running analyses may be most appropriate. Comparison of results between multiple analysis parameterizations can also increase completeness, if time for multiple analysis runs is available. When analysis runtime is not constrained, the most reliable approach may be to combine results across brute force, enumeration analyses that can consider 0 and 1 integer weights and evolutionary optimization analyses that are not limited by fixed grid spacing. A hybrid analysis that incorporated elements of both gridded weight enumeration and free weight exploration may be promising for future development.

The gameplay trials and analyses presented in this chapter have limitations. They demonstrate proof of concept but additional work is needed to further these ideas to the point where they will be ready for application in practice. Two types of analysis approaches were demonstrated; additional analysis parameterizations, combinations of these two approaches, and additional related approaches for inverse problem solution (see Appendix A for a brief discussion) could be implemented to refine this work. Additional gameplay trials could be carried out to further test the strengths, weaknesses, and limitations of this approach as implemented through different analysis parameterizations.

The text-based game used to generate observed gameplay decisions is simple, and application to more sophisticated games remains as a future extension of this work. The decision points used in the game in this chapter are explicit. Future games could try applying these analyses to games with implicit decision points, alternatives, criteria, and/or value scores that are fluid with the game environment (see Appendix A for a brief discussion). Application to more complex games might also include graphic-based games instead of text-based games, such as strategy games with a top-down graphical view, first-person games with free interaction in a digital world, games that incorporate virtual or augmented reality, or games with more realistic resource management or system operation scenarios.

The analyses in this chapter show that sensible weights can be inferred from gameplay analysis but do not address the extent to which those weights have external validity. Future human-subjects experiments could compare the results of traditional MCDA weight elicitation through surveys and interviews with the results of this novel weight inference from gameplay logs to judge whether or not they produce similar results. Even more sophisticated human-subjects experiments could compare the results of traditional MCDA weight elicitation and novel gameplay weight inference with the results of observational studies of real-world, physical decision making to see which weight-development approach more accurately predicts decision making in practice.

CONCLUSIONS

The analyses developed and applied in this chapter provide proof of concept that preference weights for decision models can be inferred from analysis of observed choices made during videogame play. A simple, text-based, water management game was developed to test the proposed approach. In the game, the player makes investment choices to develop water projects that they believe will create the best water-resources future for their region across a range of objectives. They make their decision with awareness of data for each alternative's expected outcome on five criteria (and corresponding metrics) for cost ($K), urban (# homes), industry (% GDP), agriculture (# acres), and environment (# acres) outcomes. After each decision is made, these performance data are recorded for both the selected alternative and all non-selected alternatives. At the end of a pre-determined number of rounds, the game ends and the gameplay data are analyzed to identify weight sets of best fit for producing the observed outcomes, assuming an additive MAVT decision model with linear value-functions anchored to the distribution ranges from which the alternative data are drawn.

The author played the game through seven gameplay trials. Five trials were played using fixed decision rules that always selected the available project alternative with the best cost score, always selected the alternative with the best environment score, or iteratively selected alternatives with the best urban or industrial scores. Some of these trials were played in games with greater and fewer numbers of rounds, to enable comparison of results with differing levels of detail. Two additional gameplay trials were played using the author's own implicit, subjective preferences as experienced during gameplay. Trials with fewer rounds resulted in 6-8 observed decisions and trials with more rounds resulted in 20-26 observed decisions.

After all gameplay was completed, two types of analysis were applied to the gameplay data to identify weight sets of best fit, each run with multiple parameterizations that traded off analysis runtime and completeness of results. One type of analysis used a brute force, enumeration approach that discretized the continuous weight space into weights spaced at fixed increments and tested all combinations of weight sets having those weights. Two different parameterizations were used for this analysis, having weight increments of 0.02 and 0.05 that generated 10,626 and 316,251 candidate weight sets, respectively, to test. Each candidate weight set was used in the MAVT decision model and applied to the recorded performance data for each alternative for each decision in each gameplay trial. The number of times that each weight set correctly or erroneously predicted the selected alternative was tracked and the sum of squared error across all decisions in a gameplay trial was used to identify weight sets of best fit. Most analyses resulted in a Pareto-efficient set that contained many weight sets of equal best fit (i.e., all sharing the lowest observed sum of squared error). A near-Pareto set was also recorded for each trial, containing weight sets with the next-lowest sum of squared error, to consider how a relaxation of fit might change the resulting conclusions.

A second type of analysis used evolutionary optimization to generate and evaluate candidate weight sets. The Differential Evolution algorithm was used with a best/1/bin search strategy, leveraging stochastic search rather than gradient descent to seek weight sets having the lowest sum of squared error. The initial generation of candidate weights sets for each analysis was populated via Latin Hypercube sampling of the entire weight space. As above, each candidate weight set was used in the MAVT decision model and applied to the recorded performance data for each alternative for each decision in each gameplay trial. Randomly mutated recombination of the best and other weight sets in each generation of candidate weight sets were used to generated candidate weight sets in subsequent generations. Four different parameterizations were used for this analysis, using different values to govern the Differential Evolution search that traded off a larger search radius and greater exploration with quicker runtimes. At convergence or after 1,000 generations, Pareto-efficient and near-Pareto sets of weight sets were recorded for each analysis parameterization for each gameplay trial.

For each of the seven gameplay trials, all six attempted analysis parameterizations successfully identified Pareto-efficient and near-Pareto sets having weight sets of best fit. For the five gameplay trials that followed a fixed decision rule, the resulting weight sets consistently led to conclusions about the relative priority of the criteria that were consistent with that decision rule. The Pareto sets sometimes but not always included the exact decision rule used, and never produced results that were inconsistent with the priorities expressed by the fixed decision rules. For gameplay trials following decision rules that ascribed integer 0 and 1 weights, the gridded weight spaces of the brute force, enumeration analyses were better able to find those exact solutions than were the evolutionary optimization analyses that generated real number candidate weights. When compared to the weight increments commonly used by MCDA analysts in practice, which often are no finer that 0.1 or 0.05, the precision of the resulting weight estimates produced by weight-inference analyses seems reasonable. As would be expected, the gameplay trails that contained fewer observed decisions resulted in inferred weight ranges that were wider, with more uncertainty about the players actual preferences, than inferred weight ranges from analyses based on greater numbers of observations.

For the two gameplay trails where the author played using his own preferences, the resulting inferred weight ranges led to similar but not identical solutions between trials. The general rank order of criteria preference was the same between trials but the magnitude of preferences expressed was more pronounced in the second gameplay trial. It is not known whether this reflects a strengthening of preference during the play experience, random differences in the alternatives available in each trial, or inconsistencies in human decision making between trials. If implemented in practice, one option would be to continue gameplay until it can be established that the inferred preferences are remaining stable within each gameplay session, with gameplay sessions repeated at different times to verify that the expressed preferences are stable across play sessions.

Strengths and weaknesses were exhibited by both the brute force, enumeration and evolutionary optimization analyses. For gameplay trials having fewer decisions, the brute force, enumeration analyses produced slightly more comprehensive Pareto sets for the same level of error. In contrast, the evolutionary optimization analyses produced slightly more comprehensive Pareto sets for gameplay trials with more observed decisions. There was also considerable difference in the degree of exploration used by the analysis, with analysis testing between 240 and 316,251 candidate weight sets and taking between 2 seconds and over 54 minutes to run using a standard laptop computer. For use cases where time is of the essence, e.g., if the results of early decisions in the game will shape the scenarios presented in later gameplay, then quick running but less precise analyses may be more useful. In other cases where the results will fit into larger decision processes spanning days, weeks, months, or years, then longer running analyses and comparison of results across multiple analysis types and parameterizations may be most useful.

Future work remains to test the utility of this approach in practice. This chapter verifies that the proposed approach can work and produce sensible results, but does not prove that it will always do so. Follow-on studies could use human subjects research with many participants to compare the inferred weighs found through gameplay analyses with those expressed through traditional MCDA survey and interview methods, or even to compare both gameplay inference and traditional elicitation methods with real-world, physical, observational decision experiments to test the predictive ability of each weight-development method in real decision-making settings. The gameplay weight inference approach also remains to be applied to more advanced games than the simple water-management game used in this proof-of-concept. For example, application to games with immersive visual graphics and games with implicit rather than explicit decision elements could generate play experiences that feel more like commercial video games less like convoluted revealed-preference exercises.

There are many potential benefits that could come from applying this approach to MCDA in practice. While game and analysis development take up-front time, cost, and effort to produce, the analysis is vastly more scalable than traditional approaches because it avoids the need for a human analyst to be involved in each elicitation. Weight inference from analysis of gameplay choices may also avoid several types of cognitive biases and errors that are known to be triggered by traditional MCDA interview and survey mechanisms, which may allow greater accuracy in weight development. This could represent a major step forward, especially if simultaneously being more scalable and less logistically burdensome than traditional approaches. This novel approach may also enable weight development for more extreme scenarios than other elicitation techniques while maintaining a greater degree of perceived realism for the player, e.g., though immersive, virtual-reality gameplay of rare or dangerous situations that would never be attempted using physical observational experiments and where interviews and surveys fail to provoke sufficient reactions for the situation.

Overall, this work advances the literature on the development of preference weights for MCDA.

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APPENDIX A: RELATED CONCEPTS

Game design choices for explicit versus implicit decision-model elements

It is envisioned that game developers and decision analysts may be able to make several design choices related to how the player interacts with decisions in the game in future implementations of decision-model inference from gameplay log data. In the simple water-management game presented in this chapter, all decision points, alternatives, criteria, and performance scores are explicitly shown to the user. Future implementation could explore the viability of making any or all of these implicit, i.e., sensed, inferred, or estimated from the play experience rather than being directly stated.

Implicit decision points can exist in games where the users have freer interactions with the game environment. Instead of being asked to make a decision at a certain point, the player decides what path to pursue to how to engage with different game elements. For example, a choice to navigate to and enter a shop in an adventure quest game where the player has full freedom of movement would be an implicit decision point. If a list of items is available for purchase in the shop, the selection of one or more would be from explicit alternatives. However, if the player can mix a potion from any available ingredients or choose an unconstrained direction to travel after exiting the shop, those would be decisions made between implicit alternatives. If the abilities granted by items for sale in the shop are clearly stated, those would be explicit criteria and/or performance scores. However, if the player can choose an unidentified item with unknown properties, based on look alone, that decision would be based on implicit criteria and performance scores. Similarly, the factors influencing the player's direction of travel in a free-movement environment would represent implicit criteria.

Analyses that incorporate implicit decision elements would be harder for the analysts and game designers to develop, since those elements must first be somehow inferred from the environment and then used in the analysis. If the types of factors that a player would is anticipated to consider in making their decision are recorded from the game environmental data, then the implicit decision elements can potentially be inferred from that data. However, this process would introduce additional uncertainty since the factors assumed to influence a player's decision may differ from those that actually do. Moreover, the player's evaluation of implicit performance may not exactly match the performance inferred from the game environmental data. If many potential criteria are inferred, pre-analyses that look for correlations between them can help to streamline the weight-inference analysis.

A few existing efforts in the literature have successfully inferred choices between alternatives from free-form movement or gameplay, though the inferred elements have not been incorporated into MCDA models as proposed by this chapter. Kooij et al.[69] use a non-parametric Bayesian model based on machine learning techniques to identify common movement behavior patterns in spatial movement-track data. They compare these unnamed, found movement-patterns with both real-world and virtual (non-gaming) environments. Smith and Vogt[50] allow players to design custom warfighting equipment, which represent implicit alternatives, that are then tested in play on virtual battlefields. They follow Kooij et al. in reporting on data mining to identify clusters of gameplay actions and discuss the importance these action clusters in achieving desirable game outcomes. While these techniques automatically generate clusters of common behaviors, any labels for them must be supplied by an analyst.

Tastan and Sukthankar[70] share an inverse reinforcement learning model used to train AI-controlled bots, which can switch between three modes of play, to play more similarly to human players. Here, the alternative modes of play are explicit but the criteria are implicit and inferred from the data.

Application of these types of techniques to future game-based decision-model inference efforts that extend the work of this chapter could avoid the need to inject forced decision points into otherwise free-form gameplay, enabling gameplay to achieve greater realism.

Other potential analysis approaches

This chapter used two analysis approaches to solve the weight-inference problem and identify solutions of best fit: brute force enumeration and evolutionary optimization. In principle, this type of model-fitting inverse problem can be solved by a variety of analysis methods that use different approaches to achieve similar results. For reference, several of these alternative approaches are briefly described below.

<u>Bayesian weight inference</u>

An ingenious application by Yet and Şakar[71] combines Bayesian analysis with alternative rankings provided by the decision maker to estimate MCDA weights and utility functions. Benefits of the Bayesian approach include that it estimates the entire probability distributions, can handle inconsistent input data (which will increase uncertainty in the resulting distributions), can use partial rankings if the input data are incomplete, and can be adjusted to incorporate prior knowledge from rankings, constraints on feasible weight values, or prior weight distributions. Their approach is applied in two case studies about financial investments and university rankings. While the method is different, several of the benefits of their approach are also realized with the two analysis approaches applied by this chapter.

<u>Conjoint analysis</u>

Conjoint analysis[72,73] is a prominent survey-based method from market research that helps product designers discover consumer preferences and tradeoffs. It is one of the most widely used tools in consumer product development.[74] Here, a set of alternative products is presented to the user to rate or choose between; these vary along multiple attribute dimensions of interest to the product developer (e.g., brand, size, quantity, price, packaging). The presentation of alternatives and recording of choices is repeated many times with alternatives that span a wide range of attribute levels. Analysis of the user's choices reveal "part-worth utilities" that represent their tradeoffs for relative attribute importance in the product-choice decision. Many modern versions of conjoint analysis present the consumer with a computer-based survey where they are able to choose between simulated products, and adaptive algorithms in choice-based conjoint studies use respondent choices from prior product-selection iterations to create the set of products to present in the next product-selection iteration that will maximize the analyst ability to finely discern preferences and tradeoffs in the fewest number of iterations, which is not possible with static conjoint product-rating methods.[73,75] Part-worth utility inference in conjoint analysis has many parallels with the game decision analytic concept we propose, chiefly that it decomposes choice decision problems with respect to an additive combination of per-criterion utility that users derive from each alternative with respect to the attributes of interest, and that conjoint methods can be viewed as a special case of more general random utility theory.[76] Conjoint analysis does not include a story arc, entertainment elements, or play objectives as it is not incorporated into gameplay.

Conjoint analysis has occasionally been combined with decision analysis to identify prominent criteria and infer weights in non-gaming context, and Hermans and Erickson[77] suggest that inferring criteria weights through conjoint analysis can reduce bias over best-of-class elicitation approaches in traditional decision science. Hermans et al.[78,79,80] use conjoint analysis in a decision analysis process with a stakeholder group to quantify preferences (weights) for environmental criteria in watershed management. Clement[81] uses conjoint analysis with decision analysis to identify weights for criteria related to energy policy decision-making in Vermont. Ng and Sargeant[82] use conjoint analysis and decision analysis to identify the weights of 21 criteria for evaluating zoonotic diseases in Canada. Several others have used conjoint analysis to identify preferences for criteria used in decision making, but without formal connection to decision science.

Discrete choice

Discrete choice models seek to predict user choices between alternatives based on presumed utility functions and are consistent with general utility theory.[83,84] Discrete choice experiments are frequently used in economics, marketing, and civil and environmental engineering/science to infer an individual's preferences. The user is presented with a set of hypothetical alternatives that each vary on several attributes, and indicates their choice for their most preferred alternative. Responses are used to infer the priority of the attributes, assuming the user is rational and utility-maximizing. Logistic and Probit regression can be used to solve discrete choice models. Because all attributes of an alternative and preferences of an individual cannot be known, the individual's choice behavior is described probabilistically and the resulting discrete choice models estimate the chance that a person will choose a particular alternative based on a combination of knowledge about their preferences and the alternatives.

Discrete choice experiments have occasionally been combined with decision analysis to identify prominent criteria and infer weights in non-gaming context. Mirelman et al.[85] use discrete choice experiments with decision analysis to assess weights between criteria for efficiency and equity in health interventions across several countries. Youngkong et al.[86] use discrete choice experiments to identify high priority criteria for targeting HIV/AIDS interventions in Thailand, and then apply those in a decision-analytic framework to rank project alternatives.[87] Baltussen et al.[88] use discrete choice with decision analysis to identify the relative priorities of criteria for health-priority setting in Ghana. Neslo & Cooke[89] use probabilistic inversion with discrete choice models and random utility theory to validate stakeholder preference models in a health-care scenario.

Multiple linear regression

Multiple linear regression[90] is a common approach for parameter estimation used across many disciplines. It is a statistical approach used to model the relationship between several independent predictor variables with a single dependent outcome. The coefficients of each independent variable estimate the expected change in the dependent variable with a unit change in the independent variable. Multiple linear regression benefits from a robust mathematical framework and broad usage. It could be applied to fit a decision model to observed gameplay outcomes, with the multivariate model coefficients informing the weights in an MCDA model. The results of multiple linear regression, however, typically include a single solution of least residual error rather than a Pareto-efficient solution set.

For examples of application, Luu et al.[91] use multiple linear aggression with the technique for order of preference by similarity to ideal solution (TOPSIS) MCDA method to attribute weights in a flood risk model for Vietnam. Hwang et al.[92] use multiple linear regression with MCDA in a content-based recommendation system. And Vivas et al.[93] use multiple linear regression with the preference ranking organization method for enrichment evaluation (PROMETHEE) MCDA method to assess the sustainability of a Brazilian oil and gas firm.

Other approaches

Principle component analysis could be used with the type of analysis presented in this chapter if there were a need to assess the degree of correlation between many criteria and potentially eliminate those that are highly correlated. This could expedite the analysis, for example, if a large number of implicit criteria were to be inferred from the gameplay environment. Latent factor analysis achieves some similarity in outcome, but its substitution of interpretable criteria for latent factors with unknown meaning is generally less helpful when the results need to be used and interpreted in other decision models. Lastly, several existing software packages are available for solving inverse problems, such as *UCODE* and *Dakota,* often with geophysical data. These tools could be applied to the type of analysis proposed in this chapter with appropriate translation of the gameplay data into the specific input formats used by their software.

References for Appendix A

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APPENDIX B: HISTOGRAMS

The histograms in the following sections show the distribution of inferred weights for each criterion by each analysis parameterization in each gameplay trial, grouped by gameplay trial.

Env8 trial

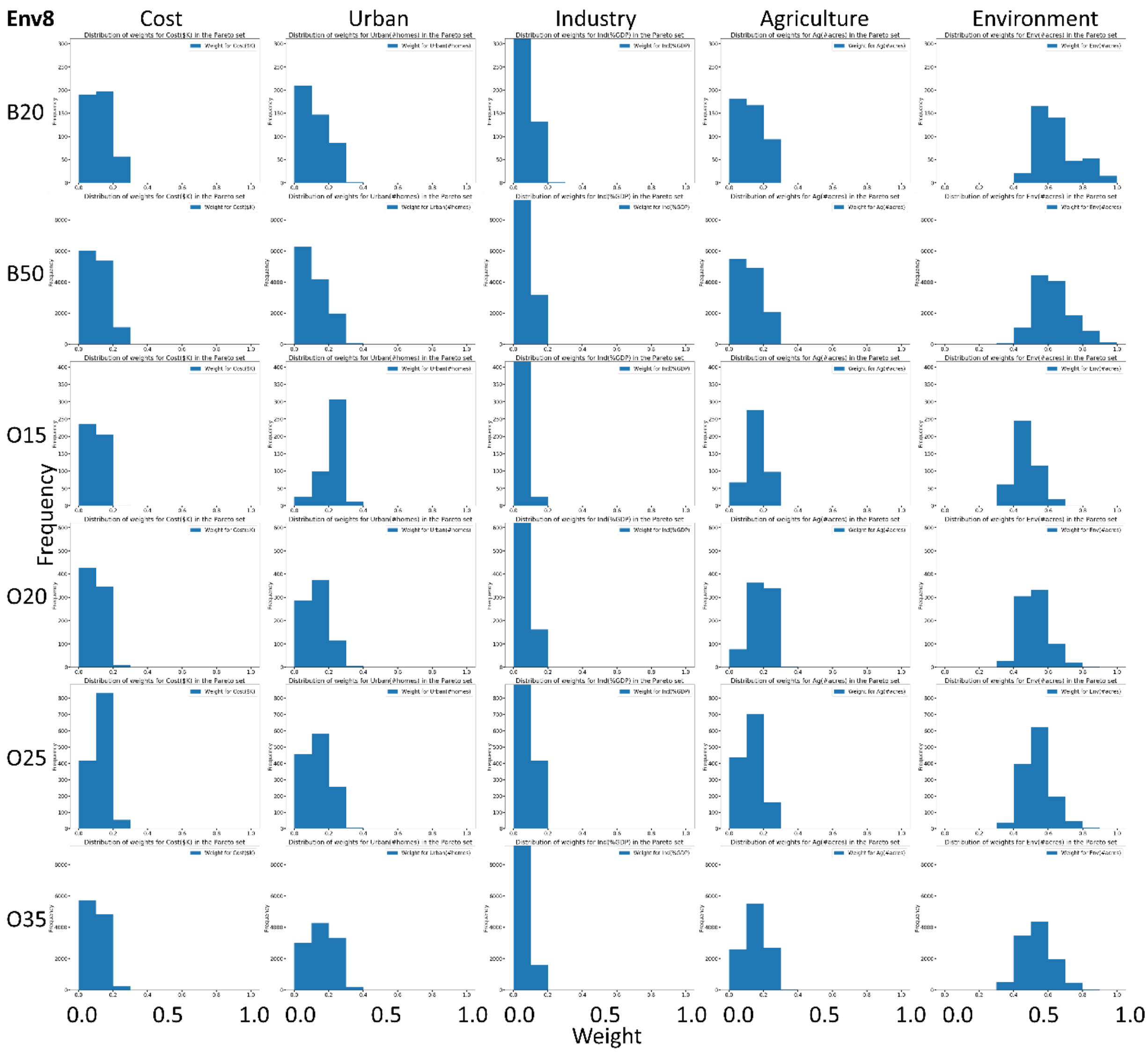

Figure 2.B1. *Histograms showing the distribution of weights for the criteria (labeled at top, see also Table 2.6) in the Pareto-efficient results for the "Env8" trial. Six subplots for different brute force, enumeration and evolutionary optimization analysis parameterizations are identified (labeled at left, defined in Tables 2.3 & 2.4).*

Env26 trial

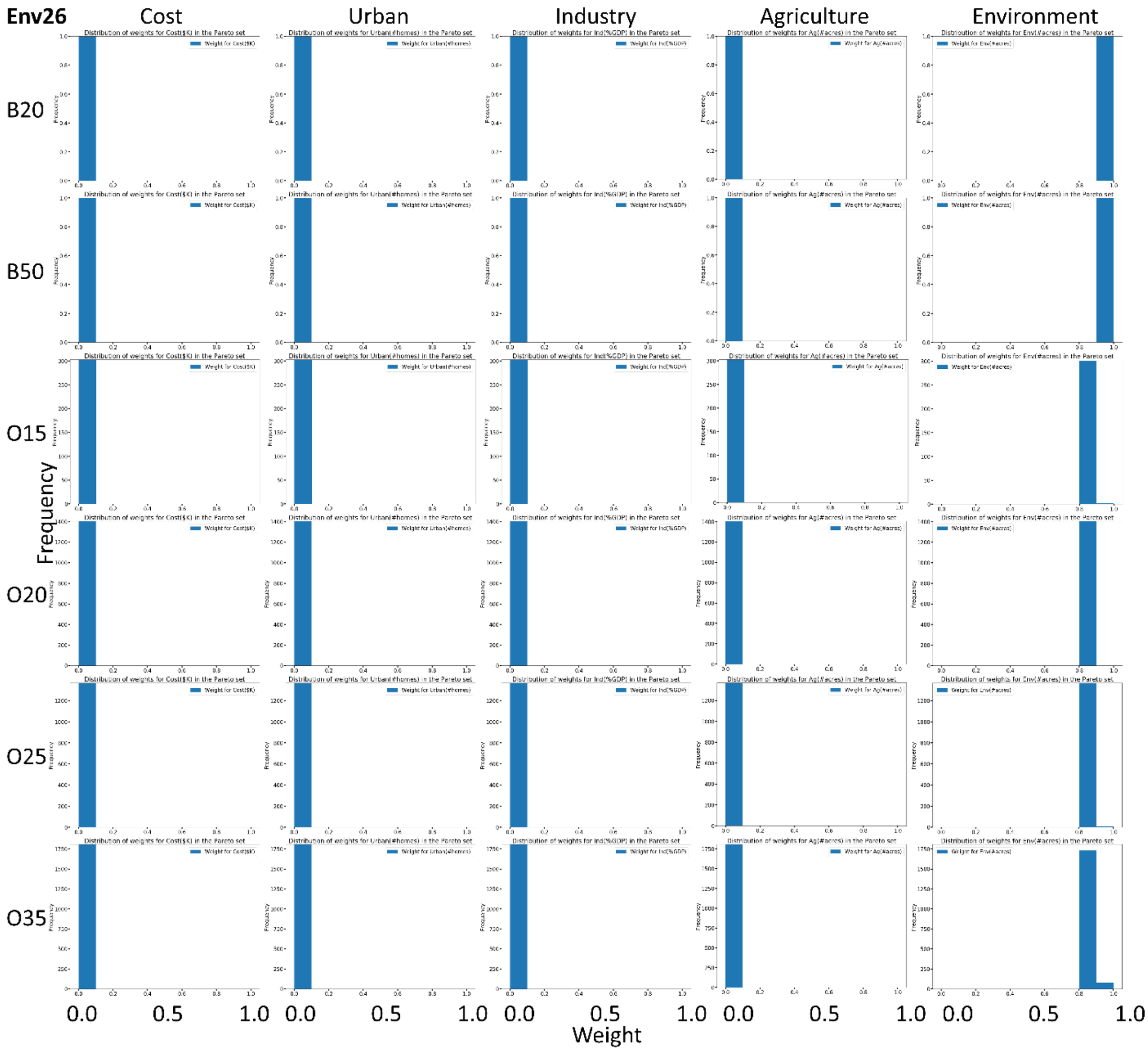

Figure 2.B2. *Histograms showing the distribution of weights for the criteria (labeled at top, see also Table 2.7) in the Pareto-efficient results for the "Env26" trial. Six subplots for different brute force, enumeration and evolutionary optimization analysis parameterizations are identified (labeled at left, defined in Tables 2.3 & 2.4).*

Cost6 trial

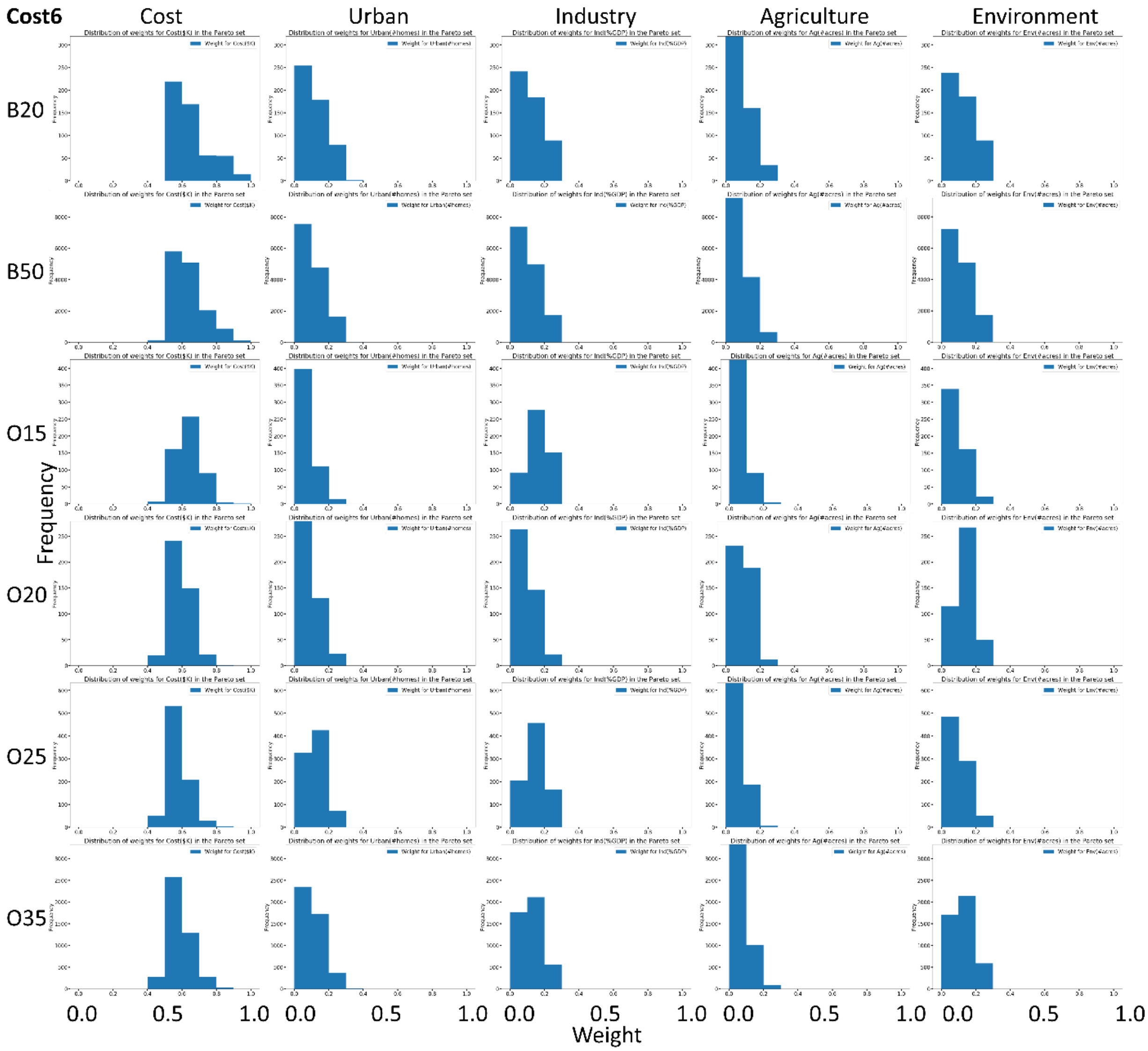

Figure 2.B3. *Histograms showing the distribution of weights for the criteria (labeled at top, see also Table 2.8) in the Pareto-efficient results for the "Cost6" trial. Six subplots for different brute force, enumeration and evolutionary optimization analysis parameterizations are identified (labeled at left, defined in Tables 2.3 & 2.4).*

Cost26 trial

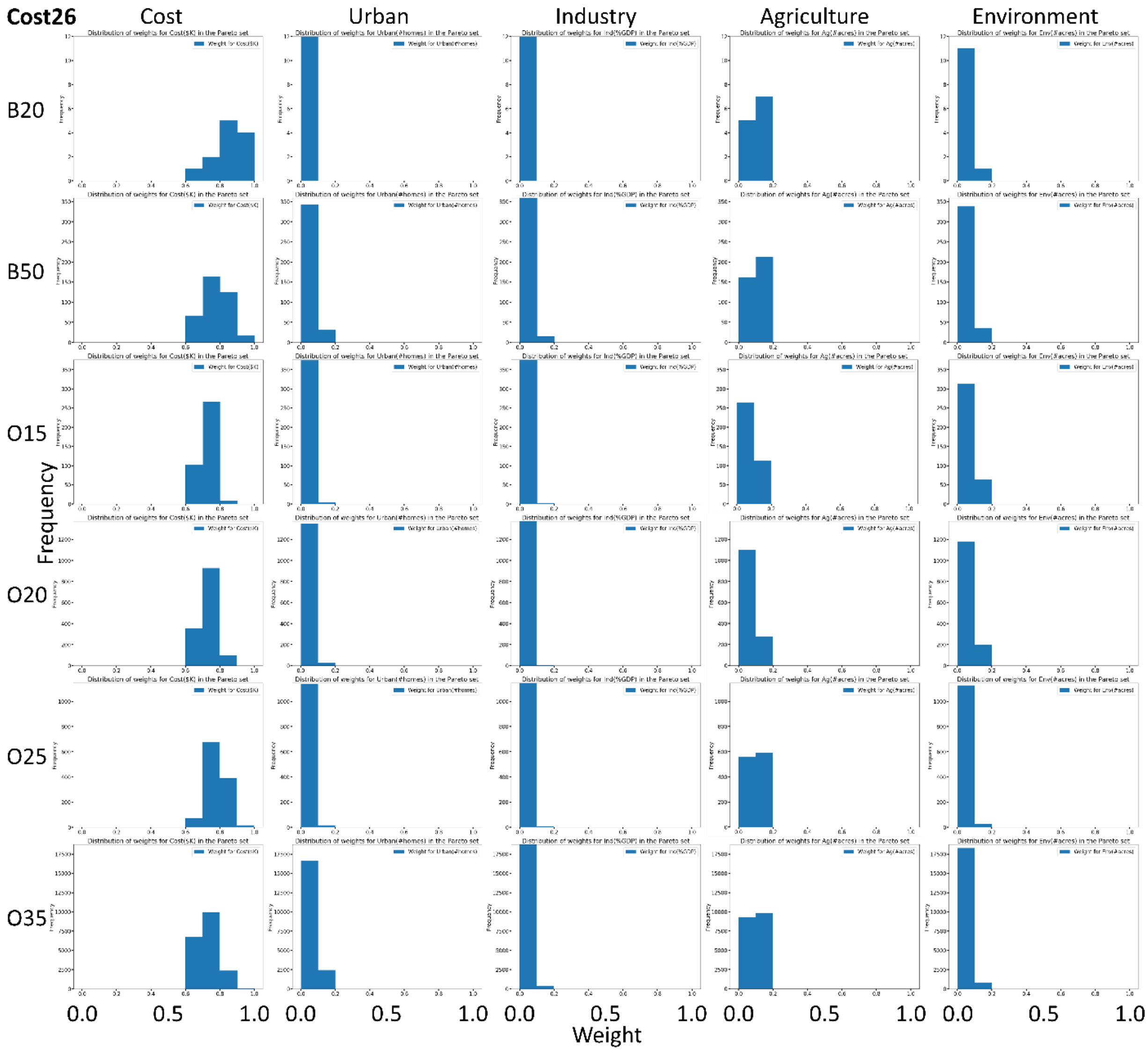

Figure 2.B4. *Histograms showing the distribution of weights for the criteria (labeled at top, see also Table 2.9) in the Pareto-efficient results for the "Cost26" trial. Six subplots for different brute force, enumeration and evolutionary optimization analysis parameterizations are identified (labeled at left, defined in Tables 2.3 & 2.4).*

Urb&Ind21 trial

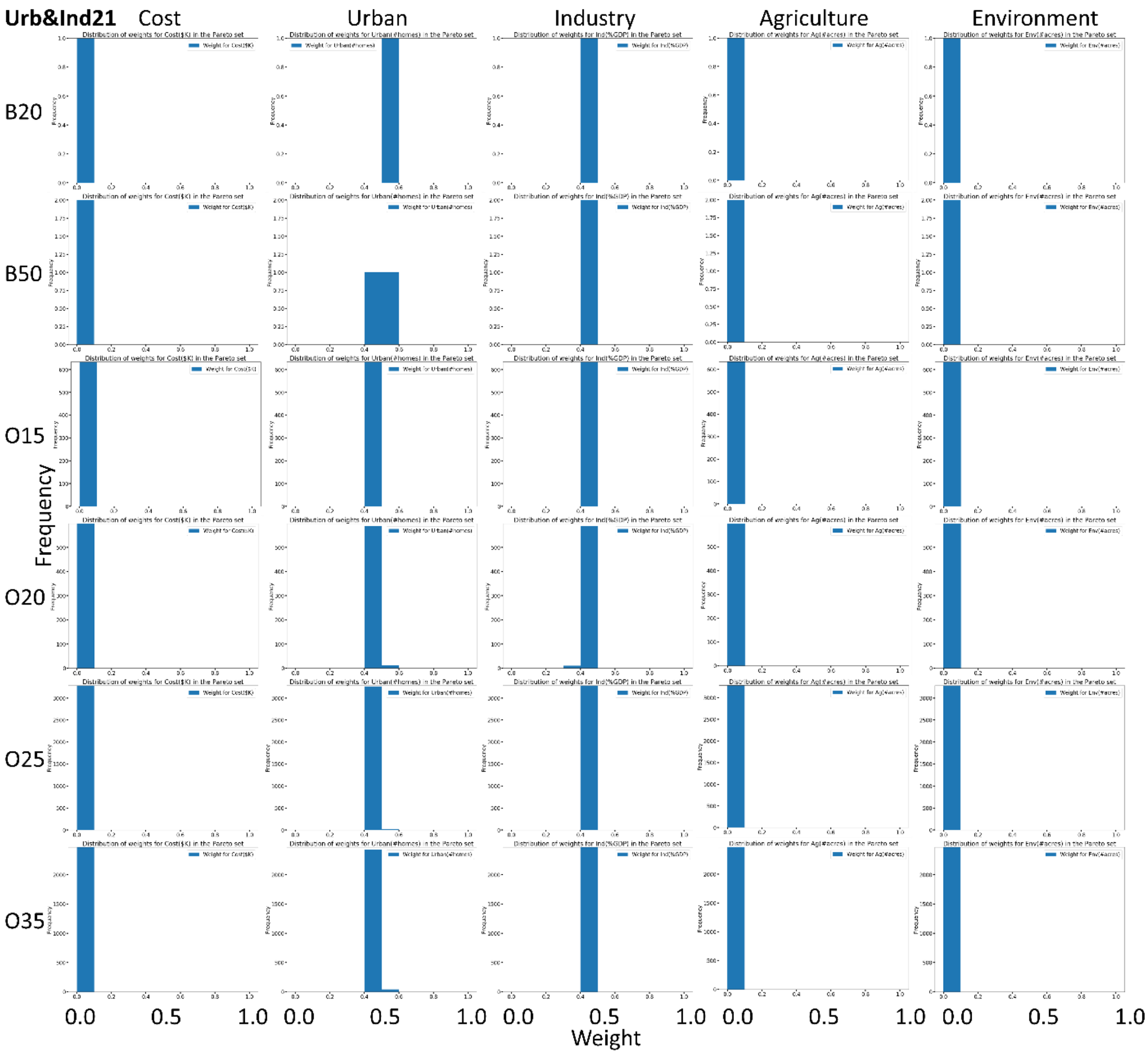

Figure 2.B5. *Histograms showing the distribution of weights for the criteria (labeled at top, see also Table 2.10) in the Pareto-efficient results for the "Urb&Ind21" trial. Six subplots for different brute force, enumeration and evolutionary optimization analysis parameterizations are identified (labeled at left, defined in Tables 2.3 & 2.4).*

Auth20 trial

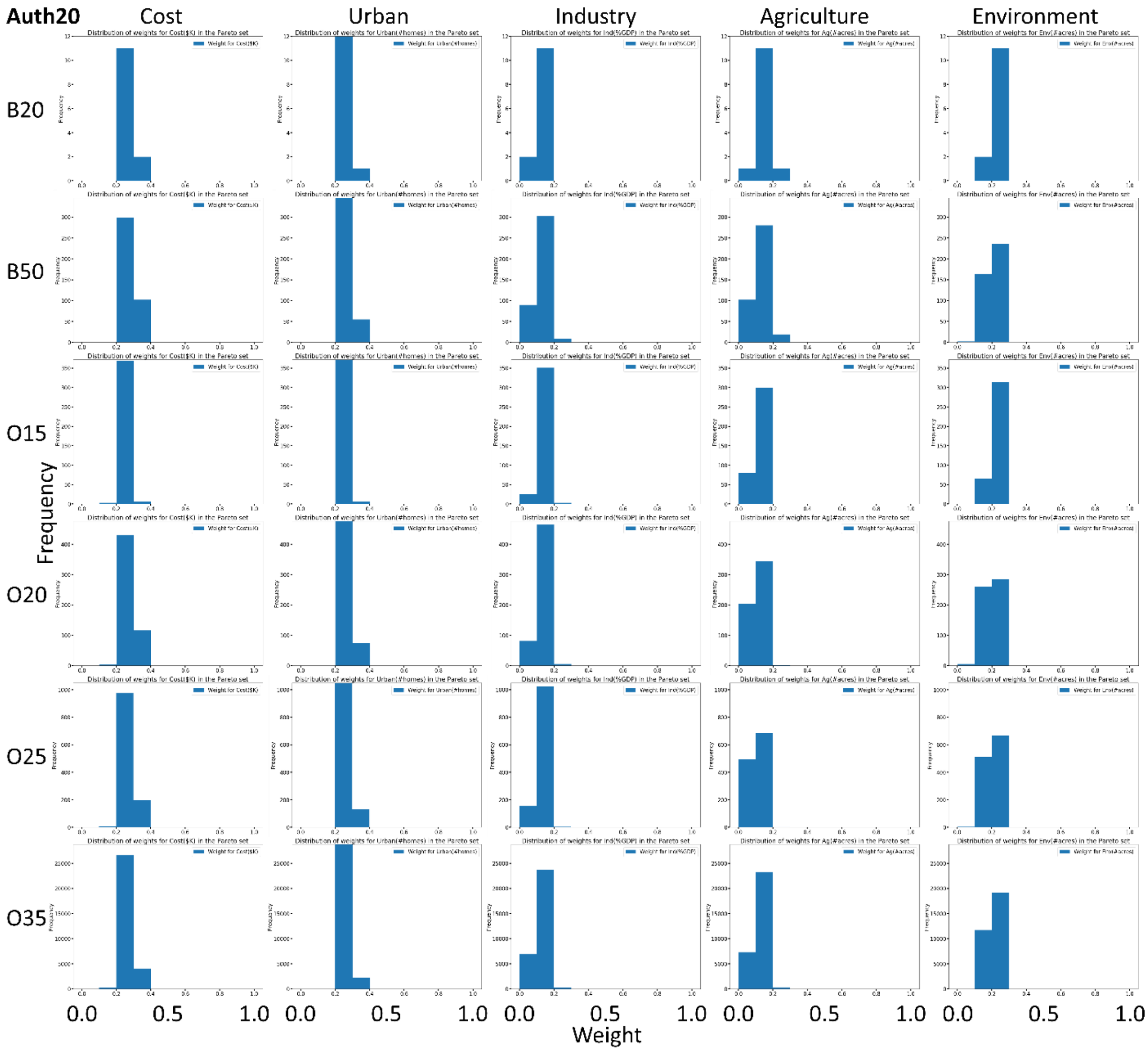

Figure 2.B6. *Histograms showing the distribution of weights for the criteria (labeled at top, see also Table 2.11) in the Pareto-efficient results for the "Auth20" trial. Six subplots for different brute force, enumeration and evolutionary optimization analysis parameterizations are identified (labeled at left, defined in Tables 2.3 & 2.4).*

Auth22 trial

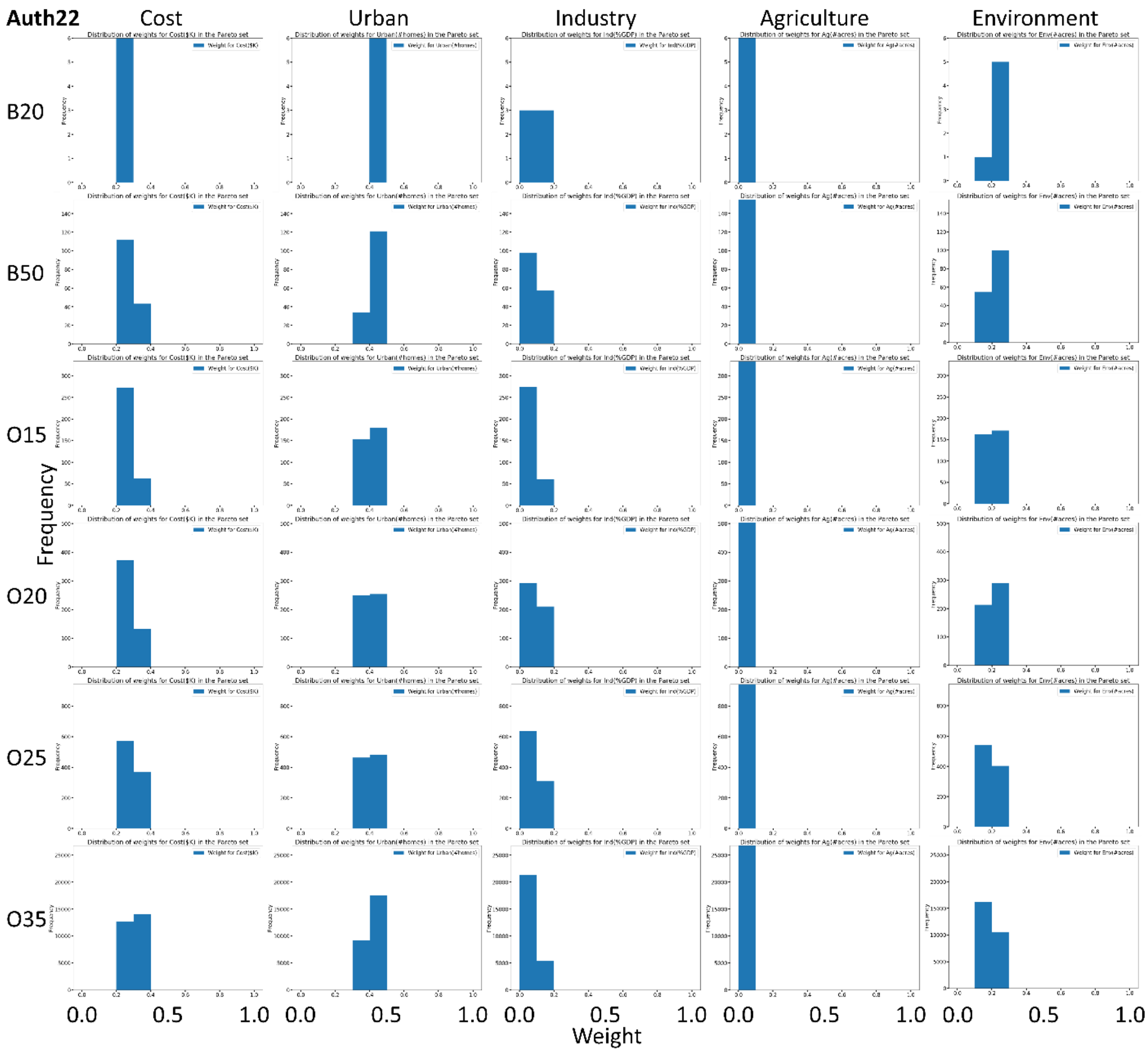

Figure 2.B7. *Histograms showing the distribution of weights for the criteria (labeled at top, see also Table 2.12) in the Pareto-efficient results for the "Auth22" trial. Six subplots for different brute force, enumeration and evolutionary optimization analysis parameterizations are identified (labeled at left, defined in Tables 2.3 & 2.4).*

Chapter 3

A Multi-Criteria Decision Model and Best Management Practices for Sustainable Use of Marine Sand

ABSTRACT

Many coastal beaches erode over time, leading to increased risk of flooding and lost habitat and recreational value. Governments and communities with management authority may engage in coastal engineering projects such as beach nourishment and dune creation to counteract these effects. These engineering projects typically require large volumes of sand to be imported and placed on or near the beach, with the greatest volumes placed initially and smaller maintenance volumes required over time. These projects typically mine needed sand from marine deposits, referred to as borrow areas, on the seafloor that may either be renewable resources that slowly accreted new sand over time or finite resources that will be exhausted after use. There is increasing concern from stakeholders to ensure that these marine sand resources are used sustainably, promoting their long-term viability for future uses and respecting the competing environmental, social, and economic considerations motivating project planning and operations. This chapter reports on a multi-criteria decision analysis (MCDA) workshop with dredging and coastal engineering stakeholders and subject matter experts from state and federal government, academia, and industry on the topic of sustainable use of marine sand resources. Results from the workshop include a generalized MCDA criteria hierarchy to be used for evaluating alternative borrow areas and use plans, suggested metrics and scoring considerations for those criteria, best management practices to promote borrow area sustainability, and a list of remaining observed challenges and future considerations related to using marine sand sustainably.

INTRODUCTION

Coastal beaches often erode over time due to wave action. This narrows the beach, resulting in increased risk of coastal flooding, lost recreational opportunities, and lost ecological habitat. Even where beaches are normally stable or accreting, episodic erosion from large storm events, such as from Hurricane Katrina or Superstorm Sandy, can rapidly erode the shoreline.[1,2] In response, coastal communities and local, state, and federal government agencies often engage in beach nourishment projects that import and deposit sand to replenish those beaches. Beach nourishment projects typically place a large volume of sand on the beach during an initial construction project phase, followed by a maintenance phase where smaller volumes are placed periodically to offset continued erosion. Once placed, the new sand shifts and settles with the tides and waves, eventually stabilizing as a widened beach.

Beach nourishment is an important tool for coastal communities seeking to proactively reduce flood risk and susceptibility to sea level rise. Related projects to build or restore sand dunes can further absorb wave energy and reduce the chance of flood damage to homes, businesses, and infrastructure[3,4]. While early coastal engineering projects often used hard rock and concrete structures to armor shorelines, planners in recent decades have prioritized beach nourishment and dune construction projects as more nature-based solutions to reduce coastal flood risk. The use of sand for coastal engineering projects may also provide aesthetic, ecological, and recreational benefits that hard structures do not typically provide.[3]

These large coastal engineering projects often require hundreds of thousands or millions of cubic yards of sand for their initial construction and ongoing maintenance. Given the large quantities of material involved, there is increasing interest from stakeholders to ensure that the extraction and placement of sand for these projects is done sustainably. Sustainability, in this context, includes prolonging the useful life of the sand resource (known as a “borrow area”) for future uses and extracting and placing the sand to achieve a balance of environmental, social, and financial objectives that maximize the benefits and minimize impacts from construction activities and resulting changes to the landscape.

This chapter presents a generalized multi-criteria decision analysis (MCDA) framework to support and evaluate decisions about the sustainable extraction of sand from marine (i.e., ocean) borrow areas and the use of that sand for coastal engineering projects such as beach nourishment, with suggested metrics and scoring considerations. It also presents a list of best management practices for planning and operating coastal engineering projects that use marine-sand borrow areas. A preliminary list of MCDM criteria was developed as a starting point for discussion, from review of the literature. A facilitated MCDA workshop convened stakeholders and subject matter experts involved in dredging and beach nourishment to: develop a final MCDA criteria hierarchy, suggest metrics and scoring considerations for those criteria, develop a list of best management practices for sustainable borrow areas use, and provide further observations and recommendations on remaining challenges and future opportunities. These materials are intended to support decisions regarding the development, evaluation, and selection of scoping-level plans to use individual or combinations of borrow areas (or borrow-area regions) for repeated sand dredging for coastal engineering projects.

This chapter is organized as follows: A background section provides context relevant to the topic. A methods section describes the preliminary criteria list and the MCDA workshop, especially with respect to the process of developing the final criteria hierarchy, suggested metrics, best management practices, and additional observations and recommendations. A results section presents the final MCDA criteria hierarchy and related discussion, the suggested metrics and scoring considerations, the best management practices, and the identified remaining challenges and future considerations. A discussion section comments on how these results compare to the findings of others. A conclusions section summarizes these contributions and their potential usefulness for implementation.

BACKGROUND

Physical processes

Modern beach nourishment and dune construction projects typically extract sand from deposits nearby on the ocean floor.[1,2,5] In previous decades, coastal engineering projects tended to use sand mined from terrestrial locations, usually excavated from "borrow pits" on land with otherwise low economic and use value. Changing social and environmental concerns, population growth, trucking costs, logistical barriers, and supply exhaustion have reduced reliance on terrestrial sand sources.[6] Alternative terrestrial construction material, such as crushed rock or fine gravel, are sometimes used in coastal engineering but typically provide material that is a poor match for existing beach sand and still face trucking cost and logistical barriers. Material excavated from concurrent navigational dredging projects can be efficient to use for beach nourishment, though its use is complicated by the need to align project timing, logistics, sediment compatibility, and transport-distance concerns. (Future changes to navigational-dredging and sediment-placement policies may lower some of these barriers.) Even when used beneficially for coastal engineering projects, the grain sizes, geotechnical characteristics, and silt fractions from navigational dredging material may pose problems for the receiving beach. In practice the simplest and most economical sand source for coastal engineering projects in recent decades has typically been to mine it from available nearby marine sediment deposits (known "borrow areas," the aquatic equivalents of terrestrial borrow pits). [1,6]

Marine sediment typically consists of small rock and fine particles such as sand, gravel, and silt, often mixed with shell and organic matter. Marine sediment typically originates from terrestrial soil, created through weathering and erosion. Sediment is transported to and deposited in the ocean by river and ocean currents and wave activity, often driven by prevailing winds and current, storms, and long-term sea level changes. Sediment mixing is driven by these currents and by biotic activity, such as the burrowing of benthic invertebrates. Sediment particles that are smaller, less dense, and have higher surface area to volume ratios are typically the first to dislodge and be picked by currents and the last to settle. Stronger currents also may transport larger and heavier particles, such as sand, over farther distances. Rather than being uniformly distributed, interactions between currents and seafloor topography lead to the development of shoals that have defined areas of unconsolidated sediment detached from the surrounding seafloor. Shoals of similarly graded sediments tend to develop in regions where currents transition from higher to lower energy (e.g., at bends in rivers or changes in seafloor topography).[7,8] Shoals with areas of high sand content are promising as borrow areas for coastal engineering projects.

Near the shore, sediment composition and characteristics on the ocean floor are closely tied to physical processes on their adjacent landmasses. Here, sediment deposits contain particles with a wide variety of sizes and have accumulation rates commonly in the range of a few millimeters per year. Sediment deposits near a shoreline or river mouth are most likely to actively accrete greater volumes of new sediment. Somewhat farther into the ocean, on the outer continental shelf (OCS), fewer deposits actively accrete much new sediments. Shoals on the OCS within a few miles of the mouths of large rivers can receive substantial sediments from powerful river currents flowing into the ocean. Some offshore ocean currents are strong enough to transport heavier particles to lower energy areas of the OCS. However, most OCS sediment deposits were created by terrestrial, riverine, or wave-driven physical processes in past eons with lower sea levels (e.g., throughout the Holocene), when areas of today's OCS were active rivers, lakes, glacial till, marshes, dunes, beaches, lagoons, bays, or spits, etc. These deposits are finite, non-renewable resources that can be exhausted if mined. Much farther into the ocean are deep ocean sediments so removed from land that they only receive deposition of small, clay-sized particles at rates of a few millimeters per millennium.[8,9,10,11]

Legal and regulatory context

In the United States, seafloor resources near the coast are legally owned and managed by each state. The legal extent of state waters is defined by the Outer Continental Shelf Lands Act of 1953 to generally be within three miles of shore, with a few exceptions. Beyond state waters, the OCS Land Act ascribes OCS seafloor resources to US federal ownership up to the edge of the US exclusive economic zone, generally 200 nautical miles offshore, with a few exceptions, an area of 2.5 million square miles.[12,13] Seafloor resources beyond the US's exclusive economic zone are governed by international law at the United Nation and regulated by the International Seabed Authority.[14]

Within the zone of US federal ownership, the US Submerged Lands Act of 1953 establishes the federal government's exclusive sovereign claim to all natural resources in the waters, seabed, and subsoil, both living and nonliving, and over their exploration, use, management, and conservation. This enables the government to take management actions to protect, develop, or extract various resources. Within this authority, the US Geological Society (USGS) leads many seafloor surveys and the US Bureau of Ocean Energy Management (BOEM) manages, protects, and grants leases that authorize the use of seafloor resources, including sand shoals, to interested parties.[15] Amendments to the OCS Land Act in 1994 and 1999 allow BOEM to negotiate and provide non-competitive leases to marine resources intended for use in beach nourishment, shore protection, and similar coastal engineering projects, and to further make these resources available without charge to federal, state, and local governments. When coastal engineering projects lack a suitable sand source nearby within state waters, BOEM leases and interagency agreements for sand use can be an attractive alternative.

Federal OCS sand leases and interagency agreements are typically used to mine sand for beach nourishment and coastal engineering projects by the US Army Corps of Engineers (USACE, the federal agency with the greatest responsibility for coastal risk reduction) or state and county agencies, with the actual removal of material done with government or contracted commercial dredging equipment. Through the end of 2020, the BOEM Marine Minerals Program had executed 60 leases authorizing removal of 167 million cubic yards of sand for projects in 8 states on the Atlantic and Gulf coasts to help restore 388 miles of coastline.[16]

Under current federal policy, each OCS leasee drafts an independent lease with BOEM that only concerns their use of an area. These leases are typically drafted to address the current needs of the leasee without consideration of future uses. Within state waters, most coastal states have their own policies, funding programs, and/or permitting processes for beach nourishment using dredged sand, with details varying by state.[17] There is increasing concern among stakeholders that an overemphasis on current project needs (e.g., to extract the necessary sand volume at minimum cost) may limit the future usability of a site. As the use of marine sand for coastal engineering projects increases, it is important to ensure that resource extraction occurs in a sustainable way that balances environmental, social, and economic concerns and promotes long-term site useability.

Dredging operations

Dredging is the process of removing sediment from the bottom of waterways and water bodies such as rivers, lakes, ports, harbors, and the ocean. Government agencies, companies, and organizations authorize and pursue dredging projects for purposes such as to clean up contaminated waterways, enable ship navigation, or mine sand or silt for use in environmental and infrastructure projects. Dredging equipment has been used to excavate sediment from waterways of interest for at least two thousand years.[18,19]

Modern dredging equipment uses two main types of mechanisms to raise sediment to the surface: mechanical dredges scoop up the sediment and lift it to the surface, and hydraulic dredges use suction to pull the sediment up a pipeline to the surface. Mechanical dredges may be as simple as excavator on a barge that scoops sediment into a large, flat, adjacent scow or barge that transports it to a placement location, or may use custom-manufactured, self-propelled ships with large, crane-like clamshells or buckets that excavate the material. Hydraulic suction dredges have strong pumps that suction a slurry or water and sediment up a pipe to the surface. They sometimes use a rotating cutterhead to breaks up rock and sediment on the underwater surface. The sediment may then be pumped into a storage compartment on the dredging ship, into an adjacent scow, through a long pipeline to its placement site on the shore or elsewhere. Less common variations of dredging techniques include knockdown dredging where a implement is dragged along the underwater surface to smooth out high spots impacting ship traffic, and water-injection dredging, where a fluid slurry is created from sediment on the underwater surface, that then flows along the river bottom until it fills in other areas without ever being brought to the surface.[20,21]

Planning considerations for using marine sand borrow areas for beach nourishment

The texture and topographic variability of sand shoals support biodiversity in aquatic environments and provide habitat for a wide range of aquatic plants and animal species that can be affected by dredging. When dredging disrupts the local ecology, stable and productive conditions may not recover for many years. Differences in ecological resources at risk in different borrow areas, and under different potential dredging plans, can affect the intensity and spatial extent of environmental impacts and the site's recovery. Estimating these impacts in advance helps project managers design and select better project alternatives.

Dredging creates a variety of environmental impacts to the borrow area ecosystem. A common impact is the mortality of benthic organisms in the removed sediments. Reductions in benthic organism productivity also can reduce food availability for larger sea life. Changes in sediment transport and wave activity from an altered seafloor geometry also can change local ecosystems. The repeated dredging of sensitive areas, e.g., re-dredging the same linear route through a recovering benthic community, can further hamper recovery of the local seafloor ecology, as does failure to leave untouched "refuge patches" within the borrow area from which healthy seafloor flora and fauna can spread to repopulate recently dredged locations. Deep dredged pits may become anoxic, impacting sea life in that area. The removal of non-renewable sand features can cause loss of spawning grounds, essential fish habitat, and areas of refuge. Fish larvae, mobile invertebrates, fish, and turtles can become entrained in the dredging equipment and killed. Increased turbidity from dredging can temporarily harm mobile sea creatures and bury benthic organisms, eggs, and larvae. Marine mammals can collide with dredging equipment during transport and dredging operations have disrupted feeding ability and lead to loss of prey due to the dredging noise.[27,32,33,22] When designing a project's dredging plan, it is important to use best management practices that minimize ecological impacts at the borrow area.

The heavy mineral content in marine sand is often of interest during project planning, either related to potential commercial value[23] or potential environmental impacts. For example, there may be a loss of groundwater buffering capacity and mobilization of metals and metalloids that originate in pyrite oxidation after sand with a high heavy mineral content is brought from an anaerobic marine environment to an aerobic seashore environment.[24] The presence of contaminants, for example from oil exploration in OCS environments or pesticide runoff and industrial activity in terrestrial environments, is also of interest for its potential to cause of environmental and ecological impacts in beach or dune ecosystems. Sediment-born contaminants such as polychlorinated biphenyls (PCBs) and Dichlorodiphenyltrichloroethane (DDT) metabolites, are linked to abnormal reptile development, decreased sea turtle egg survival, and impacts to the sex and health of the turtle hatchlings. [32] In addition to causing impacts at the placement site, the dredging process can re-suspend contaminants in the water column, making them available for bio-uptake by nearby aquatic life.

In addition to minimizing impacts, it is desirable to match as many physical characteristics as possible between the borrow area and beach or dune placement site, when identifying suitable sand sources for coastal engineering projects. Having compatible sediment characteristics ensures that the resulting geotechnical beach or dune profiles, ecological function, and aesthetics, etc. are compatible with the project design expectations for that area.[25] To the extent possible, sand color should match between borrow and placement areas. Color affects the aesthetic value of recreational beaches[26] and also affects beach thermal conditions, due to differences in absorption of solar radiation, with impacts to turtle nesting conditions and hatchling sex.[27] A common way to measure color is with the Munsell classification system that quantifies a color's hue (basic color), value (degree of lightness or darkness), and chroma (color intensity or saturation).[28]

Sand mineralogy, or mineral composition, is another factor important to match between the borrow area and destination beach. In addition to sand mineralogy's influence on color and heat retention, mismatched mineralogy can increase sand-particle wear, erosion, and turbidity and decrease the re-nourished beach's durability.[29,30] Sediment texture is another important factor to match between borrow area source and destination beach, including grain size, sorting (standard deviation of mean grain size), skewness (degree of asymmetry in the grain size distribution), shape, and the percent of different types of particles such as fine sediment, sand, gravel, rock, and shell, with implications for beach fill longevity.[31] Levels of silt or clay in the placed sediments that are high compared to the native sediments can increase compaction and cementation of the beach as they dry, affecting both recreational value and ecological burrowing and nesting activity, e.g., for sea turtle and shorebird nests. [32] Placed sediment that is too coarse or high in shell content compared to native sediment can reduce the ability of shorebirds to retrieve food in the sand, whereas placed sediment that is too fine can increase water turbidity, which affects shorebird feeding in other ways.[33] Sediment sources with a low overfill ratio, all else being equal, are typically preferred for logistical and economic reasons; the overfill ratio is the ratio of the volume of sand needing to be dredged at the borrow area to achieve the desired placement volume on the beach or dune after accounting for losses from fine sediments washing away and screening to remove coarse sediments.

With long-term resource leases available from federal and state agencies, sand for both the initial construction and ongoing maintenance components of coastal engineering projects is often taken from the same offshore borrow area. This can lead to the same or adjacent areas being repeatedly dredged for decades, compounding any dredging impacts on the resource and depleting the resource.

In areas with limited sand availability, multiple users may need to compete for or share different parts of the same resource. And since the use of offshore sand has been increasing, while supplies are largely limited, resource conflicts are expected to increase in the future. Most agencies performing coastal engineering projects with marine sand plan their projects independent of other uses of the offshore resource and without considering long-term sustainability. For example, commercial dredging contracts to extract the sand are typically awarded to the lowest bidder, constrained only by logistic factors such as regulatory timing and equipment availability, without consideration of broader sustainability concerns, dredging and coastal engineering best practices, effects of dredging intensity, potential impacts to the seafloor ecology, or potential impacts to other concurrent or future users of the site.

Dredging also can create physical impacts that threaten the resource itself. Project effects that change the flow of currents around and morphology of the sand body can erode the remaining shoal or lead to the loss of features that previously captured new sand or sediment from ocean currents. Cost effective but shortsighted techniques, such as dropping dredging rock back onto the surface of the shoal, can lead to “armoring” or “pavementing” of the shoal surface, making remaining sand beneath the new rock layer uneconomical to retrieve. Dredging plans or dredge imprecision that leave a highly variable surface topography can make it more difficult and costly to dredge that borrow area in the future. Dredging that leaves a thin remaining sand layer may effectively result in loss of that resource if it cannot be economically dredged in the future without also excavating undesired underlying material. In areas with both sand and fine sediment, dredging that leaves pits or holes may risk having them filled in with fine silt or mud, blocking economical access to remaining sand beneath that new layer. Most potential physical impacts are compounded by increased dredging duration and frequency. Estimating the spatial extent and intensity of physical impacts in the project planning and design phases can help project managers design and select less impactful dredging plans.

The choices of borrow area and dredge equipment type affect the effective dredging depth, distance, time delays, coordination needs, and material yield, etc., of a project, which in turn affect project efficiency, duration, and cost. The choices of dredging equipment and conveyance mode from borrow area to the beach directly affect project cost and duration. Borrow areas in shallow water will require more maneuverable dredge equipment, while those in deeper water will require more powerful equipment. Trailing suction hopper dredges, self-propelled suction dredging ships that transport the sediment to the placement site in a hopper compartment within their own hull, are used most often for borrow areas on the OCS due to water depth, transport distance, and oceanographic conditions. Cutterhead dredges, dredges that pump a sediment slurry in pipelines between the borrow area and placement site, are often used when pipeline distances are short enough to be logistically feasible (generally less than a few miles). Their use is typically more sensitive to differences in distance than hopper dredges due to the effect of increased pipeline length on project cost. The use of tugboats and scows to transport sediment from the dredge site to the beach can help when conditions require extra maneuverability, e.g., when dredging near an offshore oil field or busy navigation channel. Other types of dredges are used on occasion.[1]

Site obstructions can create hazards for dredge operators and/or reduce sand yield, even if some obstructions are manageable. Environmental and regulatory timing constraints (e.g., that restrict dredge operating windows for sensitive species at some times of the year) increase total project duration and cost. Resource conflicts with other users, jurisdictional issues, permitting difficulties, and legal challenges can increase project lead time. Being aware of such external controlling factors can help project managers design and select better coastal engineering projects.

Stakeholder and local community interests and concerns differ between projects but may substantially influence project design and operation. Diverse stakeholder interests and concerns may include effects on birds, fish, shell fish, benthic organisms, mammals, plants, and other ecological receptors, impacts to the air, terrestrial, and aquatic environmental media themselves, human health and social welfare considerations, and short-term and long-term economic considerations.[34] Some environmental impacts may benefit from being considered from a life-cycle analysis (LCA) perspective.[35] Stakeholders also may express concern with project operations or outcomes that interfere with recreational use of the beach, surf, and shore or that are visually unappealing. Some stakeholder groups, such as surfers or fishermen, may be overlooked for inclusion in formal project planning without intentional effort to contact and include them, even if these groups may be vocal in society at large.[36] The goals of different stakeholder groups often conflict, especially between proponents of environmental and economic interests, though information sharing, participatory project processes, and efforts to promote compromise can help.[37,38,39] Project managers should invest in assessing stakeholder acceptability and community opinion when sustainable project alternatives are being developed and selected.

Sustainability concepts

One component of the classic interpretation of sustainability asserts that sustainable resource use occurs when its rate of use does not leave it depleted, so that it can provide value for future generations as well.[40] This interpretation can be applied to many sand shoals nearer to the coast and to a small fraction of shoals on the OCS that accrete sediment. For these resources, it is worth considering the extent to which sand extraction should be limited to match accretion rates.

While resource exhaustion may be a binary event, it is also useful to compare degrees of sustainability between project alternatives. For example, extracting sand from a renewable resource at a rate greater than its accretion rate may not be sustainable in the long term, but may be more sustainable than an alternative that permanently consumes a nonrenewable resource. Whenever possible, discussions of sustainability marine sand use should include a long-term, multi-generational perspective.

Another component of the classic interpretation of sustainability suggests that sustainable decisions about natural resources use should balance the three broad, co-equal goals of supporting economic development/providing economic benefit, promoting societal welfare, and safeguarding the environment.[41] This conceptualization of the three pillars of sustainability can be applied to both renewable and finite marine sand resources. From this perspective, sustainable dredging decisions should consider dredging costs, project timing, operational logistics, and sand compatibility alongside factors related to ecological impacts and benefits and stakeholder concerns related to aesthetics, equitable access, recreation, health impacts, and social impacts from the construction process, etc.[42,43] Care should be taken to include advocates for the environment in the decision-making process, so that political and financial factors do not exclusively shape the perception of what is considered sustainable sand resource management.[38]

The sustainable use of marine sand resources has not been previously dealt with in the academic literature. Moreover, only a few publications in either the academic or secondary literature have discussed the somewhat related topic of sustainability for navigational dredging. Examples include a discussion applying the three-pillars concept of sustainability to the placement of sediment from navigational dredging in a hypothetical case study,[42] an evaluation of the challenges of incorporating ecological requirements in sustainable dredging planning without compromising cost effectiveness,[44] an industry book on the role of dredging in planning sustainable port and harbor infrastructure using the three-pillars view of sustainability,[45] and an trade-magazine article discussing sustainable placement of dredged sediment in the Niger Delta.[46] However, these examples provide limited guidance for sustainably managing marine sand resources such as borrow areas since they assume that dredging is necessary to remove undesired sediment and focus on the problem of placing the sediment sustainably rather than on the problem of preserving a marine sand deposit for as long as possible and trading off environmental, social, and economic effects from its use.

Stakeholder engagement through MCDA workshops

With so many considerations and competing objectives, decision-making for marine sand resources can be improved with MCDA methods. MCDA has been applied in other dredging contexts but not yet to sustainable marine sand use. The extension of MCDA to problems of sustainable borrow-area evaluation and selection is a natural next step.

Collaborative MCDA workshops and decision conferences are useful for developing MCDA models in situations where stakeholders and/or subject matter experts need to work together to frame and evaluate the problem.[47,48] In these types of interactive workshops, a facilitator guides the workshop participants through a detailed exploration of the problem to identify and prioritize key elements to include in the MCDA model. The workshop focus is on the participants' collaborative problem framing, with the facilitator guiding and focusing the discussion so all necessary components are covered with sufficient deliberation. Clear expectations must be set before the start of the meeting about its purpose, process, and intended outcomes.

The facilitator's role is to guide the process towards the desired outcomes. This includes ensuring that ground rules are followed, all workshop participants have an opportunity to contribute, the group progresses in developing the desired outcomes in the time available, misunderstood concepts are clarified, a summary of what has been discussed is reflected back to the group, and the modeling decisions made by the group are captured and summarized. This includes giving attention to nonverbal, emotional, and interpersonal dynamics to promote positive interactions and efficient progress. The role of the workshop participants, depending on the workshop scope and desired outcomes may include one or more of: proposing alternatives for evaluation and potential selection, proposing MCDA process recommendations, proposing criteria for evaluating alternatives, proposing metrics for assessing alternative performance with respect to criteria, proposing value functions that quantify the value or benefit of different levels of alternative performance on each metric, and/or proposing weights that quantify differences in priority among the criteria. By the end of a successful workshop, participants should feel that their perspectives and interests have been heard and sufficiently considered in the jointly developed MCDA model. Ideally, the group will have generated a shared understanding of the problem and, if relevant, a mutual commitment to action based on the developed model.[47,48]

Applications of MCDA in other dredging contexts

Prior studies have applied MCDA methods to other types of dredging problems such as navigational dredging and contaminated-sediment remediation, often identifying criteria related to sustainability. Examples related to navigational dredging include Yeh et al. (1999), who develop and apply a fuzzy MCDA model for dredge equipment dispatching, under uncertainty, based on a number of cost, efficiency, performance quality, safety, and reliability criteria.[49] Collier et al. (2014) worked with a stakeholder group to develop an MCDA model for sediment placement from navigational dredging that includes 18 criteria and sub-criteria for effects to the environmental media, ecological receptors, human health and social welfare, and short- and long-term economics.[34] Manap and Voulvoulis (2014) present an MCDA framework for evaluating potential dredging options with criteria that include environmental, socio-economic, management, and technical concerns combined with a screening analysis based on sediment contamination.[50] Jeong et al. (2016) develop an MCDA-based optimization model for river dredging management, based on dredging cost, social impact, and environmental impact criteria.[51]

Examples related to contaminated sediment remediation include Linkov et al. (2005), who compare MCDA and comparative risk assessment methods for contaminated sediment management and apply a hypothetical MCDA model with cost, public acceptance, human health, and ecological health criteria.[52] Critto et al. (2006) implement an MCDA model to rank contaminated sediment remediation technologies with criteria including technology reliability, hazard, effectiveness, cost, community impacts and acceptability, and logistical/technical complexity.[53] Kiker et al. (2008) develop an MCDA model for contaminated sediment management that uses weights supplies by decision makers and includes a mix of ecological risk, human health risk, land use (public acceptability), and cost criteria.[54] Kim et al. (2009) develop an MCDA model with stakeholder-supplied weights for contaminated sediment remediation with criteria for human and ecological risk, technical feasibility and project duration, social acceptability, and economic cost.[55] Sparrevik et al. (2012) and Bates et al. (2014) develop and apply MCDA models for contaminated sediment management that balance environmental effect, human health risk, societal benefit, and financial cost.[43,56]

Other examples include Sudel et al. (2008), who use MCDA to plan the schedule equipment used in dredging operations to reduce environmental risk to sensitive species.[57] Read et al. (2014) present an MCDA framework for operationalizing sustainable sediment management through the “triple bottom line” framing of sustainability and balance environmental, economic, and social criteria.[42] Bates et al. (2018) implement an MCDA approach for weight of evidence analysis to evaluate potential sediment placement sites in a navigational dredging context, with criteria for cost, historical management, technical suitability, environmental risk concerns and regulatory requirements, and socio-political concerns.[58] Todaro et al. (2021) use LCA and MCDA to evaluate the sustainability of reactive capping alternatives to remediate contaminated sediment, combining criteria for economic costs, engineering-based remediation effectiveness, and LCA-derived ecological impacts.[59]

Best management practices for beach nourishment

Consulting a list of best management practices can be helpful when designing and operating a project. While an MCDA model is useful for evaluating and selecting the alternatives, best management practices aid in developing the project plan and design, including identification of the borrow area, dredging equipment, sediment transport equipment, mitigation measures, etc. A few efforts have suggested best management practices for beach nourishment. Rice (2009) introduces best management practices to reduce environmental impacts in various types of coastal ecosystems.[60] Haney et al. (2007) include 13 best management practices for beach nourishment projects in Massachusetts to minimize erosion, minimize impacts to natural resources, promote sediment reuse, and expedite regulatory review.[61] Rosov et al. (2016) summarize 7 best management practices to protect benthic communities.[62] In Elko et al. (2020), some of the same authors apply 7 best management practices for coastal inlet engineering projects.[63]

Guilfoyle et al. (2019) summarize some best management practices for reducing impacts to shorebirds and sea turtles from coastal engineering activities, primarily drawing from practices identified in agency regulatory environmental impact reports. They conclude that a need exists to improve existing and identify additional best management practices to improve beach nourishment and coastal engineering.[64] In summarizing the history of beach nourishment in the US over the past century, Elko et al. (2021) also conclude there is a need to develop additional best management practices for beach nourishment.[65] While some of the existing lists of best practices consider environmental impacts at the dredge site, they are generally unconcerned with the long-term persistence of the sand resource itself.

METHODS

Preliminary criteria list

After reviewing the literature on marine sediments beach nourishment and coastal engineering, dredging logistics, environmental effects, community concerns, sustainability principles, and MCDA, as cited above and in the introduction to the dissertation, and after discussion with select subject matter experts, the author developed a preliminary list of criteria anticipated to be broadly relevant for sustainable borrow-area use decisions. Only criteria that could help differentiate between potential borrow area sites and dredging plans were included. These criteria cover project logistics, project costs, sand composition and compatibility, environmental and ecological impacts, and impacts to the physical resource (Table 3.1).

Table 3.1. *List of 18 preliminary criteria in 4 thematic areas for sustainable use of marine-sand borrow areas. These were identified from the relevant literature and discussion with select subject matter experts. This list was presented to dredging and coastal engineering stakeholders and experts to seed discussion during a collaborative MCDA workshop. Workshop participants added, subtracted, reorganized, and changed items from this list to develop a final MCDA criteria hierarchy.*

Sediment suitability		
Presence of contaminants	Salinity	Grain sorting
Color hue	Grain size	Grain skewness
Color lightness/darkness	Grain shape	Grain mineralogy
Borrow area access		
Travel distance	Site obstructions	Jurisdictional issues
Dredge access	Species environmental windows	
Environmental concerns		
Scale of impact to borrow site	Impacts to adjacent regions	
Future site usability		
Physical site impacts	Future accessibility	

MCDA workshop to develop the final criteria hierarchy, suggested metrics, best management practices, and additional observations and recommendations

A one-and-a-half-day MCDA workshop sponsored by BOEM and USACE was held with a group of dredging and coastal engineering stakeholders and experts. The workshop's purpose was to develop a final MCDA criteria hierarchy, suggest quantitative or scorable qualitative metrics for those criteria, and develop a list of best management practices for the sustainable use of marine-sand borrow areas. A total of 101 individuals were invited to the MCDA workshop based on their: prior participation with the Florida Sand Management Working Group or the Gulf of Mexico Offshore Sand Management Working Group; federal, state, or local government agency role; academic interests; work in the dredging and beach nourishment industry; being known to the author as subject matter experts in the field; or having been recommended by other invitees. (The two Sand Management Working Groups convene government, academic, and non-governmental organization stakeholders interested in the sustainable, resilient, and ecologically sound management of marine resources.)

A total of 40 participants beyond the author and facilitators/note takers joined the meeting, including 11 in person participants and 29 via webinar connection. These included participants from 4 federal agencies, 6 state agencies, 4 universities, and 8 industry organizations (Table 3.2).

Table 3.2. *Participant from 22 organizations joined the MCDA workshop to develop the final MCDA criteria hierarchy, suggest criteria metrics, develop a list of best management practices for the sustainable use of marine-sand borrow areas, and provide other observations and recommendations.*

Federal Government	**Academia**
Bureau of Ocean Energy Management US Army Corps of Engineers National Oceanic & Atmospheric Administration Gulf Coast Ecosystem Restoration Council	Mississippi State University University of Rhode Island University of Georgia University of New Hampshire
State Government	**Industry**
Florida Department of Environmental Protection Coastal Protection & Restoration Authority of Louisiana Geological Survey of Alabama South Carolina Department of Natural Resources Virginia Department of Mines, Minerals, & Energy St. Lucie County Erosion Control District, FL	Applied Technology & Management Chicago Bridge & Iron Company (McDermott International) Applied Coastal Research & Engineering, Inc. Coastal Technology Corporation (G.E.C., Inc.) Alpine Ocean Seismic Survey, Inc. Coastal Systems International Taylor Engineering, Inc. Humiston & Moore Engineers

Workshop participants were presented with an overview of the problem and its various facets, introduced themselves relative to the problem, were presented with an overview of MCDA methods, and participated in a group discussion on the applicability of MCDA methods to borrow-area use decisions. They also were presented with the preliminary list of criteria, participated in group discussions to develop the final MCDA criteria hierarchy, participated in group discussion to suggest metrics and scoring considerations for as many criteria as possible, and participated in group discussion to develop a list of best management practices.

When considering the preliminary list of criteria and developing the final MCDA criteria hierarchy, participants were asked to consider which aspects of a dredging or coastal engineering project would differ from one borrow area or region to another or from one dredging plan to another. They were asked to focus on aspects that would differentiate borrow-area use sites and plans from one another. They were especially asked to add new criteria missing from the preliminary criteria list and to identify which criteria from the preliminary list should be removed, reworded, split into multiple sub-criteria, or otherwise changed. They were asked to consider how factors might change over space and time, and to draw from any project-scoping considerations already in use.

When suggesting metrics for the criteria, the participants were asked to consider which measurements or data would be needed to evaluate the criteria, including quantitative data, qualitative data for the criteria that could be scored, and enumerated lists over which value could be specified. The participants were asked to consider whether the factors discussed would be broadly applicable, regionally applicable, or project specific. (Criteria for which the metrics will be project specific do not have metrics suggested on the final list of suggested metrics.) The participants also were asked to consider whether the criteria being developed were exhaustive and non-redundant, to consider whether the MCDA framework being developed would meet the stated objectives, and to look for ways the developing MCDA model could be improved.

When developing the list of best management practices for sustainable borrow area use, participants were asked to consider practices that could maximize the useful life of the borrow area, minimize unnecessary costs for future dredging events, and encourage responsible use of the shared resource. They were asked to consider long-term resource availability, cumulative effects, various time/hassle/economic costs and benefits, and to whom those costs and benefits would accrue. Several questions and topic suggestions (Table 3.3) were shared with the participants to prompt ideation of best management practices related to different aspects of sustainable use of marine-sand borrow areas for coastal engineering projects. In addition to the best practices contributed during the workshop, participants were invited to send additional best management practice suggestions after the meeting.

Table 3.3. *Questions and topic suggestions shared with the MCDA workshop participants to prompt ideation of best management practices for the sustainable use of marine-sand borrow areas.*

What strategies could…:
Reduce the cumulative impact of dredging on the borrow area?
Preserve or perhaps enhance habitat value at the borrow area?
Other borrow-area users (in a multiple-user scenario) implement now to make your job easier/better the next time that you use the borrow area?
Prevent unnecessary cost or hassle during future dredging events?
Avoid prematurely removing portions of the resource from future use?
Better (more sustainably) balance short term and long-term needs?
Better (more sustainably) balance economic, environmental, and stakeholder, etc. needs?
Reduce the cumulative need for dredging frequency or dredging intensity?
Consider best management practices related to:
Dealing with oil, gas, and utility crossings efficiently while leaving the site most usable for the future.

Developing a spatial layout for the dredging plan that leaves the site most usable for the future.
How to deal with encountered rocks to leave the site most usable for the future.
How to share sand quality fairly among current and future users.
How to fairly share the available sand volume with future users.
How to know when a borrow area is being overused (and how to reduce overuse).
How to coordinate use between projects with similar locations and timelines to improve efficiency.
Other site or project concerns.

During the workshop, participants offered many additional observations on existing challenges and recommended improvements. While these comments do not fit the structure of the MCDA criteria hierarchy, suggested metrics, or list of best management practices, they remain useful and insightful. A summary of participants' other observations and recommendations related to remaining challenges and future considerations appears in the results section.

RESULTS

Final MCDA criteria hierarchy and related discussion

A major product of the MCDA workshop was a final MCDA criteria hierarchy to guide project planning/scoping decisions concerning sustainable use of marine-sand borrow areas. Subject matter experts and stakeholders who participated in the workshop from state and federal agencies, academia, and industry collectively added, removed, adjusted, and refined the draft list of 18 preliminary criteria into a final MCDA criteria hierarchy of 35 criteria that best represented the group's joint beliefs, knowledge, and wisdom about the subject. The final MCDA criteria hierarchy is suggested for use when evaluating potential borrow-area sites/regions and their dredging plans for use in beach nourishment, dune creation, and similar coastal engineering projects (Figure 3.1).

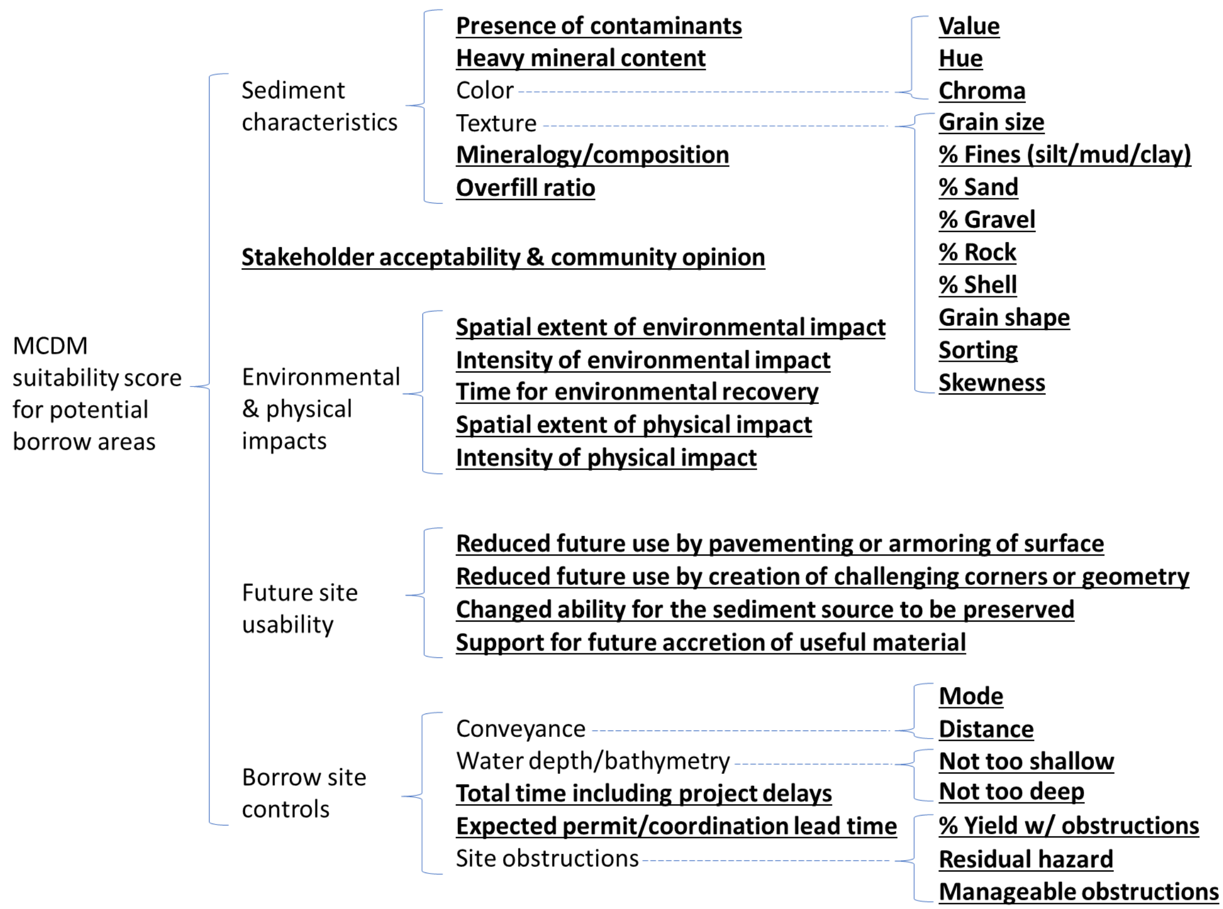

Figure 3.1. *Final MCDA criteria hierarchy developed at the MCDA workshop by stakeholders and experts from state and federal agencies, academia, and industry. The hierarchy has five top-level criteria, four of which have second-level sub-criteria and two of which have third-level sub-criteria. These criteria capture the most important factors for evaluating marine-sand borrow areas or borrow-area regions for beach nourishment, dune creation, or similar coastal engineering projects, as judged by the workshop participants. The 35 right-most criteria, for which metrics and site-evaluation scores will be provided when used, are highlighted in bold and underlined text.*

The final criteria hierarchy develop by the MCDA workshop participants (Figure 3.1) was based on the preliminary list of criteria (Table 1) presented as a starting point for discussion. In the course of group dialog, the preliminary list was transformed in the following ways: The sub-criteria in the *sediment characteristics* preliminary criteria group were reorganized by MCDA workshop participants to better reflect their collective priorities for site evaluation. Specifically, criteria for heavy mineral content and the overfill ratio were added. Color was made a second-level criterion defined by third-level sub-criteria of value, hue, and chroma, reflecting the common Munsell color characterization system. (These changes provide more specificity than the color hue and lightness/darkness criteria from the preliminarly list.) Workshop participants anticipated that, of the three color sub-criteria, value would typically be most important. They also noted that sand color may change after beach placement and oxidization. Grain mineralogy was broadened slightly and reworded to be mineralogy/composition. Texture was made a second-level criterion defined by third-level sub-criteria of grain size, percent fines, percent sand, percent gravel, percent rock, percent shell, grain shape, sorting, and skewness. Participants anticipated that grain size would often be the most important characteristic to match (followed by color). They anticipated that grain shape, which includes grain angularity and roundness, would not be much of a distinguishing consideration for sand sources on the OCS. The percent of fines, sand, rock, gravel, and shell material were all added to the criteria hierarchy. Participants anticipated that, except for offshore oil spill areas, the presence of contaminants criterion would be most relevant for sand sources near the coast. When used, the sub-criteria for color, texture, and mineralogy/composition will need to be evaluated based on their closeness of match for the specific beach, dune, or other coastal engineering application.

The workshop participants also added an additional top-level criterion for *stakeholder acceptability and community opinion*. Because stakeholder and community concerns will vary from project to project (e.g., based local community, environmental groups, industry, etc.), no second-level criteria were added to this general final MCDA criteria hierarchy; they can be developed for local projects as needed.

The workshop participants reframed the preliminary environmental concerns into an *environmental and physical impacts* criterion with sub-criteria for the spatial extent of environmental and physical impacts, the intensity of environmental and physical impacts, and the time for environmental recovery. While workshop participants anticipated that all factors might differ between borrow areas, the extent and intensity of impacts were judged as less likely to differ between different parts of the same borrow area than the time to recovery. Regions of borrow areas with greater horizontal distance to exposed hard bottom (bedrock) were anticipated to have fewer environmental impacts resulting from use because filter feeders, coral, and other organisms that live on hard bottom would be exposed to fewer impacts from increased turbidity.

The sub-criteria for the preliminary future site usability criterion also were entirely replaced by workshop participants. The final *future site usability* criterion is defined by sub-criteria related to the likelihoods of reduced future site usability from pavementing/armoring of the surface or creation of challenging corners or geometry, changed abilities of the sediment source to be preserved, and support of the site for future accretion of useful material. Workshop participants anticipated that if dredging operations newly exposure hard bottom, this hard bottom may need to be protected by a non-dredgeable buffer zone in future dredging operations. It would also generally limit future site usability if dredged depressions infill with mud in subsequent years (though in some niche cases mixed sand-mud material is still valuable, e.g., as material for island construction).

For the *borrow site controls* criterion, the preliminary species environmental windows sub-criterion was combined by workshop participants with other potential timing delays and replaced with a sub-criterion for total dredging time, including expected project delays from safety concerns, inclement weather, and environmental windows, etc. Similarly, the jurisdictional issues sub-criterion was combined with other potential coordination needs and re-envisioned by workshop participants as a sub-criterion for expected permit/coordination lead time, including coordination for tribal concerns, jurisdictional issues, regional state/county concerns about future resource availability, concerns about dredging in military-use areas, and special-circumstance permits such as USACE permits to dredge in a defined navigational safety fairway, etc. The travel distance sub-criterion was replaced with a conveyance sub-criterion that includes third-level sub-criteria of conveyance mode and distance. The dredge access sub-criterion was replaced with a water depth/bathymetry sub-criterion that includes third-level sub-criteria to assess whether a site is too shallow or too deep for the necessary equipment. The site obstructions sub-criterion was expanded to include third-level sub-criteria for the percent yield with obstructions, residual hazard, and percent of obstructions that are manageable (i.e., that are clearable or controllable).

Workshop participants provided several points of discussion related to borrow site controls. Specifically, they noted that presence of site obstructions is closely related to bathymetry and space available to safely maneuver; if a site is surrounded by linear features and closed-in, dredgers may have to cut a clearing first to create enough space to maneuver safely. Percent yield relates to the fraction of available suitable sand volume that is actually accessible in practice. The presence of unsuitable material beneath suitable sand and the depth over which the material transitions also may affect percent yield. Environmental resources have buffers around them that should be included in the obstructions to avoid. The presence of munitions and explosives of concern and unexploded ordinance (MEC/UXO) from past military activity could affect percent yield and residual hazard sub-criteria. Archaeological resources such as ship wreaks or Paleo-Indian sites (from when ocean levels were lower) also need to be avoided.

Suggested metrics and scoring considerations

While the workshop participants generally agreed that many metrics for these criteria will depend on project-specific context, some potentially useful metrics and scoring considerations were suggested, as summarized below. (The participants agreed that the criteria weights should be developed on a project-by-project basis through consultation between the project management teams and stakeholder and community groups.) These suggestions are organized using the bullet-point format shown below, progressing through the criteria hierarchy from left to right and top to bottom:

Example first-level criterion: Suggested metrics and scoring considerations.

- *Example second-level sub-criterion*: Suggested metrics and scoring considerations.
    - *Example third-level sub-criterion*: Suggested metrics and scoring considerations.

The intent of the suggestions presented here is to guide rather than dictate development of project-specific metrics and scoring rubrics. The suggested metrics and scoring considerations are as follows.

Sediment characteristics:

- *Presence of contaminants*: Measure as a binary variable based on whether the presence of contaminants is anticipated to be pose an issue or non-issue for project operations.
- *Heavy mineral content*: Measure as a percent.
- *Color*: Measure in terms of Munsell *Value*, *Hue*, and *Chroma*, which each have their own standardized scales. However, if quantitative color analysis will not be done, color suitability could be scored as a single second-level sub-criterion (i.e., without value, hue, and chroma third-level sub-criteria) on a Likert-type qualitative scale estimating the overall degree of color suitability for sand use at the placement site. If scoring color suitability qualitatively, consider: 1) how well the color matches existing material at the placement site and 2) how well suited the color is for any intended animal habitat.
- *Texture:*
    - *Grain size*: Measure in millimeters or phi units (common measurement units for sands, where phi is related to the negative log of grain diameter).[66,67]
    - *Percent fines*, *percent sand*, *percent fine gravel*, and *percent rock*: Measure by the percent of grains passing an appropriate size sieve.

    - *Percent shell*: Measure as the visual estimation of the percent of shell and shell fragments in the sediment.
    - *Grain shape*: Estimate as rounded, sub-rounded, sub-angular, or angular and score on a Likert-type qualitative scale estimating project suitability.
    - *Sorting* and *Skewness*: Measure in phi units.
    - Alternatively, if quantitative texture analysis will not be done to score texture suitability on these sub-criteria, the overall texture can be scored on a Likert-type qualitative scale estimating the overall degree of texture suitability, considering: 1) appropriateness of grain shape, grain size, and grain size distribution; 2) how well texture matches existing placement site material; and 3) how well-suited texture is to achieve the beach slope or other placement-site design performance requirements.
- *Mineralogy/composition*: Either measure as a percent difference or score on a Likert-type qualitative scale estimating how well suited the sand source is for the intended placement site (e.g., as "highly unsuitable," "somewhat unsuitable," "somewhat suitable," "highly suitable," etc.). If scoring the mineralogy/composition sub-criterion qualitatively, consider: 1) how well the sediment composition matches existing material at the placement site, independent of color or texture; 2) the relative composition of carbonate, silica, or exotic mineral constituent; and 3) if any required project threshold for mineral composition is likely to be met.
- *Overfill ratio*: Measure as the ratio of the volume of sediment needing to be dredged to the volume of sediment delivered at the placement site.

Stakeholder acceptability and community opinion: Develop metrics on a project-by-project basis to reflect whatever sub-criteria are identified as important by stakeholder and community groups for that project. In absence of sub-criteria, this criterion can be scored overall on a Likert-type qualitative scale estimating how acceptable to the stakeholders and community the sand source is perceived to be for the intended placement site. If scoring qualitatively, consider: 1) a broad range of relevant stakeholders, such as residents, county agencies, state agencies, federal agencies, environmental organizations, labor or economic groups, etc.; 2) a broad range of potential topics of concern, such as water quality, threatened and endangered species, migratory species, noise, visual aesthetic impacts, etc.; 3) past stakeholder and community member responses to similar work in the region; and 4) whether any recent or proposed legislation for the current work might be considered precedent-setting and how the stakeholders and community members would react to that new precedent.

Environmental and physical impacts:

- *Spatial extent of environmental impact*: Score on a Likert-type qualitative scale, considering: 1) regional context and area of habitat impaired relative to available habitat of that type in the region; 2) extent to which nearby habitat will be accessible to biological communities that will need to relocate; 3) potential for increased turbidity compared to local baseline turbidity; 4) potential for suspended sediment plumes from dredging to move beyond the dredge site, especially in areas with coral reefs; and 5) the full picture or extent of spatial impact, including both at the dredge site and over the sediment transport pathway.
- *Intensity of environmental impact*: Score on a Likert-type qualitative scale, considering: 1) the species present (especially considering that if any endangered species are present, as impacts to them from disturbances may have exceptionally high consequences); 2) the amount of benthic habitat to be removed relative to the total amount of benthic habitat at the borrow area; 3)

how rare the habitat is that will be impacted; 4) the duration and/or frequency of the dredging activity related to the ability/thresholds of local species to withstand disruption; 5) changes to the substrate characteristics and sediment landscape (e.g., from holes, mounds, or new geometric formations) that may affect the distribution of species at the borrow area; 6) impacts to water qualify (e.g., anoxic depressions) if no infilling occurs; 7) impacts to future breeding at the site; 8) important sub-populations of affected species (e.g., juveniles, females); 9) the rate of recovery for individual species, which may be different that the overall time for ecosystem recovery; and 10) how much is known about the ecosystem at the borrow area and the uncertainty surrounding that knowledge, for example knowledge about the spatial distribution of species, their concentrations in the area, the size of the special populations at the borrow area relative to in the region overall, whether some regional species congregate in high density at the borrow area, why they congregate there, and if whether they are anticipated to stay or move elsewhere if impacted.

- *Time for environmental recovery*: Score on a Likert-type qualitative scale, considering: 1) whether the disrupted species are likely to return or to be permanently displaced; 2) what the short- and long-term effects are expected to be for migrating species that only periodically use the area; 3) what the short- and long-term effects are expected to be for the benthic community; 4) whether full ecosystem recovery can be expected or just biomass recovery, where full ecosystem recovery involves a complete return to the pre-dredging species types, species distributions, and food chains; and 5) regional recovery rates and habitat-specific accretion rates. Note, recovery rates will vary by location but may typically be on the order of a few years.
- *Spatial extent of physical impact*: Score on a Likert-type qualitative scale, considering: 1) changes in wave attenuation due to sand removal; 2) changes in coastal erosion rates relative to the historical record; 3) the length of coastline impacted by changes in wave energy; 4) changes in sediment transport, including the potential to impact shoals between the borrow area and shoreline; and 5) changes in water energy and direction on scour, erosion, and accretion for the nearest coastline. Note, physical impacts to other features are most common within an approximately 1,000-foot range of the borrow area, which is why many archeological artifacts and existing pipelines are given a 1,000-foot buffer. It is also most common to see wave regime effects when the dredge site is in water that is 40-feet deep or less.
- *Intensity of physical impact*: Score on a Likert-type qualitative scale, considering: 1) the volume of sediment to be removed relative to the volume of the marine-sand resource as a whole; 2) the distribution of the total sediment volume to be removed and whether a greater portion will be removed from the shore side or off-shore side of the sand feature; 3) changes in sediment characteristics that may affect the stability of the sand feature, potentially leading to its collapse or rapid settling; 4) changes to the relative height or shape of the sand formation, e.g., due to holes, linear scars, created ridges, etc.; 5) whether any physical changes are within the depth of closure where wave height may be affected (note, the depth of closure is the depth nearest to shore beyond which there is no significant net sediment exchange between the nearshore and offshore systems); 6) how any changes in wave climate in one dredged region of a borrow area will affect the rest of the borrow area; 7) how any changes in wave climate will affect wave height at the shore; 8) the importance of any affected onshore resources, such as infrastructure, landmarks, or recreation sites, etc., and 9) the expected frequency of dredging activity at the

borrow area. Note, any evaluation of the effects of changes in wave height will need to be site specific. Commonly, a change of 10-20% in wave height may be acceptable if monitored for effects, whereas greater changes in wave height may lead to more serious effects. Note also that some National Marine Fisheries Service regions have standards for the maximum fraction of sand that it is acceptable to remove from a habitat area.

Future site usability:

- *Reduced future site useability due to pavementing or armoring of the surface*: Score on a Likert-type qualitative scale, considering: 1) whether the site will or will not ever be used again; and 2) the likelihood that the planned dredging method will lead to pavementing or armoring of the surface of the borrow area by filtering out or dumping larger rock back on the surface.
- *Reduced future site use ability by creation of challenging corners or geometry*: Score on a Likert-type qualitative scale, considering: 1) whether the site will or will not ever be used again; 2) the thickness of desirable sediment layers and the characteristics and acceptability of the substrate material; 3) the type of dredge head to be used and its precision with respect to depth and lateral tolerances; 4) whether the dredging plan includes penalties for dredging over-depth that may incentivize dredgers to leave some suitable sand at the site in thin layers that will be difficult to recover in the future; 5) the configuration of any existing pipelines, archeological features, or potential MEC/UXO, along with their required buffers; and 6) whether the dredging operations will expose new hardbottom that will need to be protected by a buffer in the future, thus excluding sandy material in the buffer zone from use. Note, some examples of challenging corners or geometry include small, disconnected pockets of remaining suitable material, non-linear dredge-area boundaries for remaining suitable material, and remaining suitable material left in thin layers.
- *Changed ability for the sediment source to be preserved*: Score on a Likert-type qualitative scale, considering: 1) whether the site will or will not ever be used again; 2) the quality and stability of offsite features that provide sediment to the area; 2) the sediment transport processes in the area; 3) the likelihood for hurricanes or major storms to change sediment transport processes to the site; 4) changes to the erosional environment that may result in the loss or degradation of surface material in the borrow area, including redistribution of the existing sand volume into a layer that is too thin to dredge; and 5) if the sand can naturally replenish, how the replenishment rate or ability will be affected. Note, at 1 mile offshore, a sustained replenishment rate of 1/10 foot would commonly be considered very slow. At 3 miles offshore, sediment transport processes are even slower and most sand removal can effectively be considered permanent. Replenishment is also a function of water depth; in the Gulf of Mexico, recovery in 3-5 years could be considered rapid but in the deeper Atlantic, recovery in in 5-10 years could be considered rapid.
- *Support for future accretion of useful material*: Score on a Likert-type qualitative scale, considering: 1) whether the site will or will not ever be used again; 2) whether post-dredging bathymetry will affect the type of material being accreted at the site; 3) whether the development of any new features or geometry adjacent to the site would act as natural screens or change flow rates to alter the fraction of coarse vs fine material accreted; 4) whether changes to the wave-energy regime will impact the amount and type of new sediment being deposited; 5) if the type of material accreted changes, the utility of the expected new material for future anticipated sediment needs in the region (some regions may be able to beneficially use accreted

mud and silt while others may only be able to beneficially use accreted sandy material); and 6) the likelihood for hurricanes or major storms to change sediment transport processes to the site.

Borrow site controls:

- *Conveyance*:
    - *Conveyance mode*: Measure as the number of conveyance modes feasible for that borrow area.
    - *Conveyance distance*: Measure in miles or kilometers.
    - Alternatively, if better suited for the project considerations, conveyance can be scored as a single sub-criterion on a Likert-type qualitative scale estimating the overall degree of conveyance suitability, considering: 1) the number of dredge types that are feasible for use at that site and how constrained their operations would be; 2) the distance of sediment transport between the borrow and placement areas; 3) the efficiency of the anticipated dredge and transport equipment types; and 4) the complexity of the sand body and suitability of different types of drag heads for it.
- *Water depth/bathymetry*:
    - *Not too shallow*: Measure in feet or meters.
    - *Not too deep*: Measure in feet or meters.
    - Alternatively, water depth/bathymetry can be scored as a single sub-criterion on a Likert-type qualitative scale estimating the overall degree of water depth/bathymetry suitability, considering: 1) how much of a challenge the water depth and bathymetry at the borrow area will present for dredging operations; 2) the maximum and minimum water depths at the site and any constraints that water depth imposes on the type or timing of equipment use; and 3) any entrance channels to the borrow area or other bathymetric features that influence the direction from which the borrow area can be accessed.
- *Total time including project delays*: Measure in weeks or months.
- *Expected permit/coordination time*: Measure in weeks or months.
- *Site obstructions*:
    - *Percent yield with obstructions*: Measure as the percent of suitable sand in the borrow area that is effectively available for dredged given the presence of site obstructions. Alternatively, if quantitative calculation of percent yield with obstructions will not be performed, yield suitability can be scored on a Likert-type qualitative scale, considering: 1) the presence of rock, the presence of MEC/UXO, site geometry, undesirable cover material above the suitable sand, shipping routes to avoid, oil and gas pipelines, underwater communications cables, wind farms, archeological artifacts, hard bottom habitat, essential fish habitat, and aquaculture; 2) required buffers around any of those features; and 3) any resulting increase in the complexity of dredging operations or reduction in percent yield as a result of the obstructions.
    - *Residual hazard*: Measure on a Likert-type qualitative scale estimating the residual hazards to dredging at the site after any removable obstructions have been removed, considering: 1) the known presence of MEC/UXO and hazardous underwater cables; and 2) the possibility of unidentified or unmarked hazards such as MEC/UXO or underwater cables that will require extra caution to be exercised over much of the dredging site.

- *Manageable obstructions*: Measure on a Likert-type qualitative scale estimating the extent to which obstructions to dredging at the site are clearable or controllable, considering: 1) the number of active oil and gas pipelines and/or cables crossing the site and the extent to which they are adequately covered by a protective layer of material; 2) any legacy oil and gas pipelines that failed to be removed (e.g., if the owners secured a removal waiver from BOEM); 3) any existing site obstructions that can be removed or managed to reduce interference with dredging operations; 4) the effort and time required to remove, clear, or control any manageable obstructions; and 5) the timing of whether the obstructions will be removed at the time of dredging or before.

Best management practices for the sustainable use of marine-sand borrow areas

The following best management practices were contributed by subject-matter-expert and stakeholder participants at the MCDA workshop on sustainable use of marine-sand borrow areas and in subsequent correspondence. Some practices relate to specific activities while others provide general considerations to be incorporated into project planning and implementation. The motivation to catalog these practices is to help borrow area users delay resource depletion, limit environmental and physical impacts from dredging, balance short- and long-term objectives, reduce project cost and hassle, and ensure equitable borrow-area access across multiple present and future users. These practices are grouped into four thematic areas of project planning and design, physical effects, environmental effects, and stakeholder engagement and coordination between multiple users.

Project planning and design

1) **Plan with a holistic view of the beach erosion and sand-replacement cycle.** Before withdrawing resources from a marine sand deposit to replace eroded beach sands, prioritize alternative erosion control methods and implement strategies to extend the presence of existing beach sands.
2) **Beneficially use suitable sediments from other dredging projects.** If the dredged sediments from another project (e.g., from navigational dredging) are suitable for use with a coastal engineering project and would otherwise be disposed of without or with lesser benefit, prioritize their beneficial use for the coastal engineering project before using limited virgin sands from a marine borrow area.
3) **Develop a *Borrow Area Conservation Plan***. This plan should outline where and how much the dredger should dredge to efficiently conserve and allocate the resource across current and future uses. For example, it could be used to ensure that all suitable sand gets taken from a sub-region in clean cuts, leaving an uncomplicated surface geometry and volumes suitable for future dredging with minimal loss.
4) **Encourage dredge operators performing the work to be precise and thorough**. Provide detailed specifications, guidance, and incentives for dredgers to take enough time to be precise in dredging instead of rushing a project in ways that may reduce current operating costs at the expense of future dredging efficiency. Promote and reward sustainable dredging.
5) **Limit use of renewable sites to their renourishment rate.** Dredging at a rate similar to or less than a site's renourishment rate will help prevent overuse and potential permanent loss of a renewable feature. Plan projects so the projected time between the initial dredging for project construction and subsequent dredging for project maintenance is similar to or exceeds the time needed for renourishment. (This is most applicable to sand deposits near the coast since many deposits on the OCS are relic sand features that do not have appreciable renourishment.)

6) **Avoid leaving small, scattered sand pockets.** It is preferable that each dredging operation either leave behind enough sand for the next dredging cycle or no sand at all since small, scattered pockets of remaining sand may not be economical to dredge in the future. This can help reduce long term costs and extend the collective life borrow areas in the region.
7) **Avoid leaving behind sand layers that are too thin.** Leave any remaining sand layers with sufficient vertical depth to be economically dredged in the future. If the sand layer is too thin, it may be difficult or costly to dredge again without also capturing unsuitable underlying material.
8) **Consider the infilling rate and sediment type when creating the dredging plan.** For example, if infilling material (new material that replaces removed material over time) is primarily mud, aim to remove most available sand on the first pass so that little sand will be left to be covered by mud, becoming unviable for later dredging for most coastal engineering uses.
9) **Do not automatically exclude borrow areas with slightly elevated silt content.** When dredged material is placed it often has slightly different characteristics than when it was dredged, for example some fine sediment often washes away during dredging and placement. This may result in placed sediments being more compatible than what was characterized at the borrow site. (For example, in some circumstance it might be more feasible to use sand from an under-utilized area with 85% sand content rather than an over-utilized area with 90% sand content.)
10) **Do not automatically exclude borrow areas if wave models show only small potential increase in erosion along the shoreline.** There is always uncertainty in wave modeling. When selecting a borrow-area, consider the accuracy of the wave model projection compared to any predicted increase before excluding a borrow area.
11) **Consider tradeoffs between dredging efficiency and cost.** Since many marine sand resources are finite, removal operations should be done with highly efficient recovery rates even if that increases near-term cost. For example, using a shorter dredge pipe may increase cost but will increase recovery rate because less energy will be used at the dredge head, stirring up less material to be washed away and potentially lost. Using a longer dredge pipe may be cheaper in the near term but uses more energy at the dredge head, stirring up more material and reducing capture efficiency. Short-term costs that improve recovery rates can delay long-term costs related to exploration for alternative marine sand resources and increased transport distance from farther borrow areas.

Physical effects

12) **Avoid armoring the post-dredging surface.** Avoid dredging that leaves or drops dredged rock back onto the surface of the sand, armoring it and leaving remaining sand uneconomical to retrieve under the new layer of rock. Prioritize the use of uniform sand ridges that have little gravel in them to avoid leaving a gravel layer behind on the post-dredging surface.
13) **Rotate regions used in renewable dredge areas.** Dredge renewable borrow areas in a rotating pattern, similar to a farm crop or grazing rotation system, to allow sand sources to refill and the ecology to recover more effectively.
14) **Selectively dredge the accreting or leading edge of a sand deposit.** Prioritize dredging at the recently accreted or leading edge of the feature. This will allow the feature to remain more stable and it will better support natural physical recovery for future use. (Sand dredged from other parts may be less likely to renew).
15) **Define the maximum dredge depth based on each sand resource.** Consider the context of the resource when defining a reasonable maximum dredge depth. A one-size-fits-all recommended dredge depth may not be optimal for every borrow area. Also, since different dredgers may interpret depth differently in difference circumstances, specify any depths and clearances in clear terms that the dredger can understand with respect to their equipment.

16) **Construct reinforced side slopes**. If the post-dredging slope is steep or vertical, the sand structure may adjust or redistribute too quickly and destroy habitat. Avoiding this may require leaving a small amount of material behind to reinforce the slope. When making step cuts, also make sure that the wall sizes between cells are consistent.
17) **Leave behind a flat surface and avoid digging holes.** The priority should be to dredge away elevated shoals first. It is generally better to remove sand to a flat surface rather than to start with a flat surface and create a hole.
18) **Consider the tradeoffs between shallow and deep cuts.** Consider whether to take the sand volume from the entire surface area, in a shallow layer, or from a deeper cut into just a portion of the surface area. The first option prevents holes that may change wave propagation, while the second option preserves surface area vital to the benthic community. Balance maintaining surface area for benthic organisms with leaving a geometry that maintains wave propagation.
19) **Consider trade-offs between unnecessary use of MEC/UXO screens and future borrow area usability**. Screens on dredge intakes are sometimes used to prevent capture of MEC/UXO that may have been left on the ocean bottom from past military exercises. MEC/UXO screening typically also screens out rock and can lead to rock armoring of the post-dredging surface. This can render the site unusable and lead to premature loss of remaining sand resources. Make risk-informed judgements about areas where MEC/UXO screens are needed.
20) **Use dredged rock to protect sand resources.** Sometimes dredgers screen for rock and then have a rock disposal area adjacent to the borrow area. A potentially helpful alternative would be to use that rock to build a ridge to trap new fine material washing in to prevent it from covering sand on the existing surface of the borrow area.
21) **Consider screening for rock on the beach.** Screening for rock on the beach rather than at the dredging site may improve dredging efficiency and better prolong the useful life of the borrow area (by preventing armoring). Some beachgoers may be interested in collecting or playing with screened rock at the beach.

Environmental effects

22) **Designate an environmental "refuge patch" within the borrow area.** Leaving un-dredged refuge patches can speed recolonization to dredged areas. If ecological communities are expected to be densest on the crest of a shoal, for example, leaving a portion of that crest intact should help seed flora and fauna recovery across the shoal.
23) **Prioritize borrow areas that will replenish with the same type of habitat.** For example, given borrow areas that will replenish excavated sand with either more sand or with mud, selecting the one that will replenish with more sand will encourage habitat consistency.
24) **Use dredged rock to create habitat.** Fish habitat tends to occur where sediments are poorly graded (more diverse) rather than well graded (more uniformly sized), often including rock. Dredged rock could be used to create essential fish habitat. If the habitat is created away from the sand resource, the new habitat should not preclude future dredging.
25) **Use species-specific environmental mitigations to reduce dredging impacts**. For example, include species-specific considerations in the design of a turtle deflector/excluder.
26) **Prioritize borrow areas that support maximum ecosystem recovery.** Some ecosystems may recover from perturbations more quickly than others. Prioritizing those that recover quickly should reduce cumulative environmental impacts across multiple dredging events.
27) **Minimize cumulative dredging intensity for benthic communities.** To decrease the degree of disturbance experienced by the benthic community in a borrow area, avoid repeating excavations in sensitive areas, e.g., avoid following the same linear route through a recovering benthic community.

28) **Consider tradeoffs between efficiency and overall dredge time when planning dredging geometry.** Dredging in strips rather than a large square may have lower impact on the macroinvertebrate system but may increase impacts on elements of the ecosystem sensitive to suspended sediments from longer dredge times. Seek a dredging plan that will help protect the most sensitive and valuable habitat at each site.
29) **Optimize dredging geometry to minimize environmental and physical impacts**. If an assessment shows that a dredging plan will cause unnecessary environmental and physical impact, then the geometry should be reassessed and models rerun to identify a better dredging plan that will leave a post-dredging geometry that minimizes environmental impact. For example, instead of taking the entire volume from the top of a shoal, take it in evenly spaced increments and leave a rolling ridgeline or make a cone shape. Alternatively, collect the volume from the slope of the ridge rather than the top.
30) **When planning the dredging geometry, consider tradeoffs between impacts to the physical feature vs to the macroinvertebrate ecosystem**. Wide, shallow, uniform dredging may maintain the shape of the feature but removes macroinvertebrates from the entire top layer, whereas dredging focused on specific areas may have a lower impact on macroinvertebrates but a large impact on feature shape. Consider tradeoffs in potential impacts from dredging geometry in the context of what is present at the resource. For example, while a large, shallow depression may harm more benthic organisms during removal, it may increase dissolved oxygen level and accelerate recovery if the environment can sustain the oxygen demands of recovering organisms. In contrast, small, deep holes that harm fewer benthic organisms during removal may be more harmful over the long term due to lower dissolved oxygen levels in the hole and an inability to sustain a productive ecosystem in that area.
31) **Use notches to mitigate effects of lost surface area.** For benthic organisms that rely on the surface area of a shoal, lost surface area from dredging may be partially offset by creating notches in the dredging geometry that increase the shoal's surface area.
32) **Use turbidity curtains when coral reefs are down-current.** Turbidity curtains can help prevent settling silt from harming corral.
33) **Consider tradeoffs between different environmental impacts when evaluating risks to high value resources.** Removing sand in a way that reduces risk to a high value resource may be preferable in some cases even if it increases turbidity and other resulting ecosystem impacts. A mild ecosystem disturbance from one type of impact may be acceptable if it allows dredgers to avoid operating at a site that poses a risk to a higher value environmental resource.
34) **Consider tradeoffs in the use of different dredge equipment types.** If suspended sediment is of critical concern, prioritizing a trailing suction hopper dredge may reduce turbidity.

Stakeholder engagement and coordination between multiple users

35) **Form a stakeholder working group to share plans and data.** A working group with stakeholders in a region, including potential project sponsors and other interested parties, is encouraged to openly disclose information about planned use of shared sand resources, including discussion of planned projects, volumes, timing, etc. These working groups can serve as a mechanism for reviewing data and discussing the results of physical and biological monitoring efforts. Sharing data may prevent the need for multiple users to perform duplicate assessments.
36) **Include commercial fishing groups in pre-dredge planning.** By including commercial fishing groups, specific high-value fishing areas at a borrow site can be removed from planned dredging. Early compromises with commercial fishing stakeholders may save a project team from expensive borrow area investigations and also may reduce long-term litigation costs.
37) **Share projections of future resource use.** When developing a coastal engineering project that will require repeated nourishment over time, estimate the ballpark timeframe and volumes of

future dredging events and share this information with interested parties who may also have a stake in marine sand use in the region.

38) **Maximize transparency and cooperation between stakeholders.** All stakeholders, including federal/state/regional agencies, regulators, the fishing industry, community interest groups, etc., can help avoid political disputes, resentment, and litigation by eliminating non-transparent and non-cooperative practices that result in short-term gains for one party but long-term impacts for other borrow-area users in the region as a whole.
39) **To help prevent site-use conflicts, federal partners should proactively reach out to state and local borrow-area users**. State and local government users may also be planning dredging operations, but are less likely to be involved in the federal planning process.
40) **Develop a detailed inventory of marine sand resources to manage stakeholder expectations.** Knowing exactly what is available and where can help manage expectations for long-term shared resource use and encourage conservation of finite resources. Knowing the spatial distribution and volumes of resources available can provide greater flexibility to stakeholders in planning their dredging geometries. Having a resource inventory can also help with communication between stakeholders; if other stakeholders understand that volume is limited, they may be more willing to compromise to preserve the resource, e.g., through volume controls and allowing longer periods between dredging events.
41) **Perform a detailed *regional* Environmental Impact Statement before allowing multiple stakeholders to share sand resources in a region.** A single, simple Environmental Assessment may not be thorough enough to evaluate all impacts to essential fish habitat, ecological recovery times, archaeological features, and the needs and future resource uses of other stakeholders in the region.
42) **Consider resource uses and dredging distances for other stakeholders when selecting a borrow area.** Developing a shared understanding of the long-term dredging needs of all stakeholders in the region will support the coordinated selection of borrow areas to preserve everyone's best options.
43) **Consider replacing the term "competitive use" with "shared use" in project discussions.** "Competitive use" implies that there is a winner and a loser. The objective of coordination between multiple users should be reasonable compromise between the stakeholders without resentment.
44) **Share sand quality fairly.** It is recommended to not unilaterally take the best sand for one's own project and leave less useful remaining deposits for other stakeholders. To encourage exploration while sharing fairly, consider offering some advantage to the party that performed the assessments to identify a viable resource.

Remaining challenges and future considerations

Beyond contributing to the MCDA criteria hierarchy and list of best management practices, the MCDA workshop participants shared many observations and recommendations on existing challenges and future potential improvements for sustainable use of marine sand borrow areas. The bulleted list below summarizes observations and recommendations grouped by topics related to multiple borrow area uses and users and project implementation.

Challenges and considerations related to multiple uses and users

- The concept of multiple-use borrow areas should be expanded to capture more than just multiple users of the same resource. It should also include using a borrow area for multiple purposes, e.g., for sand extraction, for an underwater communications cable pathway, for a commercial fishing hot spot, or for the foundation for an offshore wind farm, etc.

- A cooperative agreement developed between 13 states after Hurricane Sandy provides a good avenue for coordination between state and federal users.
- Inter-agency politics complicate planning and coordination. These are often related to not-in-my-backyard preferences and perceptions of entitlement to resources based on proximity.
- BOEM leases are non-exclusive, meaning that two agencies could be granted use of the same sand resource at the same time (e.g., one using it for single-use emergency beach re-nourishment after a large storm and another for ongoing, extended beach-nourishment maintenance. There could be conflicts about priority should both users want to extract the same sand.
- BOEM leases are typically for 3-5 years but state leases may be for 15 years. Non-USACE users also may need a USACE permit for yet another timeframe. While there are reasons for these different timeframes, bringing them into sync would help users.
- BOEM often grants wavers to the requirement to remove sediment-slurry delivery pipelines after dredging operations are finished. However, the accumulation of abandoned pipelines in a borrow area decreases usefulness to future users.
- Sharing the cost of removing abandoned pipelines in a borrow area may help prolong its useful life. For example, a new project sponsor could pay a portion of the total cost to gain access to the sand, the state or federal lease owner could pay a portion to improve the quality of the resource, EPA could pay a portion to achieve water quality improvements, and/or the past pipeline owners could pay a portion to responsibly retire the asset, etc.

Challenges and considerations related to project implementation

- GIS data are available, but not all available in one place. It would help to have a centralized online data portal that could integrate or link to different existing GIS data.
- Sand compatibility is important for engineering performance and aesthetics. Yet, dredging contract specifications that are overly specific with respect to sand compatibility make the dredgers' job more difficult and increase project cost.
- A major challenge for project sponsors is knowing locations of suitable sand resources, e.g., finding sands of color, shape, and grain size, etc. that are compatible with the intended use.
- For recreational beach nourishment, it is preferable for the borrow-area sand to be a close visual match to the native beach sand, which complicates finding a suitable borrow area.
- Placing sand on a beach that is coarser than the native sand can lead to a steeper beach profile. (If dramatic enough, this may increase beach hazard for the public.)
- Sometimes, borrow areas are so deep offshore that contractors with lower-power suction dredges are only able to pull up smaller grain sizes, leaving the surface littered with rock, which complicates future use.
- The material content in a borrow area is generally well known from surveys before dredging begins, so one could estimate in advance how much rock will be left given a proposed dredging plan.
- If the dredging plan will change the composition of the bottom habitat (e.g., by armoring the surface with discarded rock or creating a depression in a sandy feature that will fill with mud), then that change could be made part of the permitting process.

- If much rock will be encountered, it would help to require a rock management plan. Rock is not valueless and can be useful in the right places. A plan needs to be in place for how to deal with and minimize impacts and create benefits.
- More awareness is needed of the implications of the choice of dredging equipment on the post-dredging borrow-area composition. Some equipment choices may coarsen the post-dredging surface. In other cases, sand left behind due to equipment choices may soon be covered by infilling mud, leaving it uneconomical to recover in the future.
- In some cases, dredgers leave millions of cubic yards uncaptured because dredging more completely would be more difficult (and costly), because they don't want to get close to noncompatible material, or because they don't want to risk going over their planned dredging depth. It would be useful to quantify, in such cases, how much extra it would cost to require dredging more completely. (This would inform long-term cost-benefit tradeoffs since dredging more completely should delay the need to access new borrow areas.)
- It should not be assumed that all changes to post-dredging borrow-area bathymetry have a negative impact. Some bathymetry changes may improve habitat value in some conditions for some species.
- Some cutterhead dredgers are required to have their drag heads firmly in the ground to not endanger turtles, which increases dredging complexity.
- Hopper dredges are often required to have a turtle excluder device on the dredge head. This type of technology has not evolved significantly since it was developed and was not developed with dredge efficiency in mind. There is a need to develop innovative turtle excluders that support greater dredging efficiency.

DISCUSSION

The criteria hierarchy, suggested metrics and scoring considerations, best management practices, and other shared challenges and considerations presented above reflect central themes in the sustainability literature and share some details with other applications of MCDA to different types of dredging problems. Simultaneously, they also include details that are unique to the sustainable use of marine-sand borrow areas and that have not been previously presented in the literature. The following discussion compares and contrasts the products developed through the MCDA workshop with the broader literature on sustainability and dredging MCDA.

Interpreting products of the MCDA workshop in the context of sustainable development

Many of the products developed through the MCDA workshop can be interpreted to reflect different themes of sustainable development. Classic conceptualizations of sustainable development describe sustainability as a balance between environmental wellbeing and human social wellbeing and economic development, and assert that environmental impacts from present development should not compromise the ability of future generations to meet their resource and development needs. In the hierarchy developed at the MCDA workshop, the criteria and suggested metrics related to maintaining <u>future site usability</u> and limiting <u>environmental and physical impacts</u> reflect classic sustainable development's interest in protecting intergenerational resource needs. The best management practices related to reducing the need to dredge for beach nourishment in the first place, avoiding armoring the site's surface, protecting a feature's capacity to accrete, promoting feature stability, and not creating challenging geometry, etc., also address this concern, as do some of the remaining challenges and future considerations that describe accommodating multiple uses and users also reflect this interest.

In the criteria hierarchy, the criterion and suggested metrics related to stakeholder acceptability and community opinion reflect classic sustainable development's interest in human social wellbeing. So do the best management practices related to stakeholder engagement and coordination between multiple users and some of the described challenges and future considerations related to multiple uses and users.

In the criteria hierarchy, the criteria and metrics related to sediment characteristics and borrow site controls (many of which are proxies for project efficiency, time, and cost), reflect classic sustainable development's interest in economic development. So does some of the motivation behind the criteria and metrics for physical impacts and future site usability, some of the best management practices about physical effects and project planning and design, and the described remaining challenges and considerations about project implementation.

In the criteria hierarchy, the criteria and metrics related to environmental impacts reflect classic sustainable development's interest in environmental wellbeing. So do the best management practices related to environmental effects and some of the remaining challenges and considerations related to project implementation.

Taken together, the themes of classic sustainable development are well represented in the products developed through the MCDA workshop.

Comparing the criteria hierarchy developed through the MCDA workshop to those developed in MCDA applications to other dredging problems

Many of the high-level themes of the criteria hierarchy developed at the MCDA workshop also occur in applications of MCDA to other dredging problems. This is especially true of the top-level criteria, where concern for sediment characteristics, stakeholder acceptability and community option, environmental and physical impacts, and borrow site controls are relevant for many different types of dredging and sediment decisions. While the criteria hierarchy developed by the workshop participants does not explicitly contain a cost criterion, as many of the other dredging and sediment MCDA applications do, the borrow site controls criterion is closely related to project operating costs. There is less commonality between the criteria hierarchy presented here and those in other MCDA applications with to the future site usability criterion since that is so uniquely linked to the themes of sustainable development, which most other dredging and sediment MCDA applications do not consider. There is also less commonality between this and other MCDA applications throughout the sub-criteria and suggested metrics and scoring considerations, which are more specific to sustainably using marine sand for coastal engineering projects.

With respect to sub-criteria for the sediment characteristics criterion, concerns related to the presence of contaminants are included in many MCDA applications. However, most other MCDA applications that mention sediment contamination are related to sediment remediation and use criteria that assess differences in pre- and post-remediation levels of contamination at the site.[43,52,53,54,55,56,59] While these applications do consider sediment contamination, their purpose is quite different from the purpose of this application to assesses the sustainable use of sand resources. Of prior applications, the most closely related are from Manap and Voulvoulis (2014), who perform a screening-level analysis to check for sediment contamination prior to their MCDA evaluation,[50] and Bates et al. (2018), who consider sediment toxicity as a line of evidence in an MCDA framework to assess the suitability of different potential recipient sites for dredged sediment placement. Most other MCDA applications do not consider the sediment's heavy mineral content since heavy minerals are likely to remain stable if not brought to the aerobic environment of a beach or dune. (Other MCDA applications that consider contamination tend to focus on chemical contamination from past human industrial activity.) Consideration of sand mineralogy/composition, overfill ratio, color (including its value, hue, and chroma), and texture (including its grain size, grain shape, sorting, skewness, and percent fines, sand, gravel, rock, and shell) are unique to evaluating sand for engineering uses and do not have parallels in other applications to contaminated-sediment remediation or navigational dredging and sediment placement; these criteria are believed to be unique to this application of MCDA to sustainable marine sand resource use.

Criteria related to stakeholder acceptability and community option are also often included in applications of MCDA to dredging and sediment problems. While the stakeholder acceptability criterion developed in this application leaves the sub-criteria and metrics to be developed on a project-by-project basis, the workshop participants' suggested sub-criteria, metrics, and scoring considerations consider a broad range of stakeholders and topics of concern and have parallels in other MCDA applications.[e.g., 34,52,53,54,55] More unique are the workshop participants' suggestions to consider past stakeholder and community responses to similar work in the region and whether this proposed projects might set unwelcomed precedents for the region, a suggestion that could have applicability to other types of sediment and dredging problems.

Explicit consideration of the environmental impacts created by the dredging or sediment-remediation process sometimes occurs in other MCDA applications, predominantly those not dealing with contaminant remediation.[e.g., 34, 42,43,50,51,56,57,59] However, only Collier et al. (2014) also suggests that metrics include physical impacts from changed seafloor shape, e.g., related to wave propagation and the surfing community's interest in wave patterns generated by nearby seafloor geometry.[34]

Inclusion of criteria related to future site usability (including armoring of the surface, creation of challenging geometry, changed ability for the sediment source to be preserved, and support for future accretion) are believed to be unique to this MCDA application.

Some of the sub-criteria for borrow site controls appear in other MCDA sediment and dredging applications. For example, MCDA-based sediment placement optimizations by Yeh et al. (1999) and applications of the D2M2 software (Ford 1984, Ford 1986, and chapter 4 of this dissertation) consider conveyance mode and/or conveyance distance.[49,68,69] Yeh et al. (1999) and Suedel et al. (2008) also consider criteria related to dredging equipment type and project timing.[49,57] The broader (i.e., non-MCDA) literature for dredging optimization frequently considers objectives similar to conveyance mode, conveyance distance, water depth, total time including project delays, and site obstructions. However, considerations of expected permit/coordination lead time, percent yield with obstructions, manageable obstructions, and residual hazard are not common.

Comparing the suggested best management practices developed through the MCDA workshop to those identified in the literature

The best management practices suggested by the MDCM workshop participants include many new contributions to the literature. Some of the practices suggested by the MCDA workshop participants have been suggested in prior lists of best management practices, but most of these lists focus on practices related to effects at the beach or dune placement site and not on practices related to the sustainability of the borrow site. Where prior lists do suggest practices relevant for marine borrow areas, few were not repeated in the criteria, metrics and scoring considerations, and best management practices suggested by the MCDA workshop participants. Most of prior lists are also shorter than the list developed through the MCDA workshop and contain significant overlap with each other.

Rice (2009) discusses many best management practices to reduce the environmental impact from shoreline stabilization projects.[60] Almost all of these practices are focused on limiting environmental impacts at the placement site (i.e., dune, beach, or nearshore environment). This is in contrast with the environmental best management practices suggested by the MCDA workshop participants, which focus on limiting impacts at the borrow area (which is fitting given the topic of the workshop). Of the few practices that Rice suggests for the borrow area (i.e., to use shallow dredge cuts, leave refuge patches, not dredge valuable habitat, not create holes on the seafloor, and not significantly alter the local bathymetry), most were also included in the MCDA workshop participant's list of best practices or suggested metrics and scoring considerations. The only environmental practice for borrow areas that Rice suggests that does not directly match those developed by the workshop participants is to leave a post-dredging surface at the borrow area that matches the original sediment layer as closely as possible to better promote recolonization.

Haney et al. (2007) present best management practices to minimize erosion, minimize impacts to natural resources, promote beneficial reuse of dredge material, and expedite regulatory review. These practices are suggested for beach nourishment projects that either reuse sediment from navigational dredging or use sand from terrestrial sources and explicitly omit practices for projects that mine sand from marine borrow areas. This difference in scope reduces the overlap in practice topics between their work and the products of the MCDA workshop. Many of the practices recommended by Haney et al. focus on effects at the beach placement site or consider the match between a navigational dredging project and beach placement site. A few of their suggested practices related to comparing the grain size distributions between source and placement sites to determine suitability and compatibility can be extended to borrow areas, a theme also covered in the criteria hierarchy developed through the MCDA workshop, in the sediment characteristics sub-criteria.

Rosov et al. (2016) review impacts from beach nourishment activities on benthic organisms, summarizing several best management practices and lessons learned from others.[62] Of the seven practices they present, five are directly covered in the recommendations by the MCDA workshop participants, including to: select borrow areas that are likely to refill with useful sediment, dredge a rolling ridgeline with shallow cuts and leave refuge patches, avoid creating deep pits, dredge from the leading edge of a shoal to support future accretion, and use sediment that is compatible between the source and placement areas (which is covered by the sediment characteristics sub-criteria of the MCDA criteria hierarchy). Two additional practices, to avoid project activity during peak recruitment seasons for benthic larvae and to complete project activity before the seasonal decline in population abundance (to support recolonization), capture the same sentiment as various practices suggested by the MCDA workshop participants to use species-specific mitigations and to minimize impacts to the benthic community, but with greater specificity.

Seven best management practices are suggested by Elko et al. (2020).[63] These are presented in the context of managing coastal inlets but have broader applicability to other types of marine borrow areas. Of these, five were at least partially suggested by the MCDA workshop participants, including to: implement regional sediment management, use compatible sand, modify dredging equipment and practices, design borrow areas that are renewable, and limit the frequency, duration, and area of impact. Two additional practices, to follow environmental windows and conduct monitoring, were not covered by the workshop participants but are often required for regulatory compliance as a routine part of project operations.

Other than those repeated from Rice, the practices suggested by Guilfoyle et al. (2019) for reducing impacts to shorebirds and sea turtles from coastal engineering activities do not consider activities at the borrow site.[64] However, it is noteworthy that they mention: the cost effectiveness of implementing best management practices, that monitoring is needed to ensure effectiveness for the target species, and that best practices are anticipated to be most effective when implemented with regional coordination.

Overall, of the 44 best management practices suggested by the MCDA workshop participants, 5 have full overlap with practices included in the lists cited above, 9 have partial overlap with these lists, and 30 have little or no overlap with previously suggested practices. Since the focus of the practices suggested through the MCDA workshop is on the sustainable use of marine sand borrow areas and the focus of many of the prior lists is on effects at the placement site, total sustainability can better be achieved and environmental impacts better minimized by consulting both types of lists during project development.

Discussing the remaining challenges and future considerations shared by the MCDA workshop participants

The remaining challenges and future considerations shared by the MCDA workshop participants are grouped into two broad categories but cover a breadth of topics. They discuss issues of: coordination, cooperation, and sharing between multiple users and uses; geographic resource conflicts; sharing spatial data; unaligned timing; impacts from abandoned pipelines and how to fund their removal; tradeoffs between sand compatibility and cost; effects of using incompatible sand; knowing where to find compatible sand; dealing responsibly with rock; implications of choice of dredging equipment; extra costs of dredging more completely; post-dredging bathymetry; and turtle-exclusion technology.

While some of these considerations can be incorporated into the planning for individual projects, most of them deal with broader issues that must to be addressed at the inter-agency level. These topics would be profitable for discussion at future regional sand management working group meetings, though some may require federal or state agency policy changes for resolution. Academia can also play a role in these discussions, for example by hosting data exchanges and engaging in research about physical and environmental effects. Several of the identified remaining challenges and future considerations could be developed into research agendas for sustainable borrow area sharing and use.

CONCLUSIONS

This chapter reports on the process and outcomes of an MCDA workshop about the sustainable use of marine sand. Stakeholders and experts from state and federal government, academia, and industry collaborated through this facilitated workshop to develop an MCDA criteria hierarchy for evaluating potential marine sand borrow areas to be dredged for beach nourishment and similar coastal engineering projects. The workshop participants suggested metrics and scoring considerations for the criteria in the hierarchy, recommended best management practices for sustainably using marine sand borrow areas, and shared observations about remaining challenges and future considerations for this topic.

The criteria hierarchy developed by the MCDA workshop participants is the first application of MCDA to marine borrow areas. Sub-criteria in the hierarchy are grouped through top-level criteria of sediment characteristics, stakeholder acceptability and community opinion, environmental and physical impacts, future site usability, and borrow site controls. The participants suggested metrics and scoring considerations for most criteria but recognized that some will need to be specified in the context of individual project needs. While most of the criteria are unique to this application, some have been used in prior literature applying MCDA to navigational dredging and contaminated sediment remediation. The suggested criteria well achieve their goal of incorporating sustainability into marine sand borrow area management, reflecting classic sustainable development's interests to balance economic, social, and environmental concerns and to promote inter-generational resource availability.

Of the best management practices suggested by the workshop participants 11% are duplicated in prior lists of best practices for beach nourishment, 20% have partial but not complete overlap with practices in those lists, and 68% represent unique practices contributed to the literature on marine resource management. The high uniqueness of the best practices developed through the MCDA workshop is partially because prior lists of practices have mainly focused on the placement site with limited treatment of the borrow area. Many of the best practices and criteria suggested by the workshop participants can be extended to other types of dredging and coastal engineering problems, especially those promoting resource sustainability. The remaining challenges and future considerations shared by the workshop participants reflect a need for inter-agency cooperation and coordination to remove additional barriers, and could be used to inform a research agenda on the sustainable use of marine sand resources.

This chapter represents both the first application in the academic literature of MCDA methods to marine sand borrow areas and the first application of the concepts of sustainable development to borrow area management. The products developed through the MCDA workshop can be useful to researchers and practitioners seeking to incorporate sustainability considerations into the analysis and management of marine sand borrow areas. Future work will be needed to expand these products and apply them to individual projects.

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Chapter 4

Advancement and Application of D2M2 for Multi-Objective Dredging Optimization

ABSTRACT

The Dredged Material Management Decisions (D2M2) software is a multi-objective optimization (MOO) modeling tool to identify efficient long-term, systems-level, sediment-allocation strategies through networks of dredging, temporary storage, and final placement sites. D2M2 provides a model-building interface that can accommodate any mix of financial costs and other user-defined impacts, benefit, or effect objectives in a multi-criteria-decision-making (MCDM) model of mass-balance sediment allocation using mixed (binary) integer linear programming optimization. The original version of the software was developed in the 1980s for the US Army Corps of Engineers to support navigational dredging decisions. The version presented here has been redeveloped in the Java programming language with an improved user interface and new modeling functionality to better represent cost/impact/benefit/effect relationships and system constraints. This chapter introduces the redeveloped D2M2 software, summarizes its enhancements, and applies it in a case study using site data for eight different financial, environmental impact, and beneficial-use criteria applied to dozens of dredging and placement sites along the Gulf Intracoastal Waterway (GIWW) in the region of Galveston, TX.

INTRODUCTION

Waterborne transport is of crucial importance to many nations with coasts or major rivers. Having navigable coasts and rivers enables low-cost transportation of commercial goods for foreign and domestic trade, commercial and recreational fishing, recreational boating, and coastal protection and naval defense, among other uses. However, rivers, coasts, and their adjacent ports and harbors are not static. Without human intervention, there is no guarantee that waterways previously navigable by ship traffic will remain so with gradual infilling of new sediment over time or after large storm events. Navigational dredging is dredging specifically undertaken to increase or maintain the depth of water in certain locations so that ships can safely and efficiently navigate through that area. Navigational dredging is undertaken by different organizations at smaller and larger scales. National and state governments tend to pursue large-scale dredging of rivers, shipping channels, and major ports and harbors, while local port authorities, yacht clubs, and similar entities undertake smaller projects so that vessels can access their facilities.

The dredging equipment used for navigational dredging is typically similar to that used to mine sand for coastal engineering projects, relying heavily on mechanical and hydraulic dredgers that remove sediment from choke points in the navigational channel. Navigational dredging has an added complication that suitable placement sites must be found for the dredged sediment that is removed from the channel. Placement sites may include open or confined sites adjacent to the dredged channel or in a designated area farther away in open water, in shallow water near the shore, on the shore, upland, transported to a landfill or reprocessing plant, or beneficially use for habitat restoration or industrial processes. Sediment with levels of contamination that make them unsuitable for some purposes may need to be isolated from the environment or treated before placement.

Beside mechanical and hydraulic dredging, other techniques that relocate sediment within the waterway are also possible, such as dragging, water-injection, and resuspension dredging. These can be financially and environmentally effective when used in combination with typical navigational dredging programs, but are not modeled in this chapter as they do not require involve the allocation of sediment to placement sites.

Dredged-material placement sites are chosen based on a range of criteria, including sediment characteristics, equipment constraints, transport costs, environmental impacts and benefits, and stakeholder interests, etc. Historically, dredged sediment was viewed as a waste product to be disposed of. To limit project costs and coordination challenges, dredged sediment was historically deposited in placement sites that could be reached at low cost but that were not designed for sediment reuse (i.e., the later removal of placed sediment for use as a resource in another process). In modern times, however, dredged sediment is increasingly being thought of as a valuable resource with reuse potential for engineering and environmental benefit.[1,2,3]

In the US, the US Army Corps of Engineers (USACE), is responsible for maintaining over 12,000 miles of waterways and dredges more than 200 million cubic yards (MCY) of sediment from waterways every year to maintain waterway navigability, at an annual cost of well over one billion dollars.[4] The USACE has an interest in optimizing dredging and dredged-material placement to reduce costs and environmental impacts and to provide environmental and social benefits for the ecosystems and communities near dredging and sediment placement sites, making the overall best use of dredged sediments. Potential beneficial uses of sediment include its use in beach nourishment to provide storm protection, to enhance the natural environment, to create marshes and islands for fish and wildlife habitat, and for commercial and industrial uses such as in brick making, in mulch, or for landfill cover.

Early research on dredging optimization between the 1970s and 1990s applied linear programming and related operations research methods with a systems-based approach to evaluate dredging management plans.[5,6,7,8,9,10,11,12,13,14] These studies recognized how well suited dredged-material management problems are for optimization solution techniques, since dredging needs differ from year to year based on system constraints and require re-evaluation of scheduling and costs. For example, Hochstein et al.[8] propose an optimization model to re-evaluate authorized dredging depths and conduct reconnaissance studies on four harbors in the U.S. to recommend channel depths for dredging and channel maintenance. Their results indicate significant cost savings are achievable when channel depth dredging decisions are made more regularly and are directly related to the economic value of the channel and its cargo. Risk-based approaches also were introduced to handle uncertainty with regard to sedimentation rates[10,15] and channel maintenance.[9]

Many early dredging optimization studies primarily had objectives to minimize total costs and determine optimal project scheduling, rather than to quantify and avoid impacts and provide benefits to the environment, ecology, or stakeholder community. As environmental concern has grown more prominent in society and policy in recent decades, the need for least-cost-and-least-impactful solutions has expanded the types of questions asked and optimization techniques used. Now, multiple competing criteria are now often considered when selecting dredging management plans. For example, Abood[16] proposes applying the 'Leadership in Energy and Environmental Design' (LEED) sustainability framework to award points for selecting renewable and least-impact materials for dredging and dredged-material placement, and for building innovation in dredging practices. Blazquez et al.[17] explicitly consider "environmental dredging" in their system optimization, employing environmentally-protective changes to the dredging operations to minimizing sediment contamination; they use this formulation to explore ways to both reduce losses in productivity and reduce costs for environmental dredging.

In an additional application of multi-criteria dredging planning, Agee et al.[18] describe a collaborative project where the City of Annapolis, MD, local stakeholders, and USACE worked together to dredge the harbor and channel while simultaneously completing an environmental restoration project. Ratick and Garriga[19] developed a spatial decision support system for USACE that trades-off project costs and channel reliability for maintenance dredging. Van Noortwijk and Peerbolte[20] built a decision model to aid sand nourishment placement that considers three types of costs and the risk of permanent erosion. A more recent effort engages stakeholders and managers in this type of system-level optimization through the development of web-based project management systems such as that of Skibniewski and Vecino[21], where a life-cycle cost and benefit assessment of operations is coupled with a management system to create a framework for evaluating the performance of dredging alternatives.

Several recent examples are employing advanced and combined methods of optimization to assess dredging management plans based on multiple qualitative and quantitative criteria. Mitchell et al.[22] and Nachtmann et al.[23] implement mixed integer programming and heuristic solution algorithms to optimize dredging management based on budget allocation and find that including project interdependencies affects the overall plan. Righini[24] develops a network flow model using a linear program to find the maximum capacity of the Northern Italy waterways considering cargo load, economics, and robustness of the solutions under different system profiles. Hashemi et al.[25] propose a rank-based method to identify port projects that accounts for a wide range of project risks and estimated confidence intervals using a bootstrap method.

In practice, prior to selecting a management plan to implement for a specific region, USACE projects are mandated to perform an alternatives analysis to assess feasible strategies; a process that often relies on experts' judgements to choose the final best strategy. Reliance on direct expert judgment for synthesis and evaluation of alternative strategies becomes increasingly harder and less justifiable at larger scales, over longer time horizons, and with growth in network complexity[26,27,28]. As a response, the Dredged Material Disposal Management (D2M2) dredging optimization software was created to enumerate, evaluate, and compare alternatives and determine the least cost plan for transporting and disposing of dredged sediments with limited placement area capacity and various transportation and other costs[5]. D2M2 was initially applied to dredging along the Delaware River to select the least-cost plan using a network-based approach.[6] D2M2 has been updated several times and the more recent versions explicitly support consideration of multiple project objectives in addition to financial costs. The most recent prior version of D2M2 was released in 2010 (US Army Corps of Engineers, 2010).

Unlike many of the other multi-objective optimization[29] (MOO) dredging models mentioned above that have a specific MOO problem already specified within them, D2M2 is not a MOO dredging model itself but is a MOO-dredging-model builder. D2M2 users can either upload site data via project templates or use its graphical user interface to specify a system-scale network of dredging, transfer, and placement sites, add various system constraints, and then optimize that system model to discover efficient plans for moving all required material from dredging to placement sites at least cost and/or greatest benefit over a multi-year timeframe. D2M2 models can be optimized based on a completely customizable set of user-defined criteria. Typical criteria used in recent USACE D2M2 case studies include a mix of financial, environmental impact, and stakeholder-interest criteria.

Once a system model has been specified through the D2M2 software, it can be described using a MAVT framing of the MOO problem in terms of an aggregated MAVT score that is minimized/maximized, subject to various constraints and model data and relationships. D2M2 uses linear programming solver to develop an optimal plan for system operation. The purpose of the MOO problem is to transfer all required dredging volumes in each time period from each dredging site to various available placement sites to achieve the greatest benefit and/or least cost or impact for all objectives specified by the user. The D2M2 software readily supports scenario and sensitivity analysis, where users can explore differences in weighting, addition or exclusion or additional sites or volumes, and/or application of different unit costs or constraints to see how those variations change the recommended optimal solution.

Ford[5] describes the original D2M2 mathematical problem formulation, solution technique, software development process, software structure, and application in a Delaware River case study to model a subsystem of the river between Philadelphia and the sea that included 19 dredge sites and 8 disposal sites over a 50-year time period, with input data provided by the USACE Philadelphia District. Ford[6] later furthers the Delaware River case study by applying the software to investigate potential effects of developing different alternatives for expanding sediment-placement-site capacity. Willey (1989) describes further use of the software to support strategic planning in the Delaware River system related to sediment placement strategies and capacity expansion.

A USACE SPN (1994) report introduces an updated version of the software to improve the user interface, to implement modifications needed for long-term dredging planning by the USACE San Francisco District, and describes two case study applications that model 25-year dredging planning in the San Francisco Estuary, including 14 dredging projects and 40 existing and proposed placement options optimized for financial cost under different scenarios for potential management constraints and material placement alternatives. This version of D2M2 was included in the Automated Dredging and Disposal Alternatives Management System modeling suite described by Schroeder et al.[30] This version was used by the USACE Portland District in the mid-1990s for dredging planning along the Columbia River. They modeled dredging from the mouth of the Columbia River through Vancouver, Washington and used D2M2 to efficient allocate sediment placement between upland, beach nourishment, and in-water sites (personal correspondences with Jon Gornick and Laura Hicks, USACE Portland District, 7/10/2019 and 7/15/2019). A next updated version of D2M2 was introduced in 2010 when the software was upgraded from a Microsoft DOS to a Microsoft Windows application to gain an initial graphical user interface and a few other capability enhancements.[31]

An agency report by Poindexter-Rollings[32] recommends use of D2M2 as a best management practice to increase the useful life of sediment placement areas. Another agency report by Bailey et al.[33] recommends using D2M2 to account for beneficial uses of sediment in dredged material management plans, as one of eight research and development recommendations to enable sustainable, long term placement area capacity management. An agency report by Banks & Gerhardt Smith[34] summarizes a workshop on regional sediment management and engineering with nature approaches. In it, the participants recommend the use of decision support tools such as D2M2 to "increase understanding and create cooperative agreements with stakeholders."

This chapter introduces a new and updated version of D2M2, resulting from a project led by the author with the USACE Engineer Research and Development Center. This D2M2 version includes new modeling functionalities for specifying cost/benefit/effect relationships and system constraints, for improving the modeling process, and for improving the user interface. Implementing some of these enhancements required the D2M2 optimization solver to switch from using a traditional linear programming formulation to a mixed (binary) integer linear programming (MILP) formulation. The new version uses a MILP solver called *Cbc* (COIN-OR branch-and-cut; available from COIN-OR Foundation as part of the COIN-OR Optimization Suite). The software has been completely redeveloped from previously fragmented FORTRAN and C code into a single Java-language tool that can run on any Windows, Linux, or Mac operating system. This new version of D2M2 is rechristened as the "Dredged Material Management Decisions" software, removing a connotation in prior version that dredged material is a waste material to be disposed rather than a resource that can be used beneficially.

This new version of D2M2 is applied in a case study using site data for an 81-mile portion of the Gulf Intracoastal Waterway (GIWW) system near Galveston, TX. The case study includes data for 8 different financial, environmental impact, and beneficial use (BU) objectives that reflect a broader range of sustainability-related considerations than have been implemented in past D2M2 applications or other known dredging optimizations. The case study includes 6 dredging reaches and 62 existing and potential placement sites where the sediment can be stored or beneficially used, including potential site expansions to accommodate 20-year dredging capacity needs. These data are used by D2M2 to identify an optimal dredging plan under 9 scenarios that vary the objective weighting and site availability in the system network.

CASE STUDY DESCRIPTION

GIWW system overview

The Gulf Intracoastal Waterway (GIWW) is an inland waterway for marine transportation along the Gulf of Mexico. It stretches over 1,100 miles from the southern tip of Texas through the Florida panhandle (Figure 4.1). It is used primarily for barge traffic and commercial shipping and, to a lesser extent, by recreational vessels. As a protected, inland waterway it provides safe harbor for shipping when transit of the open ocean would be threatened by high seas. At 125-feet wide and with a project depth of 12-13 feet, this man-made navigational channel is the third-busiest inland waterway in the US. Nearly 285,000 vessels used the waterway to transport more than 110 million short tons of commercial cargo in 2018 (for example, as in Figure 4.2).

Figure 4.1. *The Gulf Intracoastal Waterway is an inland, man-made waterway along the coast of the Gulf of Mexico that runs over 1,100 miles from the southern tip of Texas through the Florida panhandle. It is dredged on an ongoing basis to maintain sufficient depth for commercial and recreational marine transportation (image: Texas Department of Transportation, 2020).*[35]

Figure 4.2. *The GIWW where it connects to Galveston Bay. This photo is looking east northeast with Galveston Bay at left, the GIWW channel at center, the town of Port Bolivar, TX at center right, and the*

Gulf of Mexico at upper right (image: US Army Corps of Engineers Galveston District and Texas Department of Transportation, 2018).[36]

Sediment is continually deposited in the GIWW channel from wind, waves, tides, major storms, shore erosion, and the rivers and streams that enter the GIWW. Regular dredging is needed to keep all channel reaches at suitable depths for ship passage. Dredged material management remains a concern with limited capacity available at existing defined placement sites. As federal sponsor, the USACE monitors and maintains the waterways and, as non-federal sponsors, the State of Texas acquires real estate to use for dredged material placement areas and participates in projects to use the dredged sediments beneficially for environmental restoration and other purposes when suitable projects can be identified, though project timing, permitting, land ownership, and other logistical barriers constrain beneficial use projects.[35]

D2M2 GIWW case-study site and network data

This case study focuses on dredged material management decisions for an 81-mile portion of the GIWW in Texas between High Island and Brazos River, near Galveston Bay and the Houston Ship Channel.[37] For the purposes of modeling, the case-study segment uses 6 channel reaches based on natural and constructed transition points in the channel and its crossings (note, they are not all similar in length; Figure 4.3). Geospatial locations and geometries for channel reaches are taken from the USACE enterprise navigation geospatial web service.[38]

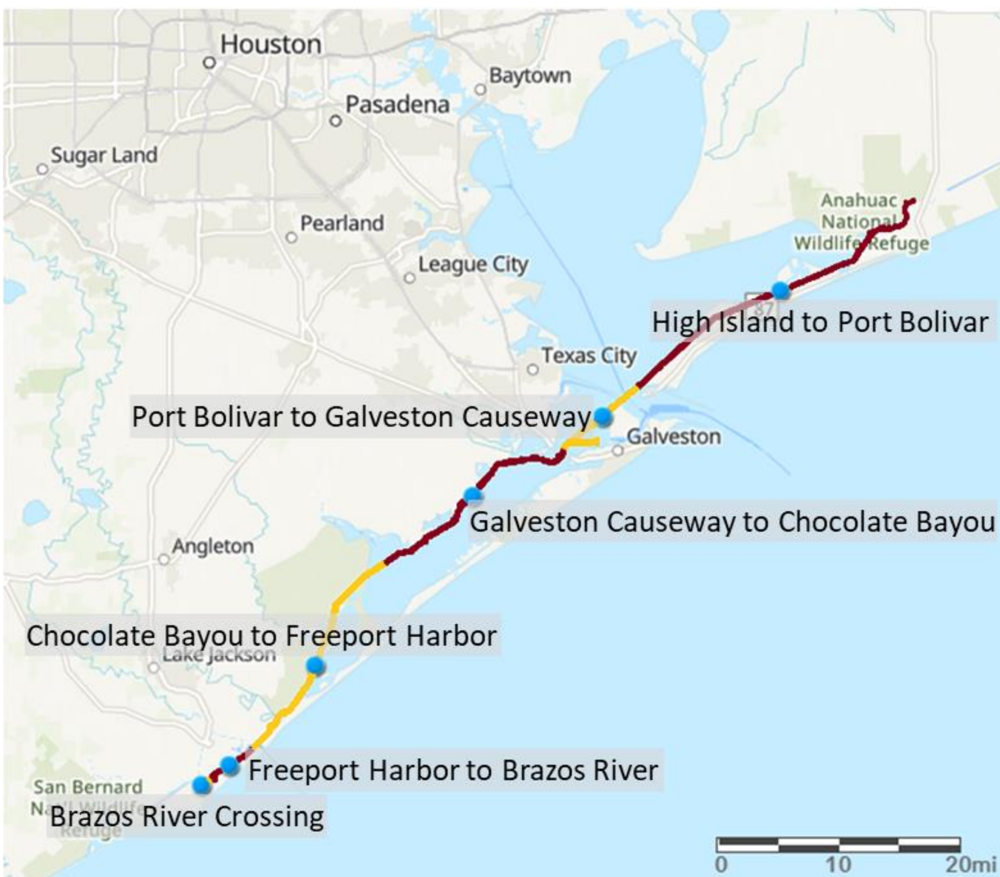

Figure 4.3. *Case study area of an 81-mile portion of GIWW between High Island and Brazos River, near Galveston, TX. For modeling purposes, this portion of the GIWW is divided into six channel reaches, shown in alternating colors for better visual discrimination, based on natural and constructed transition points along the channel (note, they are not all similar in length). The centroid of each reach is shown with a blue circle and labeled.*

Average annual sedimentation rates for each of these six reaches were previously estimated by the USACE using the Corps Shoaling Analysis Tool[39] with historical hydrographic survey data provided by the USACE Galveston District. The total average volume of annual sedimentation in the case study area is over 1.5 million cubic yards per year (CY/yr) (Table 4.1). To maintain this portion of the GIWW at a consistent depth suitable for shipping and other marine navigation, this average amount of annual sediment needs to be removed each year (on average) to avoid net infilling.

Table 4.1. *Dredging reaches in the case study area of the GIWW for which average historical sediment shoaling data have been estimated. (Data from the USACE Galveston District.)*

Reach Description	**D2M2 Reach ID**	**Average Volume (CY/yr)**
High Island to Port Bolivar	GI_02_HIB_2	698,198
Port Bolivar to Galveston Causeway	GI_03_BGC_3	33,810
Galveston Causeway to Chocolate Bayou	GI_04_GCC_4	155,028
Chocolate Bayou to Freeport Harbor	GI_05_CBF_5	217,614
Freeport Harbor to Brazos River	GI_06_FBR_6	458,342
Brazos River Crossing	GI_08_BRC_8	12,259
		Total: 1,575,251

Using sediment placement sites strategically in the GIWW remains an ongoing challenge. This D2M2 case study model connects the 6 aggregated dredging reaches to 62 placement areas (Figures 4.4 & 4.5). Geospatial locations and geometries for the placement areas are taken from the USACE enterprise sediment placement area geospatial web service.[40] These sites differ in terms of type, status, capacity, acquisition and improvement cost, and other multi-criteria outcomes from sediment placement. The sites range in capacity from 30,000 CY to over 1,000,000,000 CY, with a median of 622,220 CY and a mean capacity of 17,672,834 CY (Table 4.2 & Appendix Table 4.A1).

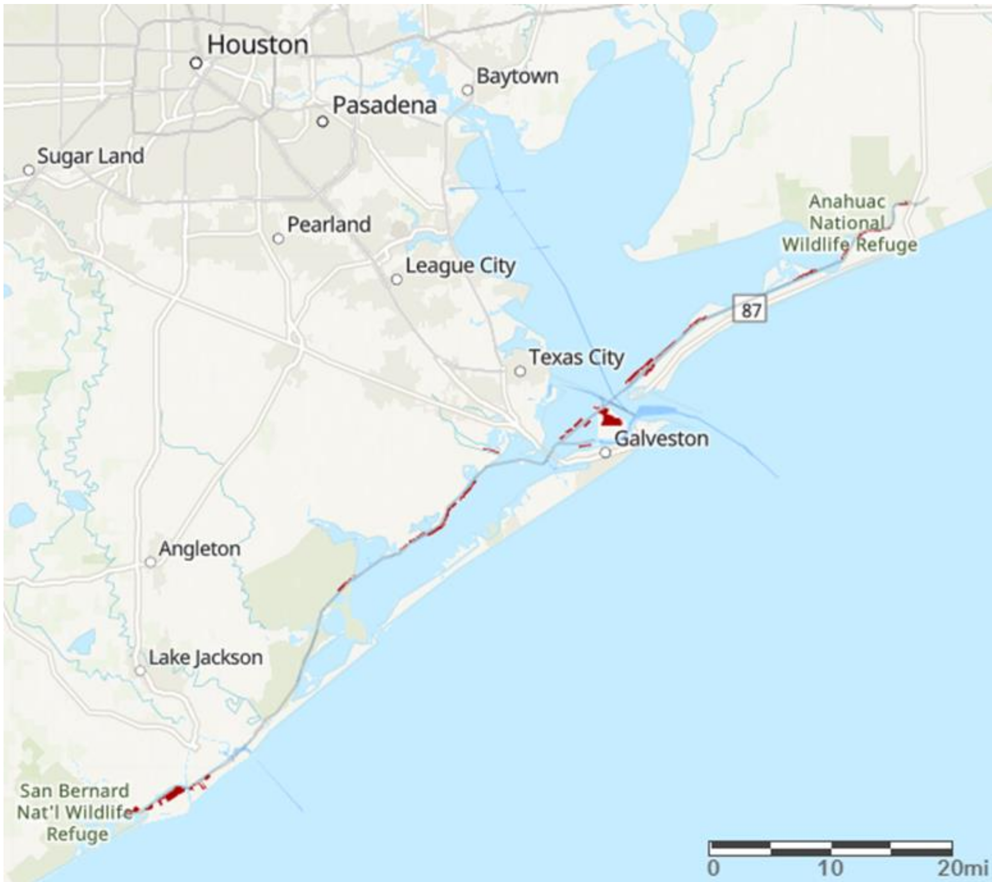

Figure 4.4. *Case study area of the GIWW, showing the geometry of existing sediment placement areas as dark red polygons, the GIWW as a gray line, and adjacent channels that cross or connect to the GIWW as light blue lines.*

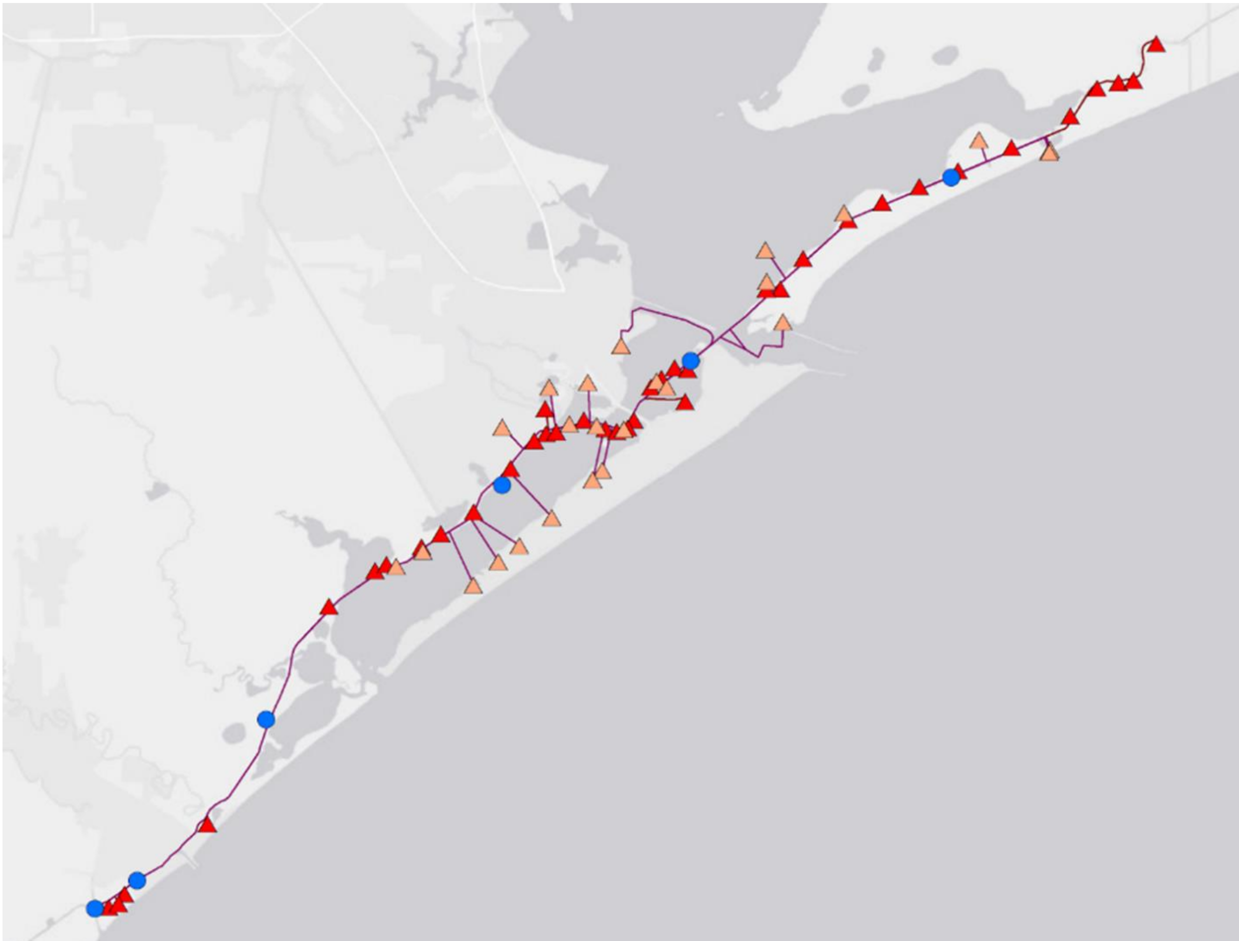

***Figure 4.5**. The D2M2 GIWW case study network of dredging sites (blue circles), existing sediment placement sites (red triangles), proposed or hypothetical sediment placement sites (orange triangles), and sediment-transportation routes (dark lines). The centroid of each placement area or channel reach is used as its representative location for calculating transportation routes and distances in the D2M2 model.*

In terms of site status (as of when these data were produced), the collection of placement areas includes 28 existing active sites used regularly in current management, 8 existing but inactive sites not used in current management but that have beneficial use potential if improvements are made to return them to operational status, 24 proposed sites with beneficial use potential that could be added to future operational use with permitting, construction, and management effort, and 2 hypothetical expansions to placement areas that are not currently proposed but that provide additional placement capacity needed for modeling the system (Table 4.2 & Appendix Table 4.A1).

In terms of differences in site type, the existing sites without beneficial use include 16 active sites that are upland confined placement areas, 1 active site that is an upland partially confined placement area, and 5 active sites that are open water placement areas. The existing sites with beneficial use potential include 3 active sites and 4 inactive sites that are beneficial use islands, 2 active sites and 4 inactive sites that are beneficial use shoals, and 1 active site that is a beneficial use wetland. The proposed sites, which all have beneficial use potential, include 5 sites with beneficial use for bars or shoals, 2 sites for beach nourishment, 1 delta site, 2 island creation or restoration sites, and 14 wetland sites. The two hypothetical sites are modeled as expansions to existing sites (namely to add 5,000,000 CY each to sites PA 38 and DA 88) to increase capacity in the system. They include 1 upland confined placement area and 1 beneficial use island (Table 4.2 & Appendix Table 4.A1).

In terms of acquisition and improvement costs, existing active sites without beneficial use potential are assumed to be already available without additional cost. However, existing active sites with beneficial use potential are assumed to require $25,000 each for improvements so their beneficial use potential can be realized and for special sediment handling needs. Existing inactive sites (which all have beneficial use potential) are assumed to require $75,000 each in improvement cost to restore them to operational readiness and for special handling so their beneficial use value can be realized. The proposed sites (which all have beneficial use potential) are assumed to require $100,000 each in acquisition and construction cost to make them operationally ready and for special handling so their beneficial use value can be realized. The hypothetical expansion sites are assumed to require $200,000 each in acquisition and construction cost to make them operationally ready. Site acquisition and improvement costs are only incurred in the D2M2 model if the optimization solver chooses to use that site for sediment placement (Table 4.2 & Appendix Table 4.A1).

Table 4.2. *Abbreviated table showing 10 rows of placement areas included in the D2M2 case study model, differentiated by site name, type, current status, sediment capacity, and acquisition and improvement cost. See Appendix Table 4.A1 for full table with 62 rows of data.*

Name	Type	Status	Capacity (CY)	Acquisition & Improvement Cost
	…			
PA 70	Upland Confined	Existing Active	1,445,340	.
DA 79	BU Island	Existing Inactive	30,000	$75,000
DA 86	Upland Confined	Existing Active	1,905,710	.
DA 87	Upland Confined	Existing Active	1,445,872	.
DA 88	Upland Confined	Existing Active	2,246,260	.
PAEX1 (similar to PA 38)	BU Island	Hypothetical	5,000,000	$200,000
PAEX2 (similar to DA 88)	Upland Confined	Hypothetical	5,000,000	$200,000
Bird Island Cove	Potential BU Wetland	Proposed	1,506,853	$100,000
Bolivar Ferry Landing/Little Beach	Potential BU Beach	Proposed	400,000	$100,000
Bolivar Marsh	Potential BU Wetland	Proposed	250,000	$100,000
	…			

While the actual distance between the dredging equipment and the sediment placement area varies with every movement of the dredge, for the purpose of modeling, the centroids of each channel reach and placement area are used as standardized, representative points for calculating distances between every potential site pair. Sediment transportation distances between dredging and placement sites are calculated based on the actual distance along the GIWW channel centerline (and possibly connecting channels if needed for the route) from the centroid of the dredging reach to the place along the channel where the centroid of the placement site is adjacent to the channel, and then following a straight-line path from the channel centerline to the centroid of the placement site, as calculated using a new D2M2 plugin for ESRI ArcGIS geospatial software. The D2M2 GIWW case study model includes 118 routes (available connections) between dredging and placement sites that share a transport distance of 20 miles or less, reflecting the limits of current management practice (Table 4.3 & Appendix Table 4.A2; Figure 4.5).

Table 4.3. *Abbreviated table showing 10 rows of routes of different distance between dredging and placement sites included in the D2M2 GIWW case study model. See Appendix Table 4.A2 for full table with 115 rows of data.*

Route #	Dist. (mi)	Dredging Site	Placement Site
	…		
15	13.61	CESWG_GI_02_HIB_2	PA 42
16	14.42	CESWG_GI_02_HIB_2	PA 43
17	2.38	CESWG_GI_02_HIB_2	PAEX1 (PA 38)
18	8.14	CESWG_GI_02_HIB_2	Pepper Grove Cove
19	7.07	CESWG_GI_02_HIB_2	Rollover Beach Nourishment
20	7.04	CESWG_GI_02_HIB_2	Rollover Pass Closure
21	8.84	CESWG_GI_03_BGC_3	Bolivar Ferry Landing/Little Beach
22	7.68	CESWG_GI_03_BGC_3	Bolivar Marsh
23	9.96	CESWG_GI_03_BGC_3	DA 41
24	0.75	CESWG_GI_03_BGC_3	DA 46
	…		

The financial costs of sediment dredging, transportation, and placement are estimated based on volume and distance. Historical cost data is available for 13 dredging contracts (with 6 different dredging companies) that performed dredging projects that included portions of the case-study section of the GIWW between 2006 and 2015 (contract cost data provided by USACE Headquarters and Galveston district). For each contract, the total cost, total volume, and average sediment-transportation distance are available. A linear regression is applied to the data for distance and average cost per cubic yard, and the resulting equation $\boldsymbol{y = 4.2803 + 0.1377x}$ is used to calculate financial costs in the D2M2 case-study model, where *y* represents the unit cost ($/CY) of sediment dredging, transportation, and placement and *x* represents the transportation distance (mi) (Table 4.4, Figure 4.6). These data also exhibit a trend of increasing cost per cubic yard with increasing project size, but D2M2 does not accommodate piecewise cost curves where the cost-per-cubic-yard varies based on both distance and volume.

Table 4.4. *Historical dredging contract data for the case-study section of the GIWW. These data are used in a linear regression to estimate the average cost per cubic yard per mile in the D2M2 case-study model.*

Dredging Project Name	Distance (mi)	Volume (CY)	Cost ($)	Avg $/CY
High Island to Rollover Pass	9.12	1,448,408	$4,700,991	$3.25
Freeport Harbor to Brazos River	1.78	389,826	$2,744,259	$7.04
Rollover Pass and Bolivar Flare	11.91	526,069	$2,863,895	$5.44

Galveston Causeway to Bastrop Bayou	7.26	953,394	$3,820,509	$4.01
High Island to Rollover Pass	10.56	620,268	$3,338,066	$5.38
Freeport Harbor to Brazos River	3.28	1,128,776	$3,058,555	$2.71
Rollover Pass to Galveston Causeway Emergency Dredging	4.93	1,245,653	$6,821,473	$5.48
High Island to Rollover Pass, Bolivar Flare, & Channel	11.37	779,451	$4,939,881	$6.34
Galveston Causeway to Bastrop, Dredging & Levees	6.56	1,279,390	$10,661,000	$8.33
Rollover Pass to Galveston Causeway	7.15	642,275	$2,504,099	$3.90
Freeport to Brazos River	1.54	1,406,880	$5,120,753	$3.64
High Island to Bolivar	11.23	984,039	$4,095,581	$4.16
Rollover Pass to Galveston Causeway	11.77	431,816	$4,113,873	$9.53
Minimum:	***1.54***	***389,826***	***$2,504,099***	***$2.71***
Median:	***7.26***	***953,394***	***$4,095,581***	***$5.38***
Mean:	***7.57***	***910,480***	***$4,521,764***	***$5.32***
Maximum:	***11.91***	***1,448,408***	***$10,661,000***	***$9.53***

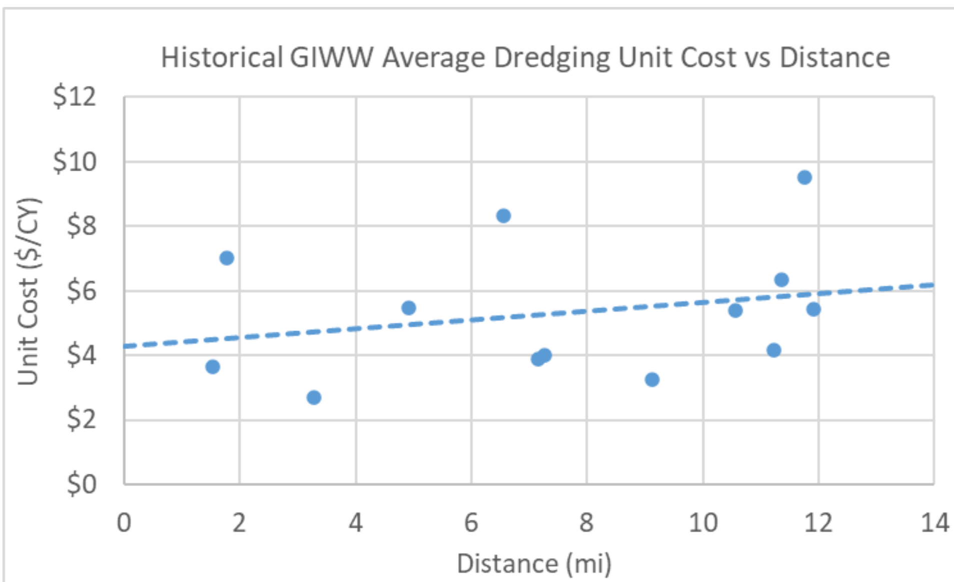

Figure 4.6. *Historical contract dredging cost data for the case-study portion of the GIWW, showing 13 points with average project distance and cost per cubic yard. The dashed line shows the line of linear regression through these data (y = 4.2803 + 0.1377x).*

In additional to financial costs, four types of potential environmental impacts from dredging and sediment placement operations are modeled in the D2M2 GIWW case study. These impacts are estimated based on geospatial analysis of overlap between sediment placement sites and environmentally sensitive areas related to: 1) threatened and endangered species, based on a database of the number of threatened and endangered species historically present in the region; 2) designated special lands (e.g., wetlands), based on a map of special land designations in the region; 3) oyster beds, based on a map of oyster bed areas in the region; and 4) submerged aquatic vegetation (SAV), based on a map of SAV habitat in the region (condensed maps in Figure 4.7; full-scale maps and descriptions in Appendix Figures 4.A1-4.A4; data for the intersection between environmentally sensitive areas and potential sediment placement sites were provided by USACE ERDC based on databases and maps from the Texas General Land Office). For the threatened and endangered species analysis, each placement area is scored based on the percent of the 14 total species in the database that were historically observed in that area; where a placement area overlaps with multiple counts of historical species present, an area-weighted average value is used. For the remaining three types of environmental impacts, the geospatial analysis shows the percent of the placement site area that overlaps with that type of environmental feature (Table 4.5).

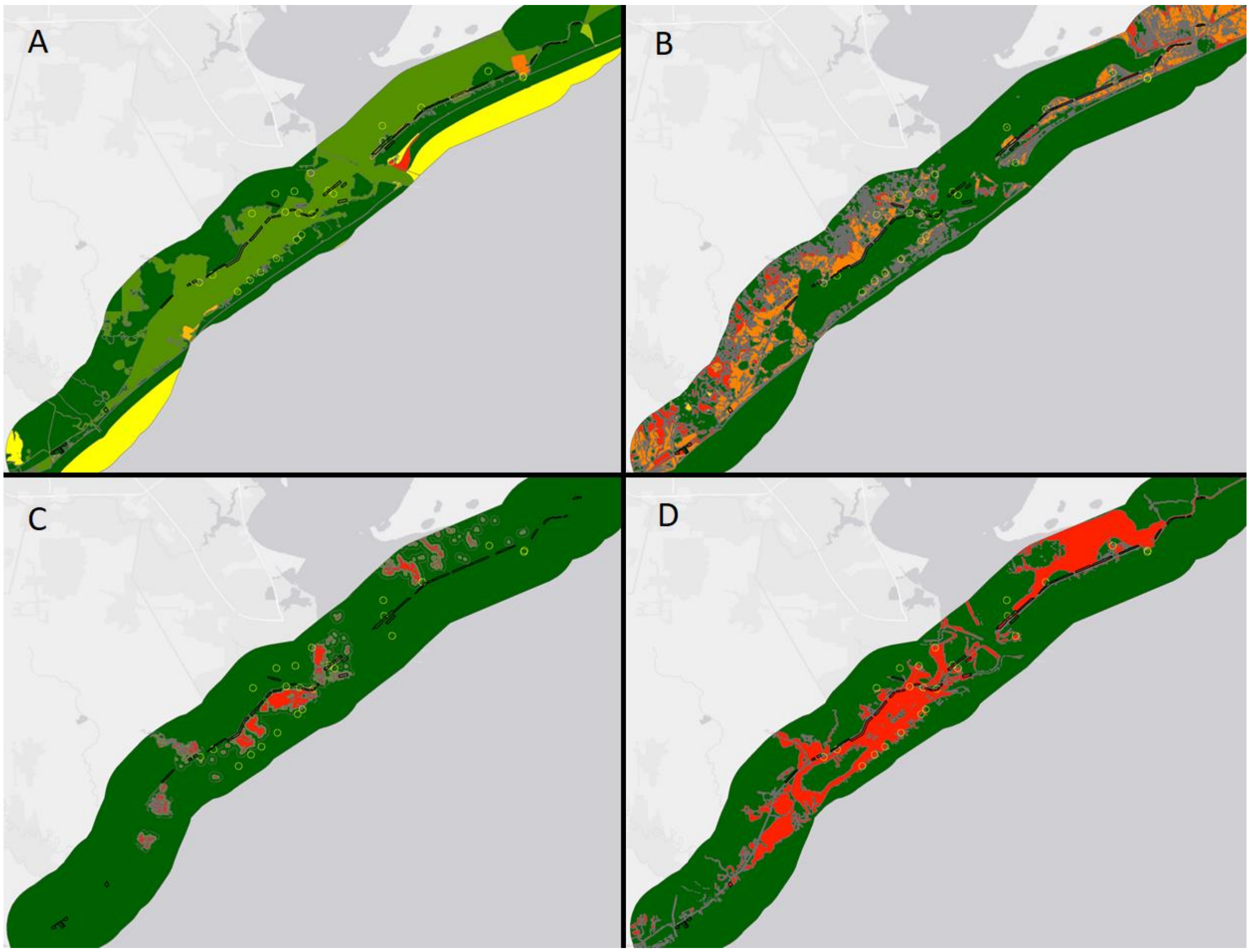

Figure 4.7. *Condensed maps of A) the number of threatened and endangered species historically present, B) special land designations, C) oyster beds, and D) submerged aquatic vegetation habitat in different areas in the GIWW study region. Black rectangles outline the perimeter of existing placement sites and yellow circles outline the approximate area of potential placement sites. See Appendix Figures 4.A1-4.A4 for full-size maps.*

In addition to financial cost and environmental impacts, three criteria related to the beneficial use of sediment are included in the D2M2 case study model. Two types of beneficial effects and one type of non-monetary cost are evaluated relatively for each BU site on a 0-100 qualitative scale. These include: 1) the direct benefits of adding or restoring habitat area (e.g., counting increased habitat land area), 2) the indirect or ancillary environmental benefits from having that increased or restored habitat (e.g., estimating increased ecological productivity), and 3) indirect, non-monetary costs required to carry out beneficial use projects (e.g., the extra time, effort, and hassle typically required to secure agreements for new beneficial use sites). Note, Because the case study optimization seeks to minimize the total, aggregated weighted score, all costs and impacts are represented with positive values and all benefits are represented with negative values (Table 4.5 & Appendix Table 4.A3).

Table 4.5. *Abbreviated table showing 10 rows of relative environmental impact and beneficial use scores per cubic yard placed. Non-monetary criteria in the D2M2 model include four different types of environmental impacts (to special lands, threatened and endangered species, oyster beds, and submerged aquatic vegetation) and three effects from the beneficial use of sediment (direct benefits from increased or restored habitat area, indirect environmental benefits from having increased or restored habitat, and non-monetary time, effort, and hassle costs typically required to carry out new beneficial use projects). All scores are qualitatively estimated per unit volume of sediment on either a 0-1 scale for the environmental impacts or a 1-100 scale for the beneficial use effects (zero values are shown as ".", for improved readability). Because the optimization seeks to minimize the total weighted score, benefits are represented as negative values. (Scores provided by the USACE ERDC and Galveston district). See Appendix Table 4.A3 for full table with 62 rows of data.*

Name	T&E Species	Special Lands	Oyster Reef	SAV	Direct BU Benefit	Indirect BU Benefit	Indirect Cost
	…						
PA 70	.14	.79	.	.04	.	.	.
DA 79	.21	.95	.	.53	-60.42	-50	33
DA 86	.14	.98	.	.05	.	.	.
DA 87	.14	.13	.	.02	.	.	.
DA 88	.14	.51	.	.05	.	.	.
PAEX1 (PA 38)	.31	.34	.	.58	-100	-60	22
PAEX2 (DA 88)	.14	.51	.	.05	.	.	.
Bird Island Cove	.16	.48	.	.61	-50	-40	60
Bolivar Ferry Landing/Little Beach	.45	.26	.	.42	-72	-20	11
Bolivar Marsh	.17	.77	.	.23	-43	-20	40
	…						

Because cost, environmental, and beneficial use data are presented in different units, with different scales and magnitudes, they are normalized as part of weighting and aggregation. Normalization transforms the raw level-of-performance data, in their original units, into normalized value scores on a common, relative scale of desirability. Two approaches for establishing normalization ranges for MAVT problems are common in practice. For problems where stakeholders or decision makers have experience with and a good understanding of the data or are dealing with data anchored between known endpoints (e.g., 0-100%), they may be able to make judgements about specific value-function shape or the upper and lower bounds used in a linear normalizing value function. In other cases, where stakeholders and decision makers have less experience with the data, are less confident in their ability to express reasonable ranges for normalization (e.g., when level-of-performance data are expressed in unfamiliar relative scores), the minimum and maximum values observed in the set of alternatives are often used to create upper and lower bounds used by the value function for normalization.[41]

In the D2M2 GIWW case study, normalization is based on the range from zero to the maximum (or to absolute value of the minimum, for benefits expressed in negative terms) value observed in the site data, per unit volume (see Table 4.5). The financial cost of dredging is an exception because it has components that both vary with distance (see Table 4.3 & Appendix Table 4.A2, Table 4.4, and Figure 4.6) and include fixed acquisition and improvement costs (see Table 4.2 & Appendix Table 4.A1). Here, the range used to normalize financial costs, per unit volume, is based on the maximum observed sum of the regressed sediment transportation cost equation applied to route distance plus the unit acquisition and improvement cost for that route's placement site, calculated by dividing that site's total acquisition and improvement cost by its total capacity. To achieve the normalization, the data (or the weights) are multiplied by a normalization factor equal to one divided by the normalization range for that criterion so that the data are scaled onto a consistent zero-to-one scale for aggregation (Table 4.6).

There are many possible approaches to normalization. Benefits of the approach used in this application include that: 1) it preserves the negative sign of the two benefit objectives so that minimization of the weighted sum of objectives makes sense for all objective types, 2) it can be applied equivalently by multiplying each criterion weight by the normalization factor for its data type instead of by multiplying all input data by the normalization factor, which saves computational effort, 3) and that the normalized results of the optimization can simply be divided by their normalization factors again to be converted back into their original cost and benefit units for further analysis or post-processing. As normalization is applied after data development but prior to optimization, future analyses can employ different normalization approaches with the same case-study data to explore difference.

Table 4.6. *Normalization ranges for the D2M2 case study data. Either the criterion weights or the input data for all sites and transportation routes in the system network are multiplied by the normalization factors to re-scale the data onto a zero-to-one scale prior to aggregation.*

Objective	Lower bound of range	Upper bound of range	Normalization factor
Financial Cost	0	$8.106	0.1234
T&E Species	0	.445	2.2493
Special Lands	0	.978	1.0224
Oyster Reef	0	.823	1.2155
SAV	0	.660	1.5152
Direct BU Benefit	-100	0	0.0100
Indirect BU Benefit	-80	0	0.0125
Indirect Cost	0	70	0.0143

Dredged material placement is optimized on an annual time step over 20 years for 9 optimization scenarios (Table 4.7). Six scenarios explore 3 sets of physical network configurations for the GIWW system for each of 2 weighting schemes. The 3 physical configurations include scenarios where the system network includes: 1) only the existing active sites plus hypothetical expansion sites, 2) only the existing active and existing inactive sites plus hypothetical expansion sites, or 3) all existing active, existing inactive, proposed, and hypothetical expansion sites. These scenarios are combined with 2 weighting schemes that place: 1) 100% weight on financial cost and no weight on other criteria, or 2) 50% weight on cost, 25% weight split between the four environmental impacts (6.25% each), and 25% weight split between the three beneficial use effects (8.33% each). These weighting schemes are chosen to represent realistic potential management interests. Combined, these site networks and weights yield 6 scenarios. Three additional scenarios modify the 6th scenario's constraints, weights, and capacities to showcase different aspects of the D2M2 software and to more broadly analyze potential operation of the GIWW system in ways that are of interest but which do not reflect realistic management priorities. The 7th scenario is identical to the 6th but places 0 weight on the financial cost and BU indirect cost criteria to show results from a strictly environmental perspective. The 8th scenario is identical to the 6th but reduces the available capacity of the 3 most used sites to force the model to identify a set of placement sites that are of greatest secondary importance. The 9th scenario is identical to the 6th but deviates from actual GIWW management to add various site and route constraints and add site properties that more fully demonstrate the capabilities of the D2M2 software.

Scenario 7 uses the same network configuration as the 6th scenario but changes the following:

- 0% weight is placed on the financial cost criterion
- 0% weight is placed on the indirect costs of beneficial use criterion.

Scenario 8 uses the name network configuration and weighting as the 6th scenario but changes the following:

- Placement capacity for site PAEX1 (which mimics an expanded PA 38) is reduced to 0 CY.
- Placement capacity for site PAEX2 (which mimics an expanded DA 88) is reduced to 3,800,000 CY.
- Placement capacity for site Long Point Marsh (another relatively large capacity site that is extensively used in the other scenarios) is reduced to 0 CY.

Scenario 9 uses the same network configuration and weighting as the 6th scenario but adds the following:

- Placement site PA 62 has its earliest available time period for use (earliest acquisition period) set to be the 5th time period. (In the solution for Scenario 6, this site was used starting in the 1st time period.)
- Placement site PA 67 is limited to a maximum addition per time period of 95,000 CY. (In the solution for Scenario 6, in time periods when it was used, it was used for between 77,158 - 217,614 CY per time period.)
- Sediment reuse (i.e., removal from the system) is enabled for placement site PA 39, beginning in the 5th time period, with a maximum rate of 50,000 CY per time period and at a financial cost of $0.10 per cubic yard removed. (In the solution for Scenario 6, this site was used in only one time period, in which its 119,462 CY capacity was completely filled.)
- Route 68 is limited to a maximum volume transported per time period of 100,000 CY. (In the solution for Scenario 6, this route transported between 7,388 - 155,028 CY in each of the 5 time periods where it was used.)
- Route 9 is required to transport exactly 100,000 CY in time period 2. (In the solution for Scenario 6, this route transported 0 CY in that time period.)

- Route 4 is limited to transport less than or equal to 400,000 CY in time periods 1-10. (In the solution for Scenario 6, this route transported 598,198 - 698,198 CY when it was used in five of these ten time periods.)
- Placement site Rollover Pass Closure is given a bulking factor of 0.75, meaning that in the long term the mass of sediment placed takes up only 75% of the volume initially placed, due to compaction and shrinkage. (In the model for Scenario 6, a bulking factor of 1.0 was used for this site.)

Table 4.7. *The D2M2 GIWW case study optimization is run for nine scenarios that vary two weighting schemes, three site configurations, and various capacities and constraints.*

Scenario #:	**Scenario 1**	**Scenario 2**	**Scenario 3**	**Scenario 4**	**Scenario 5**	**Scenario 6**	**Scenario 7**	**Scenario 8**	**Scenario 9**
Summary Description:	*Active, Cost*	*Active, Balanced*	*Active & Inactive, Cost*	*Active & Inactive, Balanced*	*All Sites, Cost*	*All Sites, Balanced*	*All Sites, Environ.*	*All Sites, Balanced Limited*	*All Sites, Balanced Modified*
Objectives					**Weights**				
Financial Cost	100%	50%	100%	50%	100%	50%	.	50%	50%
T&E Species	.	6.25%	.	6.25%	.	6.25%	.	6.25%	6.25%
Special Lands	.	6.25%	.	6.25%	.	6.25%	.	6.25%	6.25%
Oyster Reef	.	6.25%	.	6.25%	.	6.25%	.	6.25%	6.25%
SAV	.	6.25%	.	6.25%	.	6.25%	.	6.25%	6.25%
Direct BU Benefit	.	8.33%	.	8.33%	.	8.33%	50%	8.33%	8.33%
Indirect BU Benefit	.	8.33%	.	8.33%	.	8.33%	50%	8.33%	8.33%
Indirect Cost	.	8.33%	.	8.33%	.	8.33%	.	8.33%	8.33%
Sites				**Inclusion in system network configurations**					
Existing active sites	x	x	x	x	x	x	x	x	x
Existing inactive BU sites	.	.	x	x	x	x	x	x	x
Proposed BU sites	.	.	.	.	x	x	x	x	x
Hypothetical expansion sites	x	x	x	x	x	x	x	x	x
Some capacities are reduced	.	.	.	.	.	.	.	x	.
Some sites & routes are constrained	.	.	.	.	.	.	.	.	x

ADVANCES IN NEW VERSION OF D2M2

The new version of D2M2 introduced here includes several advances over prior versions to better represent costs, impacts, benefits, and effects (collectively referred to as "costs" in the bullet points below), incorporate additional system constraints, enhance the D2M2 modeling process, and improve the user interface.

Model enhancements to better represents costs, impacts, benefits, and effects:

- Because costs of sediment dredging and transportation are interrelated (e.g., by site characteristics and equipment choices), D2M2 models combine these costs and apply them to routes between dredging, transfer, and placement sites. To simplify repeated application of costs, these cost curves are specified for "equipment" that can be applied to one or more routes. Like past versions, the new version can incorporate averaged dredging and transportation costs per unit volume, per unit distance in these cost curves. The new version now additionally provides the ability to include fixed costs for using a route between two sites, regardless or volume or distance. This helps represent fixed equipment mobilization and demobilization that can be incurred when moving between locations and other non-variable costs of route use.
- To provide more granularity in modeling fixed cost, the new D2M2 version also allows fixed-cost scaling factors that can be applied to any dredging, transfer, or placement site to increase or decrease the average fixed cost for all routes that use that site. This allows D2M2 modelers to adjust fixed costs for sites that are particularly harder or easier to reach or work with or that otherwise have fixed costs that differ from the average.

Model enhancements to incorporate additional constraints:

- The new D2M2 version now enables user-defined categories to be created and applied to any dredging, transfer, or placement site, transportation route, or type of equipment. (As described below, these custom categories can be used when creating system-wide constraints or generating network routes.)
- System-wide constraints can now be added that force a specified sediment volume to be transported from, through, or to any routes, equipment, transfer sites, or placement sites in a specified time period based on their user-defined category. The specified volume can be chosen to be either equal to, greater than, or less than the specified volume. This provides the user with unprecedented flexibility in adjusting the model to more accurately incorporate unique timing and volume requirements of their system's operation.
- Transfer sites can now either be set to empty by the last optimization time period or be given the flexibility to accumulate and retain material at the end of the optimization timeframe (i.e., to also function as placement sites).

Process enhancements for D2M2 modeling:

- If user-defined equipment categories have been specified, the new D2M2 version allows any dredge, transfer, or placement site to be identified as compatible with one of those custom equipment categories. (As described below, this can be leveraged to automatically build the system network).

- With just a few clicks, the D2M2 modeler can now automatically build an entire system network by having the software automatically create routes between all possible sites combinations that share the same custom equipment category.
- Alternatively, with just a few clicks, the D2M2 modeler can now automatically build an entire system network by having the software create routes between all possible site combinations that are within a user-defined distance of each other, based on optional latitude and longitude coordinates that can be provided for each site.
- The two functionalities above can also be combined to automatically create routes of compatible custom category types within a desired distance of each other.
- A new functionality has been provided to automatically perform one type of scenario and sensitivity analysis. With just a few clicks, the software can automatically vary the objective weights in the optimization, at a user-specified increment and within a user-specified range, and iteratively re-run the optimization solver for each one of those weighting scenarios. This provides an automatic way to explore how differences in weighting affect differences in optimal network operation or to identify a weight-range over which some features of an optimal solution persist in the results.
- New functionality has been provided to automatically exclude a previously identified optimal solution from being considered again by the solver and then to re-run the optimization, forcing the solver to iteratively discover other solutions in the near-optimal solution space, as another type of sensitivity analysis. This can be used, for example, to generate alternative results in cases where the stakeholders or decision maker may not like the initial optimal solution for reasons not captured in the LP formulation, or for when seeing a range of near-optimal solutions may help the stakeholders or decision makers to build confidence in their management decisions.

These types of automatic model building and scenario/sensitivity analysis, including exploration of the near-optimal solution space, are typically missing from dredging optimization tools. If subsequent solutions differ from the original solution(s) by only a small tolerance, this procedure can be run many times to gradually explore a broader solution space.

Enhancements to the user interface:

- The software now has an updated graphical user interface that includes many small usability enhancements.
- The software now can import and export model input template files and model output result files. This helps expedite transferring data to/from the D2M2 software and promotes external analysis and post-processing of any constructed D2M2 model and its results.
- A D2M2 plugin for ESRI ArcGIS software has been developed that can quickly transform features present in existing geospatial databases into D2M2 input model files.
- A D2M2 results summarization macro for Microsoft Excel have been developed to aid further exploration and data analysis of exported D2M2 results.
- A spatial data viewer, available to USACE intranet users only, has been created by the USACE Geospatial team (USACE Mobile district) to displays D2M2 results on an online digital map alongside data incorporated from other USACE spatial data systems.

D2M2 MODEL FORMULATION

The new version of the D2M2 software uses a MILP optimization formulation, expressed below. The modeler enters costs (and impacts, benefits, effects) with consistent positive and negative signage and chooses to minimize or maximize the resulting weighted sum accordingly. The equations below are presented in simplified mathematical notation (i.e., using ∀, ∑, ∈, {}, [], and () symbols and if, $otherwise$ language) instead of full linear programming syntax to make them more concise, readable, and interpretable. A brief description is provided with the introduction of each index, variable, and equation.

Indices

$\boldsymbol{i}$ – index of a dredging or transfer site from which material is removed. If multiple sediment types (e.g., sandy and fine material) need to be included in the model formulation, multiple dredging site variants can be created with different cost curves, properties, and route connections for each material type.

$\boldsymbol{j}$ – index of a transfer or placement site into which material is placed. Transfer and placement sites are seen identically by the optimization solver, but the D2M2 user interface restricts which options can be entered by the modeler for each type of site. These differences include: 1) material can be removed from transfer but not placement sites, 2) placement but not transfer sites can have some of their material completely removed from the modeled system (i.e., not just relocated to another site) if allocated for third-party reuse, 3) placement but not transfer sites can be identified as having an initial volume at the start of the first time period, 4) placement but not transfer sites can have a bulking factor to describe the long-term change in volume of material added there (e.g., to account for dewatering and compaction that occurs over time), 5) placement but not transfer sites can be restricted to have a maximum volume that can be added per time period, separate from their total capacity, and 6) transfer but not placement sites can be set as either able or not to accumulated material at the end of the last modeled time period.

$\boldsymbol{t}$ – index of a time period (e.g., an annual time step).

$\boldsymbol{t\_max}$ – index of the final time period.

$\boldsymbol{k}$ – index of an objective. Objectives are defined by the D2M2 modeler and can include any mix of factors for which the stakeholders or decision makers have interest and data are available. Linear weights are applied to objectives to indicate their relative importance during aggregation. The weights supplied by the modeler are normalized by the D2M2 software to sum to one prior to optimization.

$\boldsymbol{x}$ – index of a user-entered point on the piecewise-linear curve of costs to transport a unit volume of sediment over a route's distance.

$\boldsymbol{i}, \boldsymbol{j}$ – note, this pairing of indices always represents a route between dredging or transfer site $\boldsymbol{i}$ and transfer or placement site $\boldsymbol{j}$. The system network for any given D2M2 model likely only include a subset of all possible routes between available dredging, transfer, and placement site pairs. Also, the D2M2 user interface does not allow creation of circular routes, i.e., it enforces that $\boldsymbol{i} \neq$

$\boldsymbol{j}, \forall \boldsymbol{i}, \boldsymbol{j}$. When referenced, the pairing $\boldsymbol{i}, \boldsymbol{j}$ should always be interpreted to mean routes that actually exist in the model and not potential routes between site pairs that could be, but are not actually, connected in the model.

$\boldsymbol{j'}$ – this variation of the typical site indexing is used when multiple items of the same type need to be referenced in the same equation. For example, to track sediment volumes both flowing into a transfer site and out of that site to another transfer or placement site in the same time period.

Decision variable(s)

$\boldsymbol{v_{i,j,t}}$ – the volume of sediment transported on route $\boldsymbol{i}, \boldsymbol{j}$ in time period $\boldsymbol{t}$.

$\boldsymbol{v\_r_{j,t}}$ – the volume extracted from site $\boldsymbol{j}$ in time period $\boldsymbol{t}$ for third-party reuse. (This quantity is modeled as being completed removed from the D2M2 system.)

Additional model variables

$\boldsymbol{v\_exact_{i,t}}$ – an exact volume required to be removed from dredging site $\boldsymbol{i}$ in time period $\boldsymbol{t}$. The D2M2 software requires specific dredging volumes per time period to be specified for all dredging sites (this value may be zero for some time periods). This parameter is required.

$\boldsymbol{v\_max_j}$ – the maximum (cumulative) volume capacity for transfer or placement site $\boldsymbol{j}$. This parameter is required.

$\boldsymbol{t\_earliest_j}$ – an optional time period during and after which transfer or placement site $\boldsymbol{j}$ is available to be used; the earliest time period for site acquisition. Note, the D2M2 software automatically sets a default value of $\boldsymbol{t\_earliest_j = 0}$ for all transfer or placement sites for which a custom value is not supplied.

$\boldsymbol{t\_latest_j}$ – an optional latest time period during which site $\boldsymbol{j}$ can be used.

$\boldsymbol{S\_j_{t\_latest}}$ – the optional subset of all transfer and placement sites that have a latest time period for use specified.

$\boldsymbol{v\_max\_t_j}$ – the optional maximum volume that can be added to placement site $\boldsymbol{j}$ in any given time period. The D2M2 software allows the modeler to specify a custom value for $\boldsymbol{v\_max\_t_j}$ for placement but not transfer sites.

$\boldsymbol{S\_j_{v\_max\_t}}$ – the optional subset of all placement sites that have a limit specified for the maximum volume that can be placed in them per time period.

$\boldsymbol{S\_j_{empty}}$ – the optional subset of all transfer sites, $\boldsymbol{j}$, that must empty by the end of the final time period. The D2M2 software allows the modeler to specify inclusion in this subset for transfer but not placement sites.

$\boldsymbol{f\_v_j}$ – the optional bulking factor, the ratio of sediment wet volume to long-term dry volume per unit mass, which describes the eventual change in volume for sediment in placement site $\boldsymbol{j}$ (e.g., due to drying and compaction). The D2M2 user interface allows custom bulking factors, $\boldsymbol{f\_v_j}$, to be entered by the modeler for final placement sites but uses a fixed bulking factor of 1.0 for intermediate transfer sites.

$\boldsymbol{v_{j,t}}$ – the sediment volume in transfer or placement site $\boldsymbol{j}$ at the end of time period $\boldsymbol{t}$. This value is calculated internally.

$\boldsymbol{v_{j,t=0}}$ – the optional initial volume already stored in placement site $\boldsymbol{j}$ at the start of time period $\boldsymbol{t = 0}$. If the modeler does not enter a custom value for $\boldsymbol{v_{j,t=0}}$, the D2M2 software automatically provides a default initial volume of 0. The D2M2 software allows non-zero initial volumes to be entered for placement sites but not transfer sites.

$\boldsymbol{v\_r\_max_j}$ – an optional maximum sediment reuse volume allowed per time period for placement site $\boldsymbol{j}$. Reused sediment is modeled as completely removed from the system, e.g., as if the sediment is mined from the placement site by a third party for reuse in unrelated engineering or environmental project that are not included in the D2M2 system site network.

$\boldsymbol{S\_j_{v\_r\_max}}$ – the optional subset of all placement sites that allow sediment reuse, up to a maximum rate.

$\boldsymbol{t\_r\_earliest_j}$ – an optional time period during and after which sediment reuse is allowable for placement site $\boldsymbol{j}$ but before which it is not. The D2M2 software automatically sets a default value of $\boldsymbol{r\_earliest_j = 0}$ for all sites for which a custom value is not provided.

$\boldsymbol{v\_max_{i,j}}$ – an optional maximum-capacity limit on the volume of sediment that can be transported on route $\boldsymbol{i,j}$ in any time period.

$\boldsymbol{S\_ij_{v\_max}}$ – the optional subset of all routes that have a $\boldsymbol{v\_max_{i,j}}$ type constraint.

$\boldsymbol{v\_exact_{i,j,t}}$ – an optional exact volume that must be transferred through route $\boldsymbol{i,j}$ in time period $\boldsymbol{t}$.

$\boldsymbol{S\_ijt_{v\_exact}}$ – the optional subset of all routes in time periods where an exact volume must be transferred on those routes in those time periods.

$\boldsymbol{v\_max_{i,j,t}}$ – an optional maximum volume that is permitted to be transported through route $\boldsymbol{i,j}$ in time period $\boldsymbol{t}$.

$\boldsymbol{S\_ijt_{v\_max}}$ – the optional subset of all routes in time periods where the volume transferred on those routes in those time periods must be less than or equal to the maximum specified.

$\boldsymbol{v\_min_{i,j,t}}$ – an optional minimum volume that is permitted to be transported through route $\boldsymbol{i,j}$ in time period $\boldsymbol{t}$.

$\boldsymbol{S\_ijt_{v\_min}}$ – the optional subset of all routes in time periods where the volume transferred on those routes in those time periods must be greater than or equal to the minimum specified.

$\boldsymbol{v\_exact_{j,t}}$ – an optional exact total volume that must be transferred to site $\boldsymbol{j}$ in time period $\boldsymbol{t}$ from any combination of dredging sites.

$\boldsymbol{S\_jt_{v\_exact}}$ – the optional subset of transfer or placement sites in time periods where an exact total volume must be transferred to those destination sites in those time period.

$\boldsymbol{v\_max_{j,t}}$ – an optional maximum total volume that is permitted to be transported to site $\boldsymbol{j}$ in time period $\boldsymbol{t}$.

$\boldsymbol{S\_jt_{v\_max}}$ – the optional subset of all transfer or placement sites in time periods where the total volume transferred to those sites in those time periods must be less than or equal to the maximum specified.

$\boldsymbol{v\_min_{j,t}}$ – an optional minimum total volume that is permitted to be transported to site $\boldsymbol{j}$ in time period $\boldsymbol{t}$.

$\boldsymbol{S\_jt_{v\_min}}$ – the optional subset of all transfer or placement sites in time periods where the total volume transferred to those sites in those time periods must be greater than or equal to the minimum specified.

$\boldsymbol{w_k}$ – linear weight for objective $\boldsymbol{k}$. The objectives in D2M2 are defined by the modeler and can include any custom mix of interests for which they have data available. The weights are applied to the objectives during aggregation to reflect the relative importance of each objective compared to all others. Before running the optimization, the D2M2 software automatically normalizes the supplied weights to sum to one. This parameter is required.

$\boldsymbol{c\_a_{j,k}}$ – the optional, one-time acquisition cost for use of transfer or placement site $\boldsymbol{j}$ for objective $\boldsymbol{k}$. This cost is incurred only on first use of a site. The D2M2 software automatically sets a default value of $\boldsymbol{c\_a_{j,k} = 0}$ for all sites for which a custom acquisition cost is not provided.

$\boldsymbol{b_j}$ – binary variable identifying whether a transfer or placement site is used one or more times over all time periods (i.e., for determining whether the acquisition cost should be applied.)

$\boldsymbol{c\_d_{i,j,k}}$ – the variable, distance-based transportation cost, per unit volume, for objective $\boldsymbol{k}$, on route $\boldsymbol{i, j.}$ (This value may be zero.) This parameter is required.

$\boldsymbol{d_{i,j}}$ – distance for route $\boldsymbol{i, j}$ (i.e., distance between site $\boldsymbol{i}$ and site $\boldsymbol{j}$.) This parameter is required.

$\boldsymbol{d_x}$ – a distance point on a piecewise-linear cost per unit volume curve specified by the modeler. At least two points on each piecewise cost curve are required.

$\boldsymbol{c\_d_{x,k}}$ – the cost point associated with a $\boldsymbol{d_x}$ distance point on a piecewise-linear cost or benefit curve specified by the modeler. At least two points on the curve are required.

$\boldsymbol{c\_f_{i,j,k}}$ – total fixed transportation cost for objective $\boldsymbol{k}$ on route $\boldsymbol{i, j}$. This value is calculated internally from the base fixed cost and fixed-cost scaling factors.

$\boldsymbol{c\_f\_base_{i,j,k}}$ – the optional base fixed cost (e.g., an average fixed cost), before potentially adjustment by scaling factors. The value of $\boldsymbol{c\_f\_base_{i,j,k} = 0}$ should be specified for routes without fixed costs.

$\boldsymbol{f\_c\_f_{i,k}}$ – an optional fixed cost scaling factor for objective $\boldsymbol{k}$ for dredging site $\boldsymbol{i}$. The D2M2 software automatically sets a default value of $\boldsymbol{f\_c\_f_{i,k} = 1}$ for all dredging sites for which a custom value is not provided.

$\boldsymbol{f\_c\_f_{j,k}}$ – an optional fixed cost or benefit scaling factor for objective $\boldsymbol{k}$ for transfer or placement site $\boldsymbol{j}$. The D2M2 software automatically sets a default value of $\boldsymbol{f\_c\_f_{j,k} = 1}$ for all transfer or placement sites for which a custom value is not provided.

$\boldsymbol{S\_ij_{c\_f}}$ – the optional subset of all routes $\boldsymbol{i}, \boldsymbol{j}$ that have a fixed cost specified for their use.

$\boldsymbol{b_{i,j,t}}$ – binary variable identifying whether route $\boldsymbol{i}, \boldsymbol{j}$ is used in time period $\boldsymbol{t}$.

$\boldsymbol{c\_p_{j,k}}$ – an optional sediment placement cost, per unit volume, for objective $\boldsymbol{k}$, at transfer or placement site $\boldsymbol{j}$. The placement cost is calculated based on actual volume placed, before any bulking factor, outgoing sediment volume, or sediment reuse volume is applied.

$\boldsymbol{c\_r_{j,k}}$ – an optional sediment reuse cost, per unit volume, for objective $\boldsymbol{k}$, at transfer or placement site $\boldsymbol{j}$.

Problem formulation

The objective function can be either minimized or maximized and includes the following components:

- Weights for each objective.
- One-time acquisition costs or benefits for the use of individual transfer or placement sites in one or more time periods.
- Variable transportation costs or benefits, per unit volume, for each distance, for transporting sediment on specific routes.
- Fixed transportation costs or benefits for routes, incurred once per time period of use, adjusted by fixed-cost scaling factors for individual dredging, transfer, and/or placement sites.
- Placement costs or benefits for placing sediment in transfer and placement sites, per unit volume.
- Material reuse cost or benefit, per unit volume, for third party extraction and reuse of sediment from a transfer or placement site, remove it from the modeled system.

Minimize or Maximize:

$$\boldsymbol{Z} = \sum_t \left[\sum_k \left(\boldsymbol{w_k} * \left[\sum_j \boldsymbol{c\_a_{j,k}} * \boldsymbol{b_j} + \sum_i \sum_j \boldsymbol{c\_d_{i,j,k}} * \boldsymbol{v_{i,j,t}} + \sum_i \sum_j \boldsymbol{c\_f_{i,j,k}} * \boldsymbol{b_{i,j,t}} + \sum_i \sum_j \boldsymbol{c\_p_{j,k}} * \boldsymbol{v_{i,j,t}} + \sum_j \boldsymbol{c\_r_{j,k}} * \boldsymbol{v\_r_{j,t}}\right]\right)\right]$$

Subject to:

$\boldsymbol{v_{j,t}} = \boldsymbol{v_{j,t-1}} + \sum_i (\boldsymbol{f\_v_j} * \boldsymbol{v_{i,j,t}}) - \sum_{j'} (\boldsymbol{v_{j,j',t}}) - \boldsymbol{v\_r_{j,t}}, \ \forall\, \boldsymbol{t} \geq \boldsymbol{1}; \forall\, \boldsymbol{j}.$ – the volume of sediment in transfer or placement site $\boldsymbol{j}$ in time period $\boldsymbol{t}$ is equal to the volume of sediment in that site in the previous time period plus the volume of incoming sediment minus the volume of outgoing sediment to other sites or to third-party reuse. Note, the D2M2 software allows custom bulking factors, $\boldsymbol{f\_v_j}$, and initial volume values, $\boldsymbol{v_{j,t=0}}$, to be entered for placement sites but not transfer sites. It applies a value of $\boldsymbol{f\_v_j} = \boldsymbol{1}$ for all transfer sites and for any placement sites for which a custom value is not entered and applies a value of $\boldsymbol{v_{j,t=0}} = \boldsymbol{0}$ for all transfer sites and for any placement sites for which a custom value is not entered.

$\boldsymbol{v_{j,t}} \leq \begin{cases} \boldsymbol{v\_max_j}, & \forall\, \boldsymbol{j} \notin \boldsymbol{S\_j_{empty}}; \forall\, \boldsymbol{t} \\ \boldsymbol{v\_max_j}, & \forall\, \boldsymbol{j} \in \boldsymbol{S\_j_{empty}}; \forall\, \boldsymbol{t} \neq \boldsymbol{t\_max} \\ \boldsymbol{0}, & \forall\, \boldsymbol{j} \in \boldsymbol{S\_j_{empty}}; \boldsymbol{t} = \boldsymbol{t\_max} \end{cases}$. – the volume in transfer or placement site $\boldsymbol{j}$ at the end of time period $\boldsymbol{t}$ must always be less than the maximum capacity for that site. Transfer sites must empty in the final time period only if required by the modeler.

$\sum_i \boldsymbol{v_{i,j,t}} \leq \boldsymbol{v\_max_j} + \boldsymbol{v\_r_{j,t}},\ \forall\, \boldsymbol{i}, \boldsymbol{j}, \boldsymbol{t}$. – the volume transported to transfer or placement site $\boldsymbol{j}$ in any time period may not exceed the maximum capacity volume for that site plus the volume removed from that site for reuse in that time period.

$\sum_j \boldsymbol{v_{i,j,t}} = \boldsymbol{v\_exact_{i,t}},\ \forall\, \boldsymbol{i}, \boldsymbol{t}$. – the sum of volumes transported from a dredging site to all transfer and placement sites in a time period must equal the required dredging volume for that dredging site in that time period.

$\boldsymbol{v\_r_{j,t}} \leq \begin{cases} \boldsymbol{v\_r\_max_j}, & \forall \boldsymbol{j} \in \boldsymbol{S\_j_{v\_r\_max}}; \forall\, \boldsymbol{t} \geq \boldsymbol{t\_r\_earliest_j} \\ \boldsymbol{0}, & \forall \boldsymbol{j} \notin \boldsymbol{S\_j_{v\_r\_max}}; \forall\, \boldsymbol{t} \end{cases}$. – for placement sites that allow sediment reuse, the volume reused in any time period must be less than that site's maximum reuse volume; this constraint is only added by the D2M2 software for the subset of placement sites in $\boldsymbol{S\_j_{r\_max}}$ that allow sediment reuse up, to a maximum rate. For transfer or placement sites that do not allow sediment reuse, the volume reused in any time period must be zero. For placement sites that allow reuse only after some time period, reuse is only allowed during and after that earliest possible time period.

$\sum_i \boldsymbol{v_{i,j,t}} = \boldsymbol{0},\ \forall\, \boldsymbol{j}; \forall\, \boldsymbol{t} < \boldsymbol{t\_earliest_j}$. – if an earliest time period for use (i.e., an earliest acquisition period) has been specified for transfer or placement site $\boldsymbol{j}$, then use of that site is not allowed before the earliest identified time period.

$\boldsymbol{b_j} \leq \sum_t \sum_i \boldsymbol{v_{i,j,t}},\ \forall\, \boldsymbol{j}; \forall\, \boldsymbol{t} \geq \boldsymbol{t\_earliest_j}$. – the binary variable that indicates whether transfer or placement site $\boldsymbol{j}$ has been used for any volume in any time period must be less than or equal to the total volume transferred into the site over all time periods. (I.e., if no volume is ever transferred into the site, then the binary variable for its use must be zero. This binary variable is used when applying the site acquisition cost).

$\boldsymbol{b_j} * \sum_t \sum_i \boldsymbol{min}(\boldsymbol{v\_exact_{i,t}}, \boldsymbol{v\_max_{i,j}}) \geq \sum_t \sum_i \boldsymbol{v_{i,j,t}},\ \forall\, \boldsymbol{i} \in \boldsymbol{route\ i}, \boldsymbol{j}; \forall \boldsymbol{j};\ \forall\, \boldsymbol{t} \geq \boldsymbol{t\_earliest_j}$. – the binary variable that indicates whether transfer or placement site $\boldsymbol{j}$ has been used for any volume in any time period, multiplied by the greatest total volume that could potentially be transferred into that site over all time periods, must be greater than or equal to the total volume actually transferred into that site $\boldsymbol{j}$ over all time periods during and after its earliest allowable period of use. The caveat $\forall\, \boldsymbol{i} \in \boldsymbol{route\ i}, \boldsymbol{j}$ is used specify that $\boldsymbol{v\_exact_{i,t}}$ should only be included for dredging sites that are actually connected to transfer or placement site $\boldsymbol{j}$. This constraint accomplishes three things: 1) it ensures that if any volume is ever transferred into site $\boldsymbol{j}$, then the binary variable for its use must be greater than zero, 2) it ensures that the total volume transferred into sites j is less than or equal to the total dredging volume of all sites connected to it, and 3) it ensures that the total volume transferred into sites j is less than or equal to the total volume allowed to be transported on routes to it.

$\boldsymbol{v_{i,j,t} \leq v\_max_{i,j}}$, $\forall\ \boldsymbol{i,j} \in \boldsymbol{S\_ij_{v\_max}}$; $\forall\ \boldsymbol{t}$. – the volume of dredged material transmitted on each route that has a maximum volume constraint must be less than or equal to the maximum allowable volume in all time periods.

$\sum_i \boldsymbol{v_{i,j,t} = 0}$, $\forall\ \boldsymbol{j} \in \boldsymbol{S\_j_{t\_latest}}$; $\forall\ \boldsymbol{t > t\_latest_j}$. – if a latest time period for use (e.g., an end of lease period) has been specified for transfer or placement site $\boldsymbol{j}$, then use of that site is not allowed after that latest identified time period.

$\sum_i \boldsymbol{v_{i,j,t} \leq v\_max\_t_j}$, $\forall\ \boldsymbol{j} \in \boldsymbol{S\_j_{v\_max\_t}}$; $\forall \boldsymbol{i, t}$. – if a maximum volume addition per time period has been specified for placement site $\boldsymbol{j}$, then the sum of volumes added to that site in any given time period must be less than that maximum value.

$\boldsymbol{v_{i,j,t} = v\_exact_{i,j,t}}$, $\forall\ \boldsymbol{i,j,t} \in \boldsymbol{S\_ijt_{v\_exact}}$. – if an exact volume is required to be transferred on route $\boldsymbol{i,j}$ in time period $\boldsymbol{t}$, then that volume must be transferred from site $\boldsymbol{i}$ to site $\boldsymbol{j}$ in that time period.

$\boldsymbol{v_{i,j,t} \leq v\_max_{i,j,t}}$, $\forall\ \boldsymbol{i,j,t} \in \boldsymbol{S\_ijt_{v\_max}}$. – if a maximum volume limits the amount that can be transferred on route $\boldsymbol{i,j}$ in time period $\boldsymbol{t}$, then the volume transferred from site $\boldsymbol{i}$ to site $\boldsymbol{j}$ in that time period must be less than or equal to that maximum.

$\boldsymbol{v_{i,j,t} \geq v\_min_{i,j,t}}$, $\forall\ \boldsymbol{i,j,t} \in \boldsymbol{S\_ijt_{v\_min}}$. – if a minimum volume limits the amount that can be transferred on route $\boldsymbol{i,j}$ in time period $\boldsymbol{t}$, then the volume transferred from site $\boldsymbol{i}$ to site $\boldsymbol{j}$ in that time period must be equal to or greater than that minimum.

$\sum_i \boldsymbol{v_{i,j,t} = v\_exact_{j,t}}$, $\forall\ \boldsymbol{j,t} \in \boldsymbol{S\_jt_{v\_exact}}$. – if an exact total volume is required to be transferred to site $\boldsymbol{j}$ in time period $\boldsymbol{t}$, then that exact volume must be cumulatively transferred from all dredge sites to site $\boldsymbol{j}$ in that time period.

$\sum_i \boldsymbol{v_{i,j,t} \leq v\_max_{j,t}}$, $\forall\ \boldsymbol{j,t} \in \boldsymbol{S\_jt_{v\_max}}$. – if a maximum total volume limits the amount that can be transferred to site $\boldsymbol{j}$ in time period $\boldsymbol{t}$, then the cumulatively volume transferred from all dredge sites to site $\boldsymbol{j}$ in that time period must be less than or equal to that maximum.

$\sum_i \boldsymbol{v_{i,j,t} \geq v\_min_{j,t}}$, $\forall\ \boldsymbol{j,t} \in \boldsymbol{S\_jt_{v\_min}}$. – if a minimum total volume limits the amount that can be transferred on to site $\boldsymbol{j}$ in time period $\boldsymbol{t}$, then the cumulatively volume transferred from all dredge sites to site $\boldsymbol{j}$ in that time period must be equal to or greater than that minimum.

$$\boldsymbol{c\_d_{i,j,k}} = \sum_x \begin{cases} \boldsymbol{(d_{i,j} - d_{x-1}) * \frac{c\_d_{x,k} - c\_d_{x-1,k}}{d_x - d_{x-1}} + c\_d_{x-1,k}}, & \boldsymbol{if\ d_{x-1} < d_{i,j} \leq d_x} \\ \boldsymbol{0}, & \boldsymbol{otherwise} \end{cases}, \ \forall\ \boldsymbol{i,j,k}; \forall\ \boldsymbol{x \geq 1}.$$

– the cost of transporting sediment, per unit volume, over distance $\boldsymbol{d_{i,j}}$ for criterion $\boldsymbol{k}$, based on the slopes and intercept of the piecewise-linear cost curve. If any routes have distances that exceed those specified on the cost curve, the D2M2 solver will not run and will display a message to the user identifying the problematic route. While not explicit in the indexing above, to maintain clarity, each $\boldsymbol{x}$ should be assumed to be specific to route $\boldsymbol{i,j}$, though multiple routes may be given identical cost curves if desired.

$\boldsymbol{b_{i,j,t} \leq \begin{cases} v_{i,j,t}, & \forall\, i,j \in S\_ij_{c\_f} \\ 0, & \forall\, i,j \notin S\_ij_{c\_f} \end{cases}; \forall\, t.}$ – if a route has a fixed cost for its use but is not used in a time period, the binary variable associated with that fixed cost must have a value of zero in that time period. (If the route is used, the value of the binary variable is not dictated by this constraint.)

$\boldsymbol{b_{i,j,t} * v\_exact_{i,t} \geq v_{i,j,t},\ \forall\, i,j \in S\_ij_{c\_f};\ \forall\, t.}$ – if a route has a fixed cost for its use and is used in a time period, the binary variable associated with its use must have a value of one in that time period; the volume transferred must also be less than or equal to the required dredging volume of the connected dredging site. (If the route is not used, the value of the binary variable is not dictated by this constraint.) This constraint is only added by the D2M2 software for the subset of routes, $\boldsymbol{S\_ij_{c\_f}}$, that have a fixed cost for their use.

$\boldsymbol{c\_f_{i,j,k} = \begin{cases} c\_f\_base_{i,j,k} * (f\_c\_f_{i,k} + f\_c\_f_{j,k}), & if\ (f\_c\_f_{i,k} * f\_c\_f_{j,k} = 0) \\ c\_f\_base_{i,j,k} * (f\_c\_f_{i,k} + f\_c\_f_{j,k}) - c\_f\_base_{i,j,k}, & otherwise \end{cases},\ \forall\, i,j,k.}$ – the fixed cost, for criterion $\boldsymbol{k}$, per time period, from transporting any sediment on route $\boldsymbol{i,j}$. The effect of entering fixed-cost scaling factors for both source and destination of a route is additive instead of multiplicative. A special case is assessed by the D2M2 software if one or both of the scaling factors have been set to zero (i.e., if their product is zero) to prevent negative fixed costs.

$\boldsymbol{c\_f_{i,j,k} = \begin{cases} c\_f\_base_{i,j,k} * (f\_c\_f_{i,k} + f\_c\_f_{j,k}) - c\_f\_base_{i,j,k}, & if\ (f\_c\_f_{i,k} * f\_c\_f_{j,k} \neq 0) \\ c\_f\_base_{i,j,k} * \left(f\_c\_f_{i,k} + f\_c\_f_{j,k}\right), & otherwise \end{cases},}$
$\boldsymbol{\forall\, i,j,k.}$ – this calculates the fixed cost, for criterion $\boldsymbol{k}$, per time period, from transporting any sediment on route $\boldsymbol{i,j}$. The effect of entering fixed-cost scaling factors for both source and destination of a route is additive instead of multiplicative. A special case is assessed by the D2M2 software if one or both of the scaling factors have been set to zero (i.e., if their product is zero) to prevent negative fixed costs.

$\boldsymbol{v\_exact_{i,t}, v_{i,j,t}, v_{j,j',t}, v\_exact_{i,j,t}, v\_max_{i,j,t}, v\_min_{i,j,t}, v\_max_{i,j}, v\_max_{j}, v\_max\_t_{j}, t\_earliest_{j}, t\_latest_{j}, f\_v_{j}, v_{j,t}, v\_exact_{j,t}, v\_max_{j,t}, v\_min_{j,t}, v\_r_{j,t}, v\_r\_max_{j}, t\_r\_earliest_{j}, w_{k}, c\_a_{j,k}, c\_p_{j,k}, c\_r_{j,k}, c\_d_{i,j,k}, d_{i,j}, d_{x}, c\_d_{x,k}, c\_f_{i,j,k}, c\_f\_base_{i,j,k}, f\_c\_f_{i,k}, f\_c\_f_{j,k} \geq 0,\ \forall\, i,j,k,t,x.}$ – non-negative variables.

$\boldsymbol{b_{i,j,t}, b_{j} \in \{0, 1\},\ \forall\, i,j,t.}$ – binary variables.

When applied to data for the nine GIWW study scenarios, the nine resulting linear programs written and solved by the D2M2 software contain between 1,280 constraints, 1700 variables, and 2986 total lines of code for Scenario 1, the simplest scenario, and 2600 constraints, 3540 variables, and 6148 total lines of code for Scenario 9, the most complex scenario.

CASE-STUDY RESULTS

Summary results show the total score for each criterion in each scenario, aggregated across all sites, routes, and time periods (Table 4.8, Figures 4.8-4.10). These results are presented in millions of dollars for financial costs, hundreds of thousands of points for environmental impacts, and tens of millions of points for beneficial-use benefits and impacts, to make them more readable and to support easier comparisons across scenarios. These total-score results show unweighted values, so data for the same criteria can be compared across scenarios, regardless of weighting scheme used. These data are not directly comparable between criteria, however, because they the criteria do not share the same units (i.e., represent different types of point scores or dollars).

Table 4.8. *D2M2 optimization results for nine GIWW case study scenarios that vary two weighting schemes, three site configurations, and various capacities and constraints. Results show total criteria costs, impacts, and benefits across all time periods, routes, and sites. These scenarios were run with an aggregated minimization objective, so positive benefits are expressed as negative values. The data are presented in millions of dollars for financial costs, hundreds of thousands of points for environmental impacts, and tens of millions of points for beneficial use benefits and impacts.*

Scenario #:	**Scenario 1**	**Scenario 2**	**Scenario 3**	**Scenario 4**	**Scenario 5**	**Scenario 6**	**Scenario 7**	**Scenario 8**	**Scenario 9**
Summary Description:	*Active, Cost*	*Active, Balanced*	*Active & Inactive, Cost*	*Active & Inactive, Balanced*	*All Sites, Cost*	*All Sites, Balanced*	*All Sites, Environ.*	*All Sites, Balanced Limited*	*All Sites, Balanced Modified*
Criteria (units)	**Total aggregated cost, impact, or benefit**								
Financial Cost ($M)	161.7	162.3	161.1	162.5	154.2	156.3	163.0	171.0	156.3
T&E Species (100K pts)	57.9	58.8	58.5	59.6	57.6	58.9	59.0	53.5	59.0
Special Lands (100K pts)	141.9	131.2	137.4	123.6	153.7	140.1	133.1	132.3	139.5
Oyster Reef (100K pts)	3.5	4.0	4.3	5.0	4.3	4.3	3.6	5.1	4.3
SAV (100K pts)	76.8	81.0	79.3	85.8	97.3	99.9	92.8	63.4	99.7
Direct BU Benefit (10M pts)	-97.2	-113.5	-101.9	-122.2	-135.3	-153.2	-161.7	-86.9	-153.4
Indirect BU Benefit (10M pts)	-59.1	-66.9	-59.9	-70.2	-80.8	-93.3	-122.3	-59.9	-93.6
Indirect Cost (10M pts)	19.8	22.5	21.8	25.0	53.6	57.4	83.3	31.2	57.6

The objective function values that result from the optimization (Table 4.9) incorporate criteria weights and total scores so are only comparable between scenarios that share the same weighting scheme, i.e., between scenarios 1, 3, and 5 that share a cost-only weighting scheme or between scenarios 2, 4, 6, 8, and 9 that share a balanced weighting scheme; the objective function value from scenario 7 is not comparable with other scenarios since it alone uses an environmental weighting scheme.

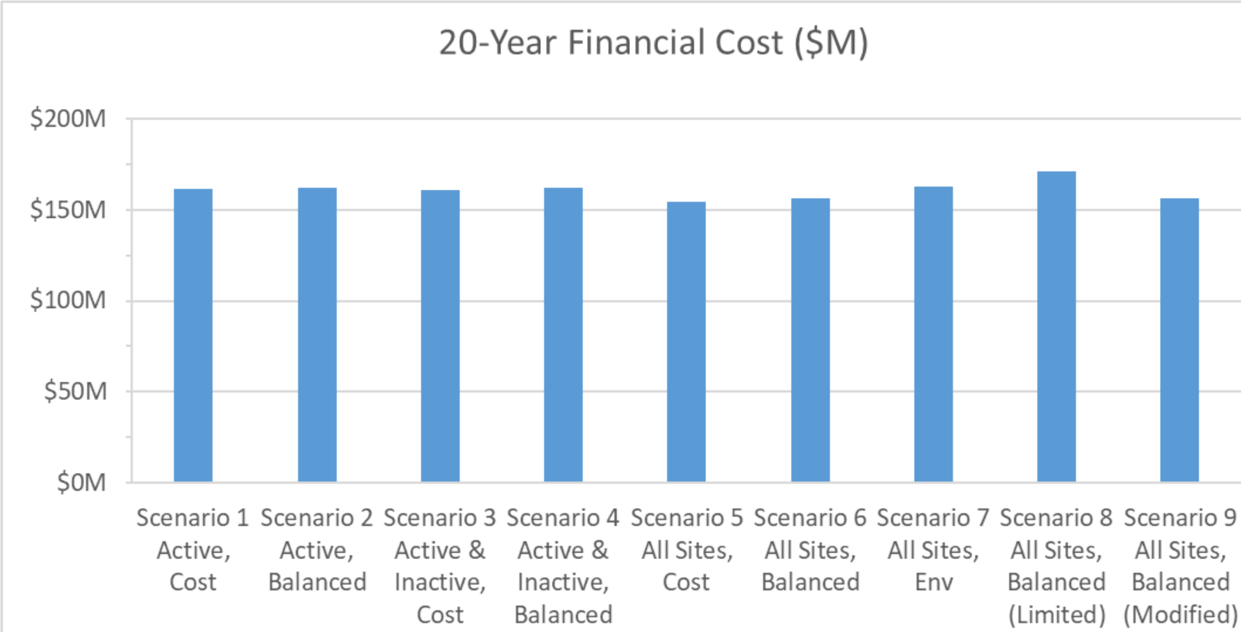

***Figure 4.8**. Graphical comparison of financial costs across nine D2M2 GIWW scenarios that vary in terms of weighting scheme, site configuration, site capacities, and constraints. Results include financial costs aggregated over all time periods, routes, and sites.*

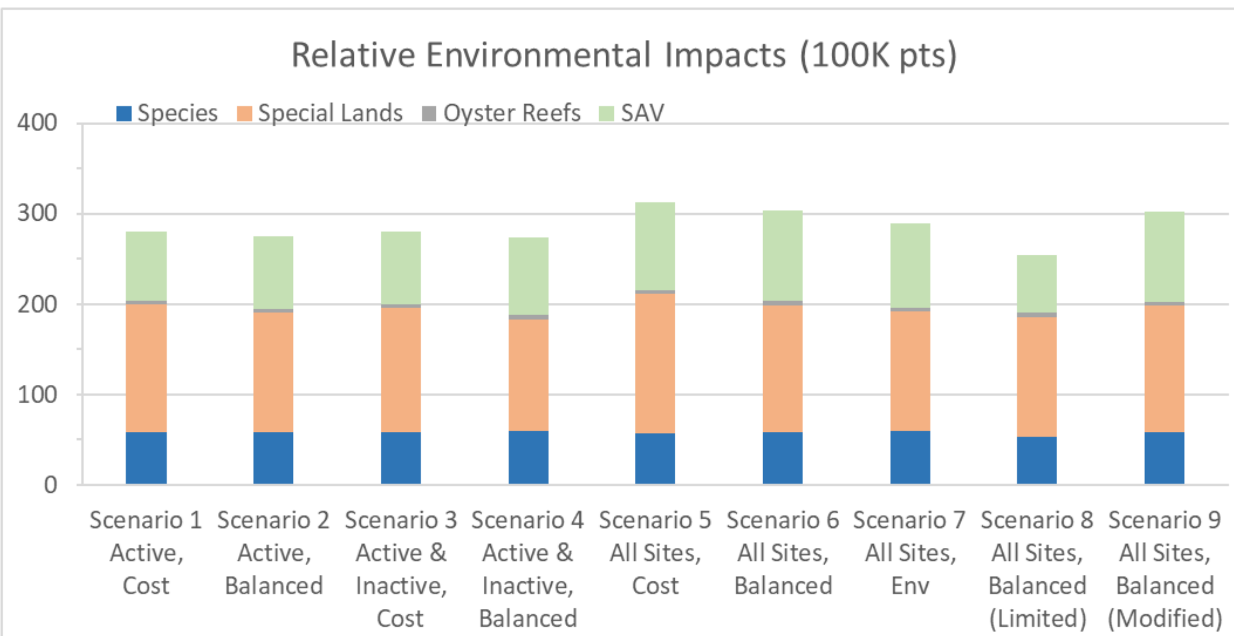

***Figure 4.9**. Graphical comparison of four types of environmental impacts across nine D2M2 GIWW scenarios that vary in terms of weighting scheme, site configuration, site capacities, and constraints. Results include scores aggregated over all time periods, routes, and sites. Blue segments represent impacts to threatened and endangered species, orange represents impacts to designated special lands (e.g., wetlands), gray represents impacts to oyster beds, and green represents impacts to submerged aquatic vegetation.*

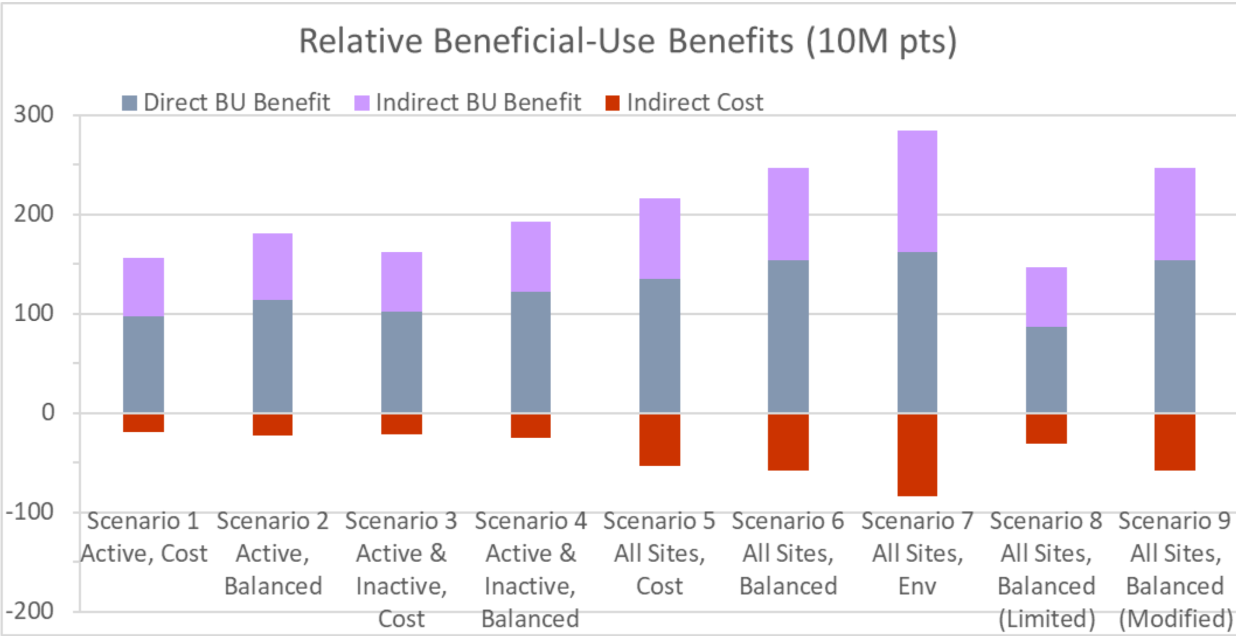

Figure 4.10. *Graphical comparison of two types of environmental benefits and one type of cost across nine D2M2 GIWW scenarios that vary in terms of weighting scheme, site configuration, site capacities, and constraints. Results include scores aggregated over all time periods, routes, and sites. Gray segments represent the direct benefits of increasing or restoring habitat area, purple represents the indirect or ancillary environmental benefits from having that increased or restored habitat, and red represents indirect, non-monetary costs required to carry out beneficial use projects.*

Table 4.9. *Objective function values that resulted from the optimization. These data are only comparable between scenarios that share the same weighting schemes, i.e., between scenarios 1, 3, and 5, between scenarios 2, 4, 6, 8, and 9, and not with scenario 7.*

Scenario #	**Scenario Summary Description**	**Objective function value (millions of weighted points)**
Scenario 1	*Active Sites, Cost Weighting*	161.7
Scenario 3	*Active & Inactive Sites, Cost Weighting*	161.1
Scenario 5	*All Sites, Cost Weighting*	154.2
Scenario 2	*Active Sites, Balanced Weighting*	25.3
Scenario 4	*Active & Inactive Sites, Balanced Weighting*	25.1
Scenario 6	*All Sites, Balanced Weighting*	24.5
Scenario 8	*All Sites, Balanced Weighting, Limited Capacities*	26.8
Scenario 9	*All Sites, Balanced Weighting, Modified Constraints*	24.5
Scenario 7	*All Sites, Environmental Weighting*	-0.1

The detailed results for each scenario also show the total volume of sediment transported from each dredge site to each placement site across all time periods (Figure 4.11 & Appendix Figures 4.A5-4.A13). These figures show the total volume transferred (in millions of cubic yards) by bar height on the vertical axis, the destination placement sites on the horizontal axis, and the source dredging sites by color.

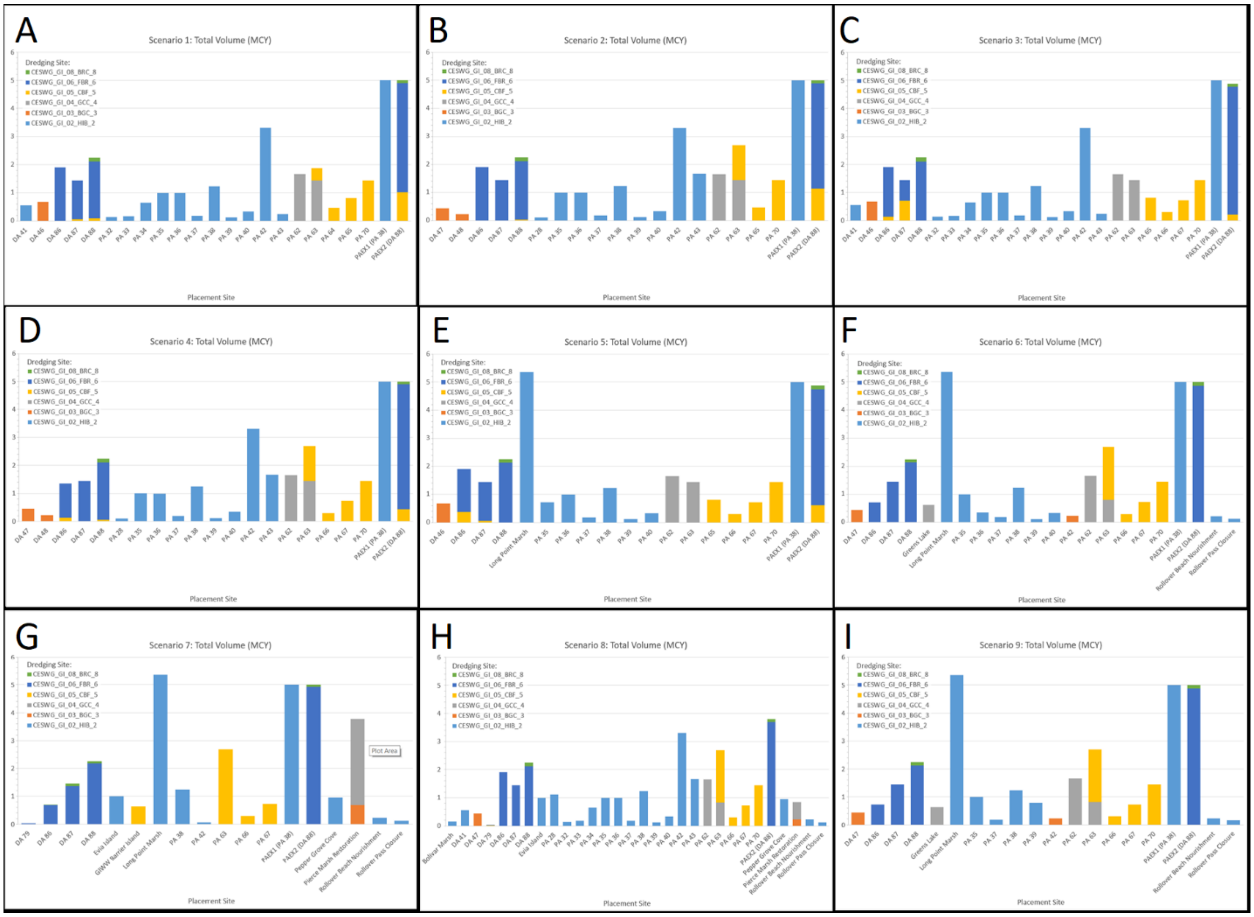

Figure 4.11. *Condensed detailed results for Scenarios 1-9 (subplots A-I) showing the total volumes (bar height on vertical axis) transferred to each placement site (horizontal axis) from each dredging site (color). See Appendix Figures 4.A5-4.A13 for full-size charts for each scenario. Placement sites that receive sediment from multiple dredging sites have volume bars of multiple colors; placement sites that receive the same total amounts of sediment have the same bar heights regardless of sediment source(s); placement sites not used in a scenario are not included on that scenario's chart.)*

The detailed results for each scenario also show the total volume of sediment transported from each dredge site to each type of placement site across all time periods (Figure 4.12 & Appendix Figures 4.A14-4.A22). These figures show the total volume transferred (in millions of cubic yards) on the vertical axis, the types of destination placement sites on the horizontal axis, and the source dredging sites by color.

Figure 4.12. *Condensed detailed results for Scenarios 1-9 (subplots A-I) showing the total volumes (bar height on vertical axis) transferred to each type of placement site (horizontal axis) from each dredging site (color). See Appendix Figures 4.A14-4.A22 for full-size charts for each scenario. Placement site types that received sediment from multiple dredging sites have volume bars of multiple colors; placement site types that received the same total amounts of sediment have the same bar heights regardless of sediment source(s).*

DISCUSSION

Some of the main findings from the D2M2 GIWW case study relate to existing capacity limitations, new flexibility that can be gained by adding beneficial use sites, and tradeoffs between financial, environmental, and beneficial-use costs, impacts, and benefits from different strategies for sediment placement (i.e., as expressed through the priorities of different weighting schemes).

The anticipated 20-year dredging volume needed by the system is just over 31.5 MCY. The placement capacity currently available across all existing active sites is only 27.7 MCY, and the capacity available across all existing active and existing inactive sites is only 30.0 MCY. Even before optimization, this comparison highlights the need to create new placement capacity in the GIWW system over the coming decades beyond simply revitalizing existing inactive placement sites. For the purposes of the D2M2 GIWW case study, it is assumed that two hypothetical expansion sites of 5 MCY each (PAEX1 with the same properties and location as PA 38, and PAEX2 with the same properties and location as PA 88) are added near either end of the system to provide the capacity necessary for the optimizations to run for the 20-year timeframe.

Because routes between dredging and placement sites are limited to 20 miles, which is a liberal interpretation of the route distances commonly used in practice, each dredging site connects to at most one of these two hypothetical expansion sites. Addition of all proposed sites with BU potential collectively adds over 37.1 MCY of capacity in Scenarios 5-9, but the BU sites with the largest capacities are similarly each only reachable from a subset of all dredging sites. With these BU sites available, the optimization scenarios are able to find a feasible solution when PAEX1 is removed but never when PAEX2 is removed (e.g., Scenario 8), due to the particular distances and route connections involved.

Without adding BU sites for sediment placement (i.e., as modeled in Scenarios 1-4), limited opportunity exists to make meaningful choices between sediment placement strategies since nearly all available capacity is needed regarding of the costs, impacts, or benefits, as noted when comparing the results between Scenarios 1 & 2 and between Scenarios 3 & 4 (Table 4.8, Figures 4.8-4.12, and Appendix Figures 4.A5-4.A8 and 4.A14-4.A17), which show greater similarly than difference when optimizing the same site networks for cost-only versus balanced weighting schemes. The addition of BU sites, as modeled in Scenarios 5-9, allows for greater variation in placement site selection (Table 4.8, Figures 4.8-4.12, Appendix Figures 4.A9-4.A13 and 4.A18-4.A22), especially when comparing the results of cost-only and environmental weighting schemes.

These results collectively highlight the importance of considering volume and location jointly when developing new sediment placement sites, since they demonstrate that new placement volumes must be added where they are reachable from the dredging sites that need them for their use to be effective. These results further highlight the important of promoting innovative solutions such as sediment reuse (e.g., as in Scenario 9) to create additional capacity at existing sites. The addition of large-capacity, open water placement sites may also help alleviate capacity limitations, though certain policy, political, and technical barriers may first need to be addressed in practice. Ultimately, a suite of solutions covering some or all of: beneficial use, sediment reuse, inactive site reactivation, and new site development may be needed for long term management.

When comparing scenarios with cost-only weighting but different site networks, the difference in cost between having only existing active sites and having existing active and inactive sites (Scenarios 1 & 3) is negligible, amounting to savings of only $0.6M over 20 years. This shows that the reactivation of inactive sites, alone, is not expected to substantially improve long-term management costs for the GIWW system. Costs are more substantial when comparing these scenarios to the scenario with additional BU sites (Scenario 5), showing a potential savings of $7.5M over 20 years (Table 4.8, Figure 4.8).

When comparing results between pairs of scenarios that share the same site network but different weights (i.e., Scenarios 1 & 2, Scenarios 3 & 4, and Scenarios 5, 6, & 7), it is noticed that scenarios with cost-only weighting have slightly lower total costs than scenarios with balanced weighting, saving about $1-2M each over the 20-year timeframe. While not insubstantial, cost savings of this magnitude, amounting to only about 1% of total project costs, may likely be overshadowed by other project considerations in practice. Scenario 7, which uses an environmental weighting scheme shows the greatest different in financial cost, being nearly $10M more costly than the scenario with the same site network but cost-only weighting (Table 4.8, Figure 4.8).

In comparing these scenario results, it is noted that tradeoffs are made between different types of environmental impacts and between environmental impacts and beneficial use benefits between scenarios, with some types of environmental impact being lower versus higher in the balanced versus cost-only weighting scenarios. Special lands impacts are 8-10% lower in the balanced scenarios than in corresponding cost-only scenarios, and 13% lower in the environmental scenario (which include environmental impact and BU benefit criteria) than in the cost scenario.

Other types of environmental impact scores are higher in the balanced scenarios than in the cost scenarios, likely because these scenarios also prioritize BU benefits and have improvements in those scores. Specifically, threatened and endangered species impacts are 2% higher in each of the balanced and environmental scenarios than in the corresponding cost scenarios. Oyster reef impacts are 14-16% higher in each of the balanced and environmental scenarios than in the corresponding cost scenarios. SAV impacts are 3-8% higher in each of the balanced and environmental scenarios than in the corresponding cost scenarios (Table 4.8, Figure 4.9). The BU direct benefits, indirect benefits, and indirect costs are all greater in the balanced and environmental scenarios than in the corresponding cost scenarios. The direct BU benefits are 12-17% greater in the balanced and environmental scenarios than in the corresponding cost scenarios. The indirect BU benefits are 12-15% greater in the balanced scenarios than in the corresponding cost scenarios, and 34% greater in the environmental scenario than in the corresponding cost scenario. The indirect costs of implementing BU projects are also 7-13% greater in the balanced than in the corresponding cost scenario and 36% greater in the environmental scenario (Table 4.8, Figure 4.10).

Scenario 8 uses the same "all-sites" network and balance weighting as Scenario 6, but limits the available capacity of the three most used sites. This results in a total financial cost that is 9% higher, oyster reef impacts that are 16% higher, and direct and indirect BU benefits that are 76% and 56% lower. However, the impacts to threatened and endangered species are 9% lower, impacts to special lands are 6% lower, impacts to SAV are 37% lower, and indirect costs for implementing beneficial use projects are 46% lower (Table 4.8, Figure 4.8-4.10). These mixed-results in terms of BU outcomes are because the two sites completely removed from these scenarios (PAEX1 and Long Point Marsh) both have BU scores that are much better than average (Appendix Table 4.A3). This scenario was created to force the model to explore secondary sites after the three main sites were removed or reduced in capacity. As a result, the number of placement sites used increases from 22 sites in Scenario 6 to 30 sites in Scenario 8 to accommodate the necessary dredging volume, an 36% increase in the number of sites used (Figure 4.11 and Appendix Figures 4.A10 & 4.A12). This results in more sediment being placed in existing active upland and BU sites, and less sediment being placed in hypothetical BU sites, hypothetical upland sites, and proposed BU sites (Figure 4.12 and Appendix Figures 4.A19 & 4.A21).

Scenario 9 uses the same "all-sites" network and balance weighting scheme as Scenario 6, but introduces seven changes to the optimization for specific added features and constraints for particular sites and routes. The most detailed results for each route in each time period (hundreds of pages, not shown) verify that each of these changes is reflected in the optimization outcomes. Because the effedt of changes is minor compared to the total magnitudes being transported, changes in total scores for this scenario are less than 1% for all criteria (Table 4.8) when compared to the base-case Scenario 6. This scenario is of greatest interest for demonstrating the capabilities of the D2M2 software to change parameter values for specific sites and to introduce different types of constraints, flexibilities that will be valuable to some future modelers. The use of most placement sites was similar between Scenario 9 and

Scenario 6; the most prominent difference is that Scenario 9 does not use sites PA 36 and PA 40 at all and instead increases the volume going to site PA 39 (Figure 4.11 and Appendix Figures 4.A10 & 4.A13).

The objective function values show weighted results and can be compared across scenarios that use the same weighting scheme. When comparing Scenarios 1, 3, & 5 that use a cost-only weighting scheme, it is noted that reactivated existing inactive placement sites leads to a <1% improvement in objective function value but including adding those and the proposed BU sites leads to a 5% improvement in objective function value. When comparing Scenarios 2, 4, 6, 8, & 9 that use a balanced weighting scheme, reactivating existing inactive placement sites leads to a 1% improvement in objective function value but adding those and the proposed BU sites leads to a 3% improvement in objective function value. Scenario 9, with additional constraints, leads to the same objective value as Scenario 6, and Scenario 8, with limited capacities for the most-used sites, worsens the objective function value by 6% (Table 4.9).

When comparing the placement areas used between scenarios with cost-only and balanced weighting without the proposed BU sites included in the site network (i.e., between Scenarios 1 & 2 and between Scenarios 3 & 4), the primary difference is a shift in volume from existing active upland placement sites to existing active BU sites in the balanced scenarios (Figure 4.12 and Appendix Figures 4.A14-4.A17). This result is intuitive because the BU sites contribute to increased BU benefits that are not valued in the cost-focused scenarios. When comparing placement sites between cost-only and balanced scenarios that do include proposed BU sites in the site network, the primary difference is a shift in volume from existing active upland sites to existing active BU sites and to proposed BU sites, which is equally intuitive (Figure 4.12 and Appendix Figures 4.A18-4.A19). In Scenario 7, with environmental weighting (i.e., with equal weight on all environmental impact and BU benefit criteria but no weight on financial and indirect cost criteria), the use of placement sites shifts more dramatically to proposed BU sites and away from existing active upland sites, existing active BU sites, and existing active open water sites, compared to the cost-only and balanced scenarios (Figure 4.12 and Appendix Figures 4.A18-4.A20).

CONCLUSIONS

This chapter advances the Dredged Material Management Decisions (D2M2) multi-objective optimization (MOO), mixed-integer linear programming software for efficiently allocating dredged sediment (e.g., from navigational channels) to available placement areas with different capacities, properties, constraints on use, and costs, impacts, and/or benefits. Rather than being a MOO model itself, the D2M2 software is a MOO-model builder, with a graphical user interface and data upload capabilities that support the modeler in building custom MOO models to represent their unique sediment-management systems of interest.

This new version of the software incorporates two types of model enhancements to better represent costs, impacts, benefits, and effects, three types of model enhancements to incorporate additional types of constraints, six other types of enhancements to the modeling process itself, and five types of enhancements to the user interface. These allow the modeler to more effectively represent a wider array of engineering and management detail in their modeled dredging and placement sites and the routes that connect them, including details such as bulking factors, fixed and variable costs, sediment reuse, site lease timing, and about constraints about site and route volumes in different time periods.

The new version of D2M2 is demonstrated in a case study that models dredged material management over an 81-mile portion of the Gulf Intracoastal Waterway (GIWW) system near Galveston, TX. This protected coastal waterway is strategically important for domestic and international shipping, commercial and recreational fishing, recreational boating, and coastal protection and naval defense. Nine different scenarios are constructed and run for this system, with different site networks, criteria weights, capacity limitations, and site and route properties and constraints. This includes scenarios with only existing active sites, existing active plus reactivated existing inactive sites, or existing active and inactive sites plus proposed sites with beneficial-use (BU) potential. These are modeled with weighting schemes that either prioritize only financial costs, a balance of all objectives, or a balance of only environmental impact and beneficial use benefit objectives (without consideration of direct and indirect costs). Two additional scenarios are included that constrain the use of the three most-used sites to force the model to explore the use of secondary sites, and that add a variety of custom route and site properties and constraints to more broadly showcase the capabilities of D2M2 beyond what is needed to realistically model GIWW system management.

A variety of figures and tables for case study input data in the main text and appendix show: 1) the case study system and site locations; 2) details for the scenarios that include the weights applied in each scenario and other differences between scenarios; 3) detailed input data for site types, current status, required dredging volumes, performance per cubic yard placed for each of the objectives, data normalization factors, and acquisition and improvement costs; 4) route fixed costs, variable costs per cubic yard, and distances; and 5) historical dredging project distances, volumes, total costs, and average costs per cubic yard. Additional figures and tables for the results show: 1) total unweighted performance scores for each objective, total scores grouped by objective type (i.e., financial cost, environmental impacts, or beneficial use benefits and impact), and total objective function values in each scenario; 2) total volumes allocated from each dredging site to each placement site in each scenario; 3) total volumes allocated to different types of existing active and inactive sites, hypothetical sites, and potential BU sites.

As might reasonably be anticipated, the scenarios with the same site networks but a balanced versus cost-only weighting schemes have better environmental and BU scores and worse cost scores. Scenarios with balanced and environmental weighting schemes also show tradeoffs between individual impact and benefit criteria, with performance on some criteria improving or worsening in different scenarios but with aggregated improvements overall. Scenarios that use the same weighting schemes see slight improvements in their weighted criteria performance with reactivation of existing inactive placement sites and more substantial improvements with inclusion of potential BU sites in their site networks.

The case study scenarios provide valuable insights for the long-term management of the GIWW system in the Galveston area, including that additional capacity needs to be added over the coming decades, that any new capacity must to be strategically dispersed so that it can be used for sediment from dredging sites throughout the system, that reactivation of existing inactive sites in unlikely to meaningfully improve system management if implemented without being combined with other measures, but that the developed of proposed sites with BU potential can make a more meaningful different in improving system management. The results also show the potential effects of different priorities between financial costs, different types of environmental impacts, and different types of beneficial use benefits and impacts that could be applied in system management, including how individual placement sites would be used in different capacities should each set of priorities be applied.

This chapter includes the full objective function specification for models built using D2M2, including all optional properties and constraints. The condensed representation in this text includes 54 types of variables that are incorporated into 24 components of the optimization objective function. When applied to data for the 9 GIWW case study scenarios, these expand to form 1,280 constraints, 1,700 variables, and 2,986 total lines of objective function code in the simplest scenario and 2,600 constraints, 3,540 variables, and 6,148 total lines of objective function code in the most complex scenario.

There are many ways that future work could improve and extend the case study implemented in this chapter, including by using engineering-design level cost estimates that are differentiated by site instead of average cost functions derived from historical data, by including site-specific acquisition and improvement costs, by including additional details about anticipated site availability and unavailability in different years, and by further differentiating site and route properties and costs based on differences in anticipated dredging and placement equipment expected to be used in different locations. Future work also remains to improve the D2M2 software, including to add Lagrange multipliers (aka shadow prices) in the results to help identify more- and less-sensitive parameters in the models, for example to illuminate the value of more flexibility and capacity for various sites. D2M2 modeling capabilities might also be improved by accommodating piecewise-linear unit cost curves that vary based on both total distance and total volume, by including site operation and maintenance cost per time period, by including a number of time periods of use after which a site must rest and the number of required resting periods (e.g., for compaction and consolidation) before next use, by including site lease annual costs and periodic renegotiation costs, and by incorporating discount rates for calculating net-present objective values across time.

The latest version of the D2M2 software can be obtained from the author, from the USACE Dredging Operations Technical Support (DOTS) program[42], or from current USACE DOTS and USACE Risk and Decision Science team leads.

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APPENDIX A

To improve the readability of the main text, several particularly long tables and series of figures with model inputs and results are shown in detail here, following condensed figures or excerpt of tables in the main text.

Additional input data

Appendix Table 4.A1. *Placement areas included in the D2M2 case study model, differentiated by site type, current status, sediment capacity, and acquisition and improvement cost.*

Name	Type	Status	Capacity (CY)	Acquisition & Improvement Cost
PA 28	Upland Confined	Existing Active	1,111,914	.
PA 32	Upland Confined	Existing Active	145,200	.
PA 33	Upland Confined	Existing Active	176,670	.
PA 34	Upland Confined	Existing Active	654,264	.
PA 35	Upland Confined	Existing Active	1,000,002	.
PA 36	Upland Confined	Existing Active	991,740	.
PA 37	Upland Confined	Existing Active	186,788	.
PA 38	BU Island	Existing Active	1,240,000	$25,000
PA 39	Upland Confined	Existing Active	119,462	.
PA 40	Upland Confined	Existing Active	337,940	.
DA 41	Upland Partially Confined	Existing Active	560,574	.
PA 42	Upland Confined	Existing Active	3,309,940	.
PA 43	BU Wetland	Existing Active	1,670,000	$25,000
DA 46	Open Water	Existing Active	1,271,520	.
DA 47	Open Water	Existing Active	444,860	.
DA 48	Open Water	Existing Active	454,300	.
DA 49	Open Water	Existing Active	368,100	.
DA 51	Open Water	Existing Active	644,440	.
PA 53	BU Shoal	Existing Active	170,000	$25,000
PA 54	BU Shoal	Existing Inactive	80,000	$75,000
PA 55	BU Shoal	Existing Inactive	290,000	$75,000
PA 56	BU Shoal	Existing Inactive	140,000	$75,000
PA 57	BU Island	Existing Inactive	440,000	$75,000
PA 58A	BU Shoal	Existing Active	210,000	$25,000
PA 59	BU Shoal	Existing Inactive	220,000	$75,000
PA 62	BU Island	Existing Active	1,660,000	$25,000
PA 63	BU Island	Existing Active	2,690,000	$25,000
PA 64	Upland Confined	Existing Active	470,204	.
PA 65	Upland Confined	Existing Active	814,324	.
PA 66	BU Island	Existing Inactive	300,000	$75,000
PA 67	BU Island	Existing Inactive	730,000	$75,000
PA 70	Upland Confined	Existing Active	1,445,340	.

DA 79	BU Island	Existing Inactive	30,000	$75,000
DA 86	Upland Confined	Existing Active	1,905,710	.
DA 87	Upland Confined	Existing Active	1,445,872	.
DA 88	Upland Confined	Existing Active	2,246,260	.
PAEX1 (similar to PA 38)	BU Island	Hypothetical	5,000,000	$200,000
PAEX2 (similar to DA 88)	Upland Confined	Hypothetical	5,000,000	$200,000
Bird Island Cove	Potential BU Wetland	Proposed	1,506,853	$100,000
Bolivar Ferry Landing/Little Beach	Potential BU Beach	Proposed	400,000	$100,000
Bolivar Marsh	Potential BU Wetland	Proposed	250,000	$100,000
Dana Cove Marsh	Potential BU Wetland	Proposed	687,280	$100,000
Evia Island	Potential BU Island	Proposed	1,000,000	$100,000
Galveston Causeway Open Water	Potential BU Bar or Shoal	Proposed	390,000	$100,000
Gangs to Oxen Bayou	Potential BU Wetland	Proposed	567,893	$100,000
GIWW Barrier Island	Potential BU Bar or Shoal	Proposed	774,400	$100,000
Greens Lake	Potential BU Wetland	Proposed	10,625,413	$100,000
IH-10 Causeway	Potential BU Wetland	Proposed	2,042,480	$100,000
Jumbile Cove	Potential BU Wetland	Proposed	1,019,627,280	$100,000
Long Point Marsh	Potential BU Wetland	Proposed	5,359,493	$100,000
North Deer Island	Potential BU Island	Proposed	225,000	$100,000
North Open Water Island	Potential BU Bar or Shoal	Proposed	600,000	$100,000
Oxen to Mentzel Bayou	Potential BU Wetland	Proposed	1,258,400	$100,000
PA 58 Island	Potential BU Bar or Shoal	Proposed	139,000	$100,000
Pepper Grove Cove	Potential BU Wetland	Proposed	948,640	$100,000
Pierce Marsh restoration	Potential BU Wetland	Proposed	6,698,560	$100,000
Rollover Beach Nourishment	Potential BU Beach	Proposed	225,000	$100,000
Rollover Pass Closure	Potential BU Delta	Proposed	130,000	$100,000
Snake Island Cove	Potential BU Wetland	Proposed	1,474,587	$100,000
South Open Water Island	Potential BU Bar or Shoal	Proposed	460,000	$100,000
Swan Lake	Potential BU Wetland	Proposed	250,000	$100,000
West Bay Mooring	Potential BU Wetland	Proposed	100,000	$100,000
		Minimum:	***30,000***	***$ 0***
		Median:	***622,220***	***$ 75,000***
		Mean:	***17,672,834***	***$ 57,258***
		Maximum:	***1,019,627,280***	***$200,000***

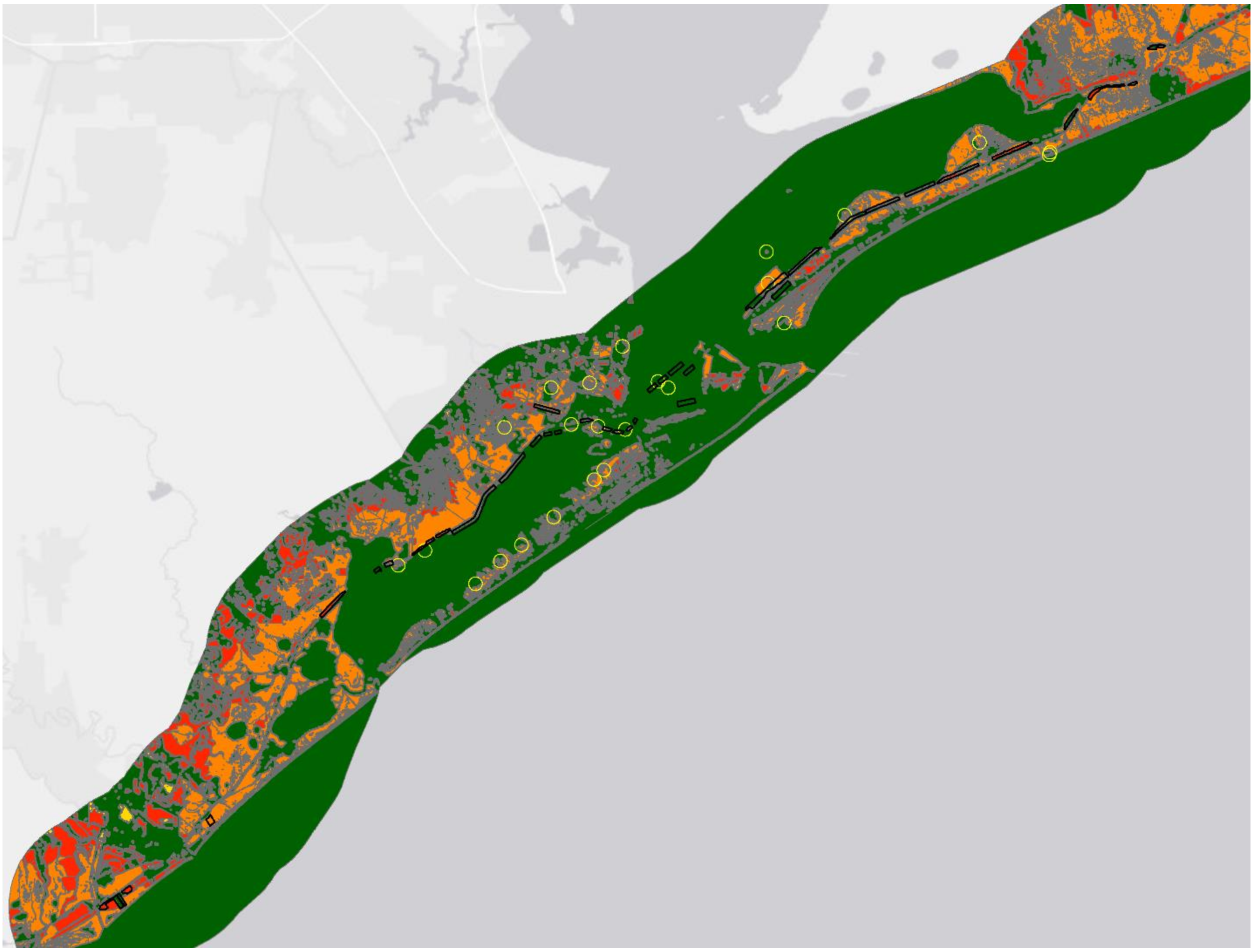
Appendix Table 4.A2. *Routes included in the D2M2 case study model and their distance between dredging and placement sites.*

Rt.#	Dist. (mi)	Dredging Site	Placement Site	Rt.#	Dist. (mi)	Dredging Site	Placement Site
1	14.79	CESWG_GI_02_HIB_2	Bolivar Marsh	59	16.07	CESWG_GI_04_GCC_4	DA 46
2	11.20	CESWG_GI_02_HIB_2	DA 41	60	15.38	CESWG_GI_04_GCC_4	DA 47
3	15.30	CESWG_GI_02_HIB_2	Evia Island	61	14.29	CESWG_GI_04_GCC_4	DA 48
4	3.52	CESWG_GI_02_HIB_2	Long Point Marsh	62	13.42	CESWG_GI_04_GCC_4	DA 49
5	17.39	CESWG_GI_02_HIB_2	PA 28	63	15.21	CESWG_GI_04_GCC_4	DA 51
6	14.04	CESWG_GI_02_HIB_2	PA 32	64	5.08	CESWG_GI_04_GCC_4	Dana Cove Marsh
7	13.07	CESWG_GI_02_HIB_2	PA 33	65	9.66	CESWG_GI_04_GCC_4	Galveston Causeway Open Water
8	11.71	CESWG_GI_02_HIB_2	PA 34	66	11.56	CESWG_GI_04_GCC_4	Gangs to Oxen Bayou
9	9.05	CESWG_GI_02_HIB_2	PA 35	67	7.02	CESWG_GI_04_GCC_4	GIWW Barrier Island
10	4.58	CESWG_GI_02_HIB_2	PA 36	68	4.40	CESWG_GI_04_GCC_4	Greens Lake
11	0.82	CESWG_GI_02_HIB_2	PA 37	69	9.87	CESWG_GI_04_GCC_4	IH-10 Causeway
12	2.38	CESWG_GI_02_HIB_2	PA 38	70	6.53	CESWG_GI_04_GCC_4	Jumbile Cove
13	4.95	CESWG_GI_02_HIB_2	PA 39	71	7.97	CESWG_GI_04_GCC_4	North Deer Island
14	7.29	CESWG_GI_02_HIB_2	PA 40	72	13.47	CESWG_GI_04_GCC_4	North Open Water Island
15	13.61	CESWG_GI_02_HIB_2	PA 42	73	11.86	CESWG_GI_04_GCC_4	Oxen to Mentzel Bayou
16	14.42	CESWG_GI_02_HIB_2	PA 43	74	11.07	CESWG_GI_04_GCC_4	PA 53
17	2.38	CESWG_GI_02_HIB_2	PAEX1 (PA 38)	75	10.52	CESWG_GI_04_GCC_4	PA 54
18	8.14	CESWG_GI_02_HIB_2	Pepper Grove Cove	76	9.85	CESWG_GI_04_GCC_4	PA 55
19	7.07	CESWG_GI_02_HIB_2	Rollover Beach Nourishment	77	9.15	CESWG_GI_04_GCC_4	PA 56
20	7.04	CESWG_GI_02_HIB_2	Rollover Pass Closure	78	7.73	CESWG_GI_04_GCC_4	PA 57
21	8.84	CESWG_GI_03_BGC_3	Bolivar Ferry Landing/Little Beach	79	6.12	CESWG_GI_04_GCC_4	PA 58 Island
22	7.68	CESWG_GI_03_BGC_3	Bolivar Marsh	80	6.54	CESWG_GI_04_GCC_4	PA 58A
23	9.96	CESWG_GI_03_BGC_3	DA 41	81	5.87	CESWG_GI_04_GCC_4	PA 59
24	0.75	CESWG_GI_03_BGC_3	DA 46	82	1.78	CESWG_GI_04_GCC_4	PA 62

25	1.41	CESWG_GI_03_BGC_3	DA 47
26	2.49	CESWG_GI_03_BGC_3	DA 48
27	3.36	CESWG_GI_03_BGC_3	DA 49
28	6.77	CESWG_GI_03_BGC_3	DA 51
29	19.05	CESWG_GI_03_BGC_3	Dana Cove Marsh
30	10.31	CESWG_GI_03_BGC_3	Evia Island
31	6.26	CESWG_GI_03_BGC_3	Galveston Causeway Open Water
32	9.71	CESWG_GI_03_BGC_3	Gangs to Oxen Bayou
33	15.07	CESWG_GI_03_BGC_3	Greens Lake
34	10.92	CESWG_GI_03_BGC_3	IH-10 Causeway
35	8.04	CESWG_GI_03_BGC_3	North Deer Island
36	2.91	CESWG_GI_03_BGC_3	North Open Water Island
37	10.95	CESWG_GI_03_BGC_3	Oxen to Mentzel Bayou
38	18.77	CESWG_GI_03_BGC_3	PA 38
39	16.17	CESWG_GI_03_BGC_3	PA 39
40	13.67	CESWG_GI_03_BGC_3	PA 40
41	7.69	CESWG_GI_03_BGC_3	PA 42
42	7.03	CESWG_GI_03_BGC_3	PA 43
43	5.60	CESWG_GI_03_BGC_3	PA 53
44	6.15	CESWG_GI_03_BGC_3	PA 54
45	6.75	CESWG_GI_03_BGC_3	PA 55
46	7.46	CESWG_GI_03_BGC_3	PA 56
47	8.89	CESWG_GI_03_BGC_3	PA 57
48	9.74	CESWG_GI_03_BGC_3	PA 58 Island
49	12.42	CESWG_GI_03_BGC_3	PA 58A
50	10.75	CESWG_GI_03_BGC_3	PA 59
51	14.75	CESWG_GI_03_BGC_3	PA 62
52	18.32	CESWG_GI_03_BGC_3	PA 63
53	18.77	CESWG_GI_03_BGC_3	PAEX1 (PA 38)
54	14.20	CESWG_GI_03_BGC_3	Pepper Grove Cove
55	13.26	CESWG_GI_03_BGC_3	Pierce Marsh Restoration
83	3.18	CESWG_GI_04_GCC_4	PA 63
84	5.95	CESWG_GI_04_GCC_4	PA 64
85	7.41	CESWG_GI_04_GCC_4	PA 65
86	10.04	CESWG_GI_04_GCC_4	PA 66
87	10.93	CESWG_GI_04_GCC_4	PA 67
88	14.55	CESWG_GI_04_GCC_4	PA 70
89	7.75	CESWG_GI_04_GCC_4	Pierce Marsh Restoration
90	8.58	CESWG_GI_04_GCC_4	Snake Island Cove
91	13.80	CESWG_GI_04_GCC_4	South Open Water Island
92	8.97	CESWG_GI_04_GCC_4	West Bay Mooring
93	8.25	CESWG_GI_05_CBF_5	DA 79
94	15.26	CESWG_GI_05_CBF_5	DA 86
95	16.16	CESWG_GI_05_CBF_5	DA 87
96	16.62	CESWG_GI_05_CBF_5	DA 88
97	16.21	CESWG_GI_05_CBF_5	GIWW Barrier Island
98	19.90	CESWG_GI_05_CBF_5	PA 63
99	17.41	CESWG_GI_05_CBF_5	PA 64
100	15.97	CESWG_GI_05_CBF_5	PA 65
101	13.37	CESWG_GI_05_CBF_5	PA 66
102	12.60	CESWG_GI_05_CBF_5	PA 67
103	8.86	CESWG_GI_05_CBF_5	PA 70
104	16.62	CESWG_GI_05_CBF_5	PAEX2 (DA 88)
105	14.24	CESWG_GI_05_CBF_5	West Bay Mooring
106	6.42	CESWG_GI_06_FBR_6	DA 79
107	1.43	CESWG_GI_06_FBR_6	DA 86
108	2.33	CESWG_GI_06_FBR_6	DA 87
109	2.79	CESWG_GI_06_FBR_6	DA 88
110	2.79	CESWG_GI_06_FBR_6	PAEX2 (DA 88)
111	9.63	CESWG_GI_08_BRC_8	DA 79
112	2.40	CESWG_GI_08_BRC_8	DA 86
113	2.05	CESWG_GI_08_BRC_8	DA 87

56	2.53	CESWG_GI_03_BGC_3	South Open Water Island	114	1.32	CESWG_GI_08_BRC_8	DA 88
57	10.62	CESWG_GI_03_BGC_3	Swan Lake	115	1.32	CESWG_GI_08_BRC_8	PAEX2 (DA 88)
58	6.53	CESWG_GI_04_GCC_4	Bird Island Cove				
			Minimum:		***0.75***		
			Median:		***9.15***		
			Mean:		***9.50***		
			Maximum:		***19.90***		

Appendix Figure 4.A1*. Map of the number of threatened and endangered species historically present in different areas in the GIWW study region. Colors (dark green, light green, yellow, orange, red) denote lower to higher sensitivity based on increasing numbers of species historically present in that area. Black rectangles outline the perimeter of existing placement sites and yellow circles outline the approximate area of potential future placement sites.*



Appendix Figure 4.A2*. Map of special land designations in different areas in the GIWW study region. Colors (green, yellow, orange, red) denote lower to higher sensitivity based on different types of special land designations. Black rectangles outline the perimeter of existing placement sites and yellow circles outline the approximate area of potential future placement sites.*

Appendix Figure 4.A3*. Map of oyster beds (in red) and buffers surrounding them (in gray) in different areas in the GIWW study region. Black rectangles outline the perimeter of existing placement sites and yellow circles outline the approximate area of potential future placement sites.*

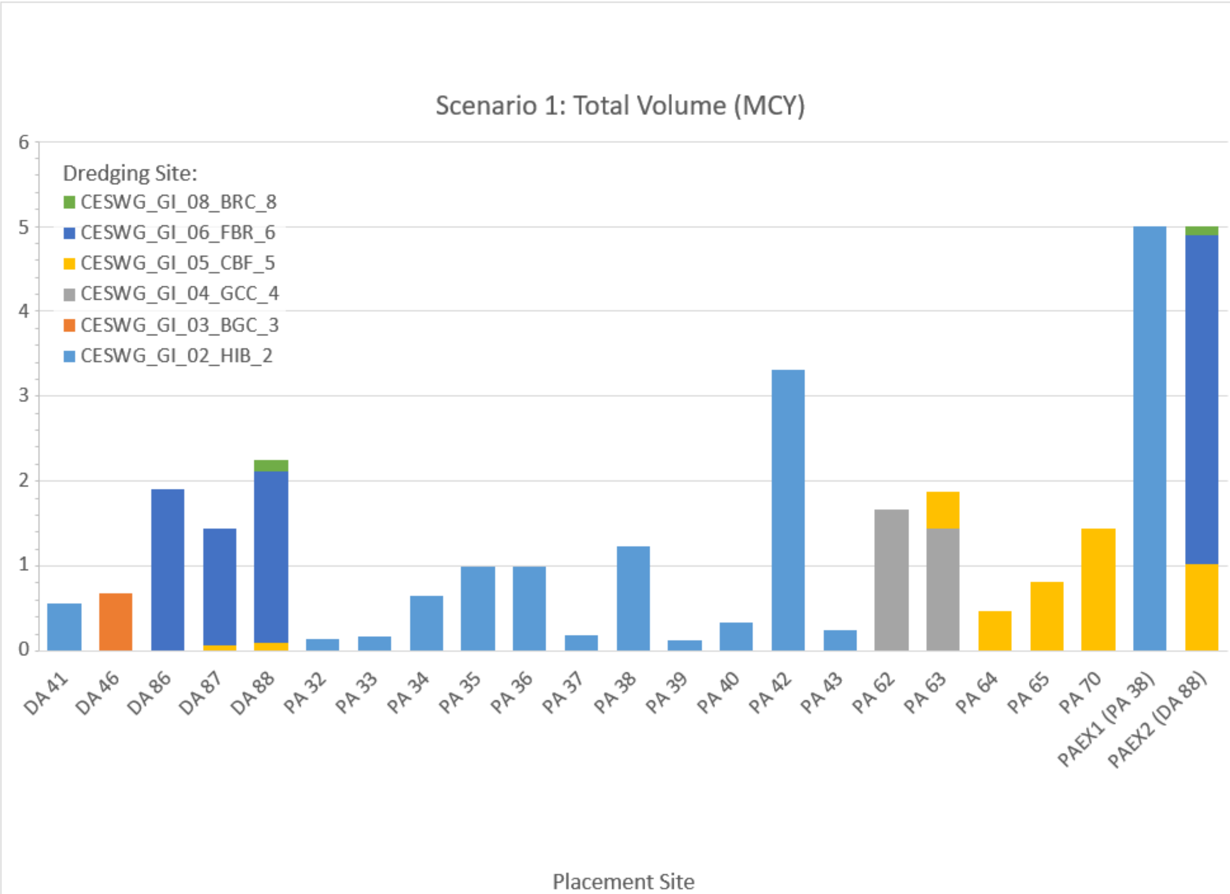
***Appendix Figure 4.A4**. Map of submerged aquatic vegetation habitat (in red) in different areas in the GIWW study region. Black rectangles outline the perimeter of existing placement sites and yellow circles outline the approximate area of potential future placement sites.*

Appendix Table 4.A3. *Relative environmental impact and beneficial use scores per cubic yard placed. Non-monetary criteria in the D2M2 model include four different types of environmental impacts (to special lands, threatened and endangered species, oyster beds, and submerged aquatic vegetation) and three effects from the beneficial use of sediment (direct benefits from increased or restored habitat area, indirect environmental benefits from having increased or restored habitat, and non-monetary time, effort, and hassle costs typically required to carry out new beneficial use projects). All scores are qualitatively estimated per unit volume of sediment on either a 0-1 scale for the environmental impacts or a 1-100 scale for the beneficial use effects (zero values are shown as ".", for clarity). Because the optimization seeks to minimize the total weighted score, benefits are represented as negative values. (Scores from the USACE ERDC and Galveston district).*

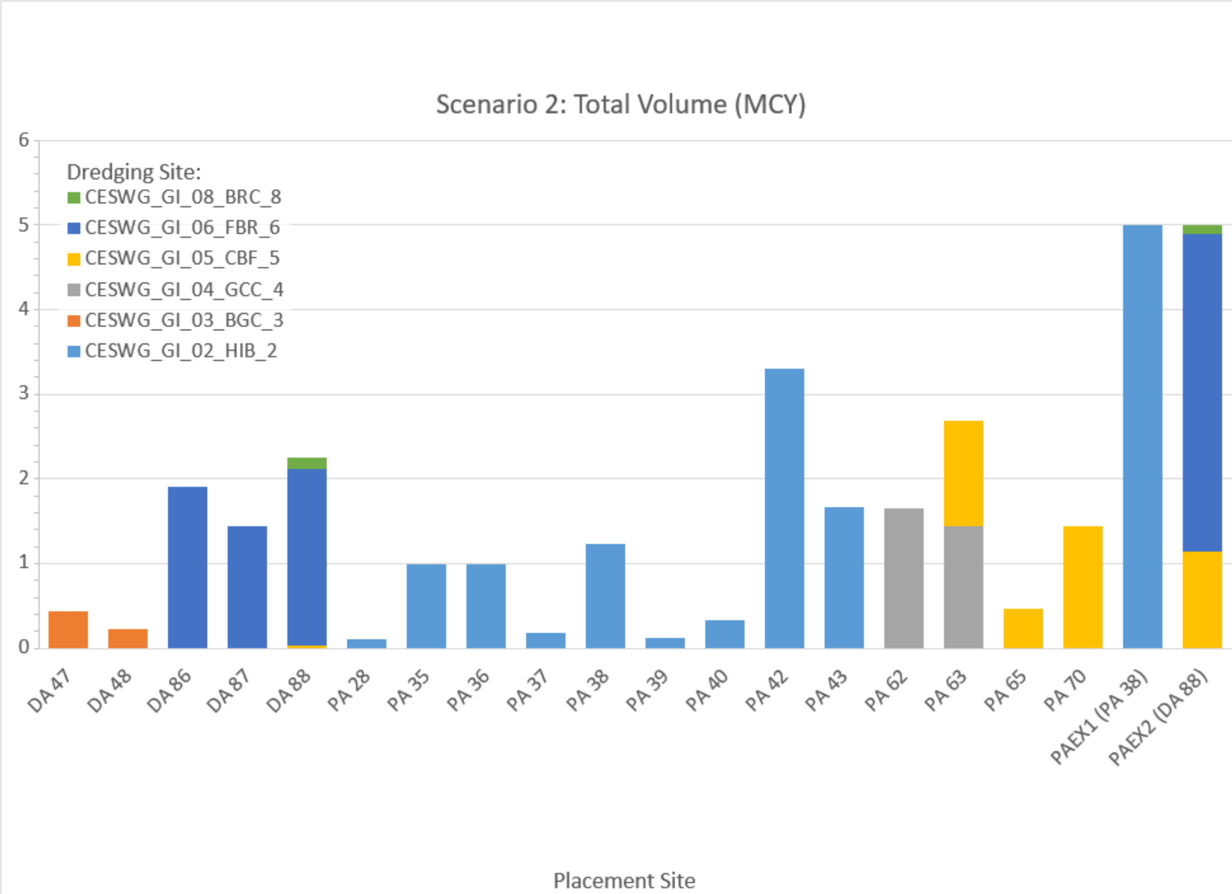
Name	T&E Species	Special Lands	Oyster Reef	SAV	Direct BU Benefit	Indirect BU Benefit	Indirect Cost
PA 28	.140	.173	.	.085	.	.	.
PA 32	.140	.938	.	.051	.	.	.
PA 33	.140	.935	.	.176	.	.	.
PA 34	.140	.969	.	.116	.	.	.
PA 35	.140	.116	.	.080	.	.	.
PA 36	.140	.909	.	.062	.	.	.
PA 37	.148	.715	.	.260	.	.	.
PA 38	.308	.343	.	.580	-100	-60	22
PA 39	.142	.582	.	.071	.	.	.
PA 40	.146	.411	.	.140	.	.	.
DA 41	.267	.571	.	.290	.	.	.
PA 42	.140	.060	.	.026	.	.	.
PA 43	.219	.427	.	.440	-59.722	-20	13
DA 46	.210	.	.334	.640	.	.	.
DA 47	.210	.	.328	.035	.	.	.
DA 48	.210	.	.342	.313	.	.	.
DA 49	.210	.	.370	.660	.	.	.
DA 51	.210	.	.704	.450	.	.	.
PA 53	.210	.	.	.660	-50	.	.
PA 54	.210	.478	.039	.645	-41.667	.	11
PA 55	.207	.235	.723	.660	-20.833	-20	30
PA 56	.203	.440	.823	.660	-25	-20	30
PA 57	.208	.432	.	.646	-83.333	-50	50
PA 58A	.140	.812	.	.065	-29.167	-25	40
PA 59	.209	.	.003	.660	-43.750	-60	22
PA 62	.188	.345	.005	.589	-94.444	-60	22
PA 63	.197	.319	.062	.633	-94.444	-60	11
PA 64	.141	.889	.	.112	.	.	.
PA 65	.140	.824	.	.167	.	.	.
PA 66	.241	.581	.	.366	-88.889	-50	22
PA 67	.210	.	.144	.658	-83.333	-25	25

PA 70	.140	.791	.	.039	.	.	.
DA 79	.210	.950	.	.532	-60.417	-50	33
DA 86	.140	.978	.	.048	.	.	.
DA 87	.140	.134	.	.018	.	.	.
DA 88	.140	.506	.	.052	.	.	.
PAEX1 (PA 38)	.308	.343	.	.580	-100	-60	22
PAEX2 (DA 88)	.140	.506	.	.052	.	.	.
Bird Island Cove	.162	.482	.	.612	-50	-40	60
Bolivar Ferry Landing/Little Beach	.445	.259	.	.417	-72	-20	11
Bolivar Marsh	.165	.771	.	.225	-43	-20	40
Dana Cove Marsh	.173	.391	.	.596	-56	-80	60
Evia Island	.210	.055	.	.	-17	-60	60
Galveston Causeway Open Water	.210	.079	.455	.474	-51	-80	40
Gangs to Oxen Bayou	.151	.754	.002	.241	-46	-40	70
GIWW Barrier Island	.195	.198	.	.422	-35	-40	40
Greens Lake	.210	.626	.	.068	-56	-60	33
IH-10 Causeway	.140	.788	.	.442	-48	-60	50
Jumbile Cove	.176	.358	.	.526	-46	-40	50
Long Point Marsh	.140	.601	.	.427	-65	-40	60
North Deer Island	.208	.439	.120	.514	-42	-60	44
North Open Water Island	.210	.	.284	.286	-39	-20	40
Oxen to Mentzel Bayou	.149	.819	.	.320	-38	-40	70
PA 58 Island	.210	.188	.030	.636	-66	-20	30
Pepper Grove Cove	.205	.575	.091	.334	-58	-60	67
Pierce Marsh restoration	.140	.393	.	.	-48	-75	44
Rollover Beach Nourishment	.217	.340	.	.093	-78	-20	.
Rollover Pass Closure	.284	.491	.	.123	-63	-60	29
Snake Island Cove	.189	.225	.	.584	-48	-60	60
South Open Water Island	.210	.	.036	.381	-32	-20	30
Swan Lake	.193	.222	.007	.634	-17	-20	60
West Bay Mooring	.225	.393	.004	.523	-40	-60	22
Minimum:	***.140***	***0.00***	***0.00***	***0.00***	***-100.0***	***-80.0***	***0.0***
Median:	***.190***	***.422***	***.079***	***.342***	***-34.3***	***-26.7***	***23.0***
Mean:	***.196***	***.402***	***0.00***	***.350***	***-38.5***	***-20.0***	***22.0***
Maximum	***.445***	***.978***	***.823***	***.660***	***0.0***	***0.0***	***70.0***

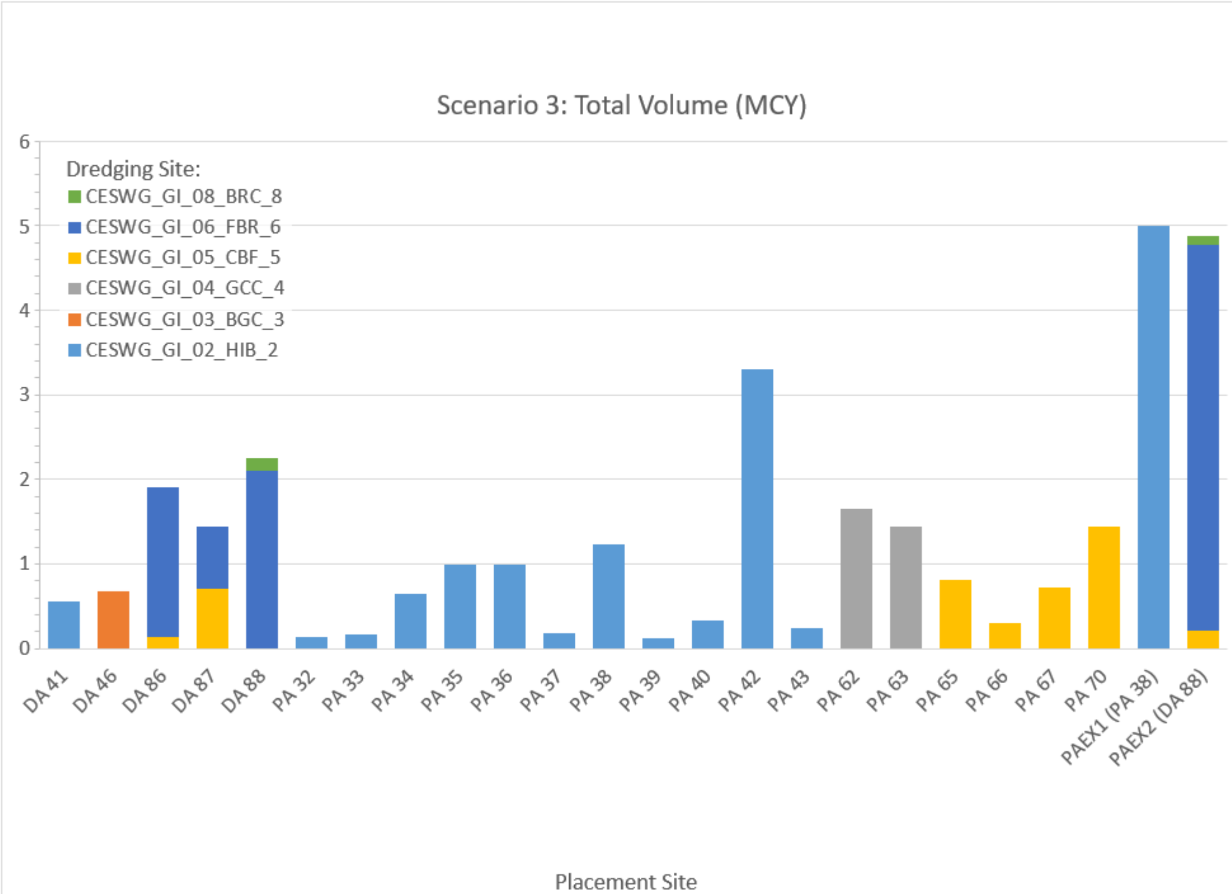
Additional results



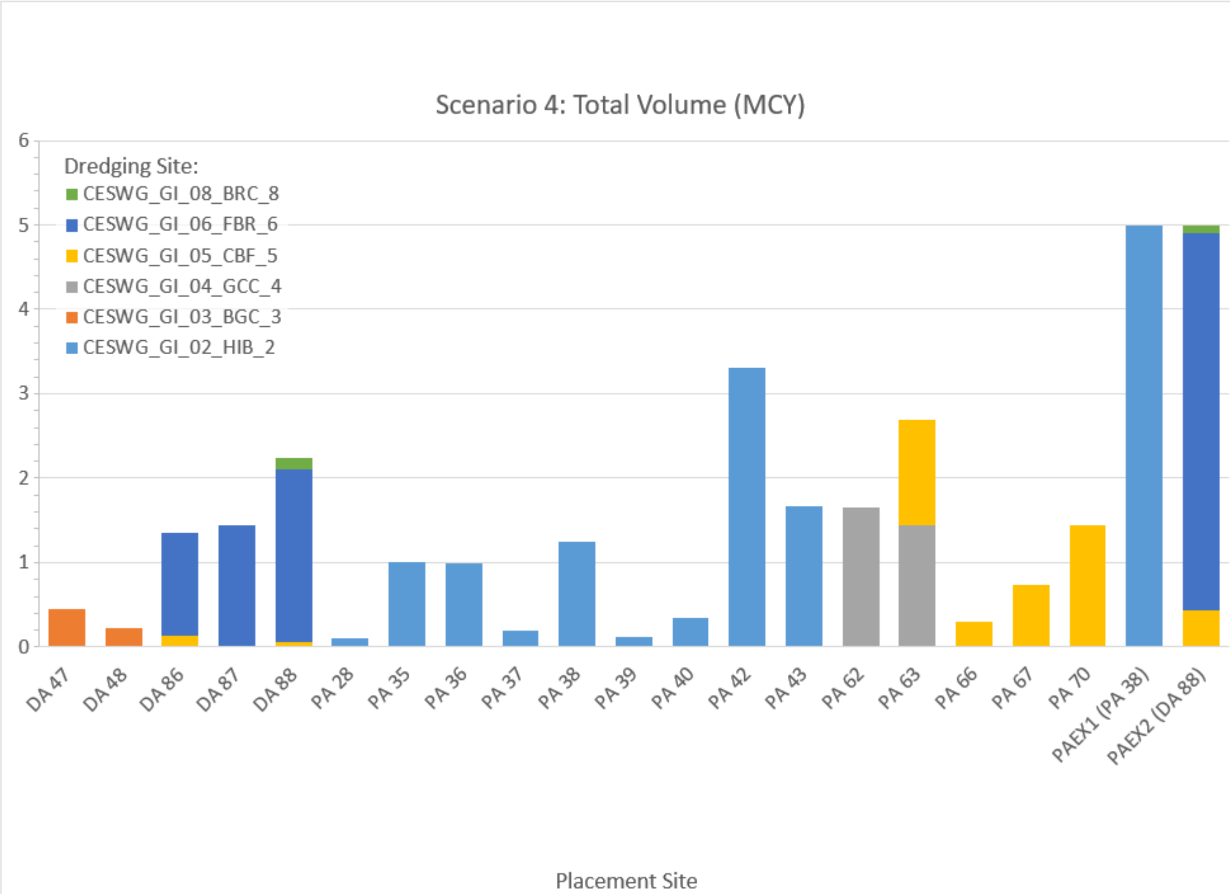
Appendix Figure 4.A5*. Detailed results for Scenario 1 showing the total volumes (millions of cubic yards) transferred between dredging and placement sites. Total volume is on the vertical axis, placement sites are on the horizontal axis, and dredging sites are in different colors. (Placement sites that received sediment from multiple dredging sites have total-volume bars of multiple color; placement sites that received the same total amounts of sediment have the same bar heights regardless of source(s); placement sites not used in this scenario are not shown.)*



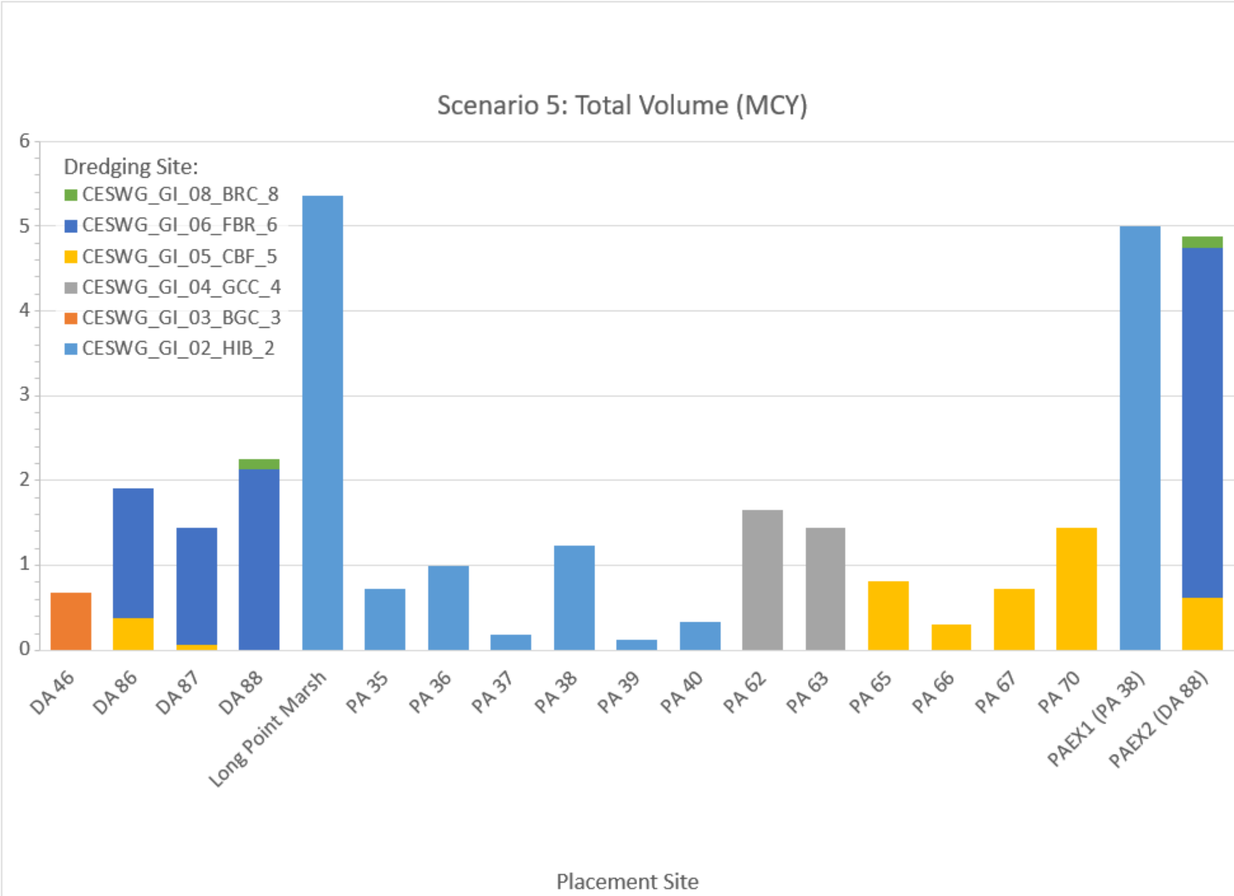
Appendix Figure 4.A6. *Detailed results for Scenario 2 showing the total volumes (millions of cubic yards) transferred between dredging and placement sites. Total volume is on the vertical axis, placement sites are on the horizontal axis, and dredging sites are in different colors. (Placement sites that received sediment from multiple dredging sites have total-volume bars of multiple color; placement sites that received the same total amounts of sediment have the same bar heights regardless of source(s); placement sites not used in this scenario are not shown.)*



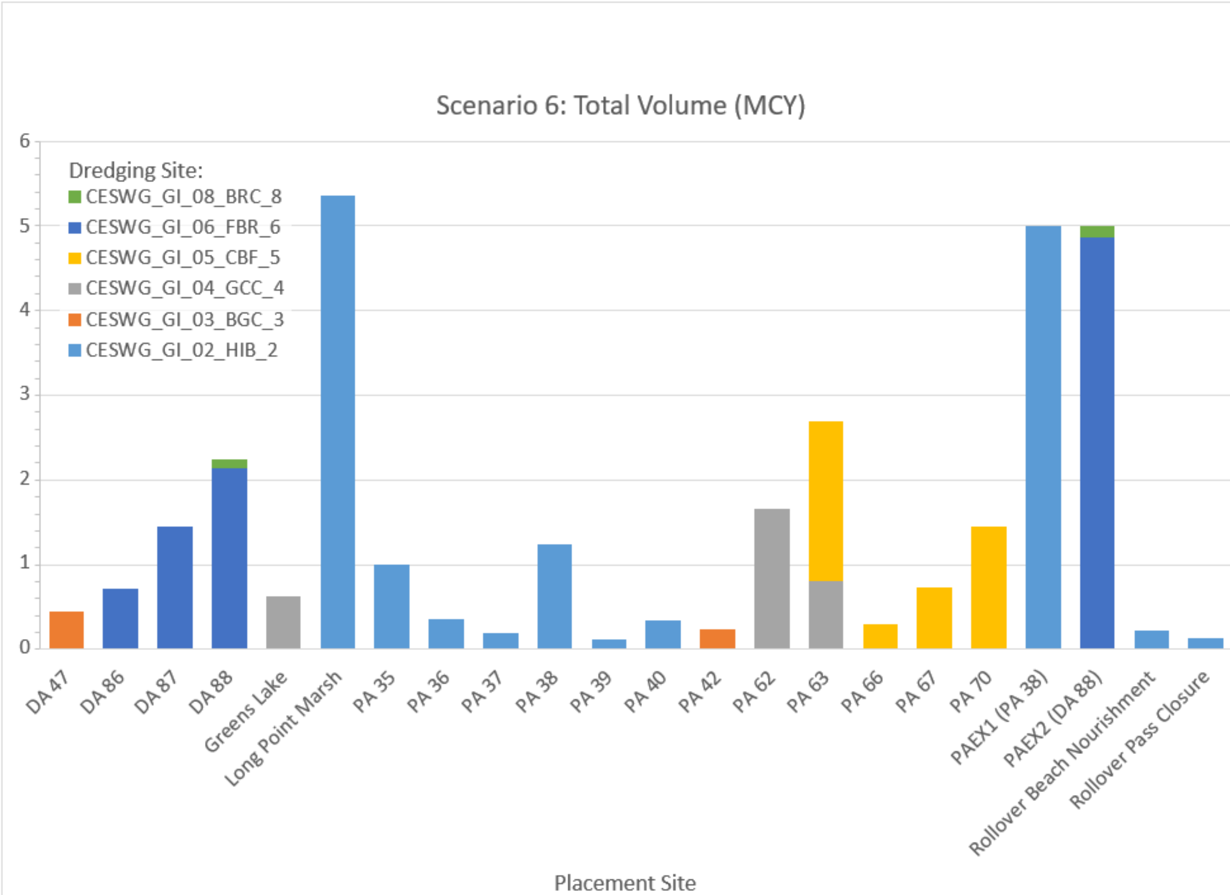
Appendix Figure 4.A7. *Detailed results for Scenario 3 showing the total volumes (millions of cubic yards) transferred between dredging and placement sites. Total volume is on the vertical axis, placement sites are on the horizontal axis, and dredging sites are in different colors. (Placement sites that received sediment from multiple dredging sites have total-volume bars of multiple color; placement sites that received the same total amounts of sediment have the same bar heights regardless of source(s); placement sites not used in this scenario are not shown.)*



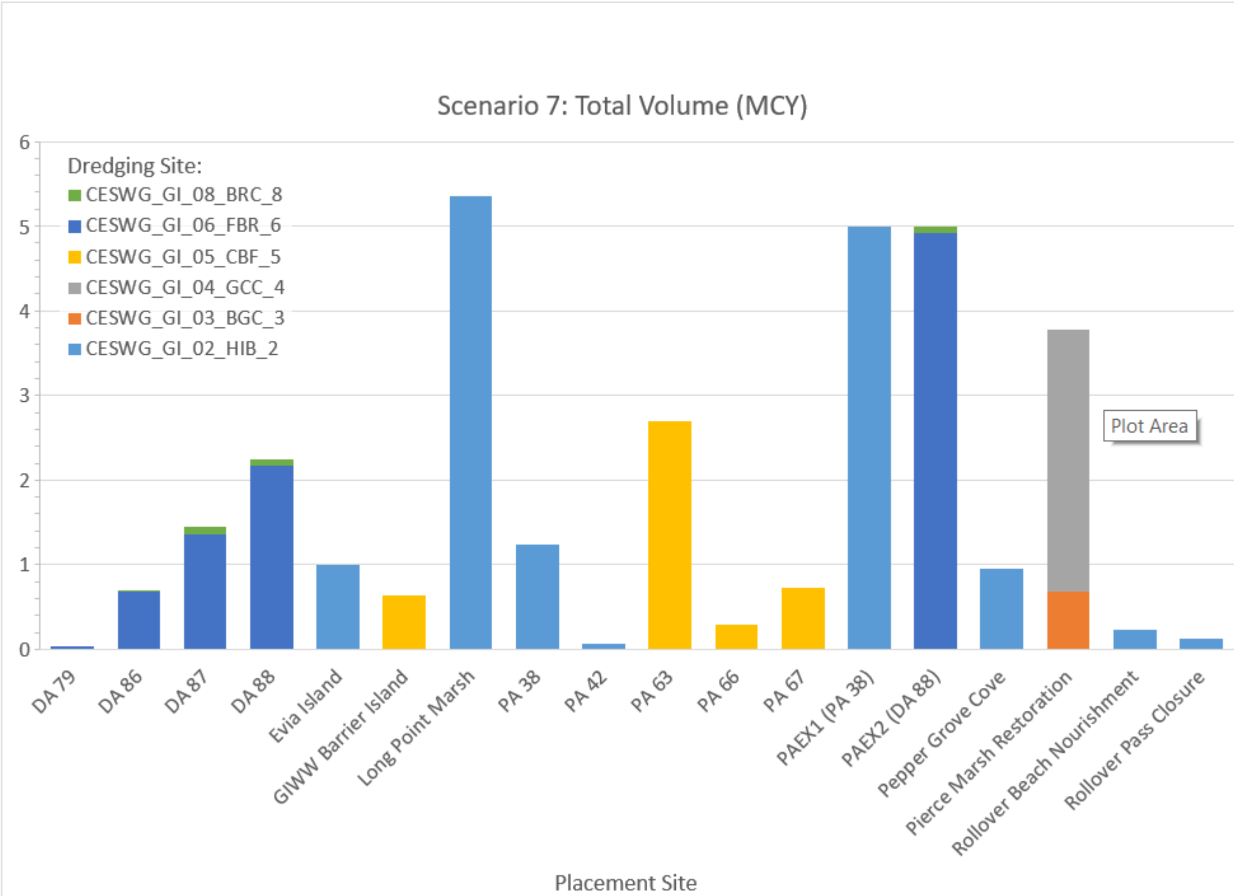
Appendix Figure 4.A8. *Detailed results for Scenario 4 showing the total volumes (millions of cubic yards) transferred between dredging and placement sites. Total volume is on the vertical axis, placement sites are on the horizontal axis, and dredging sites are in different colors. (Placement sites that received sediment from multiple dredging sites have total-volume bars of multiple color; placement sites that received the same total amounts of sediment have the same bar heights regardless of source(s); placement sites not used in this scenario are not shown.)*



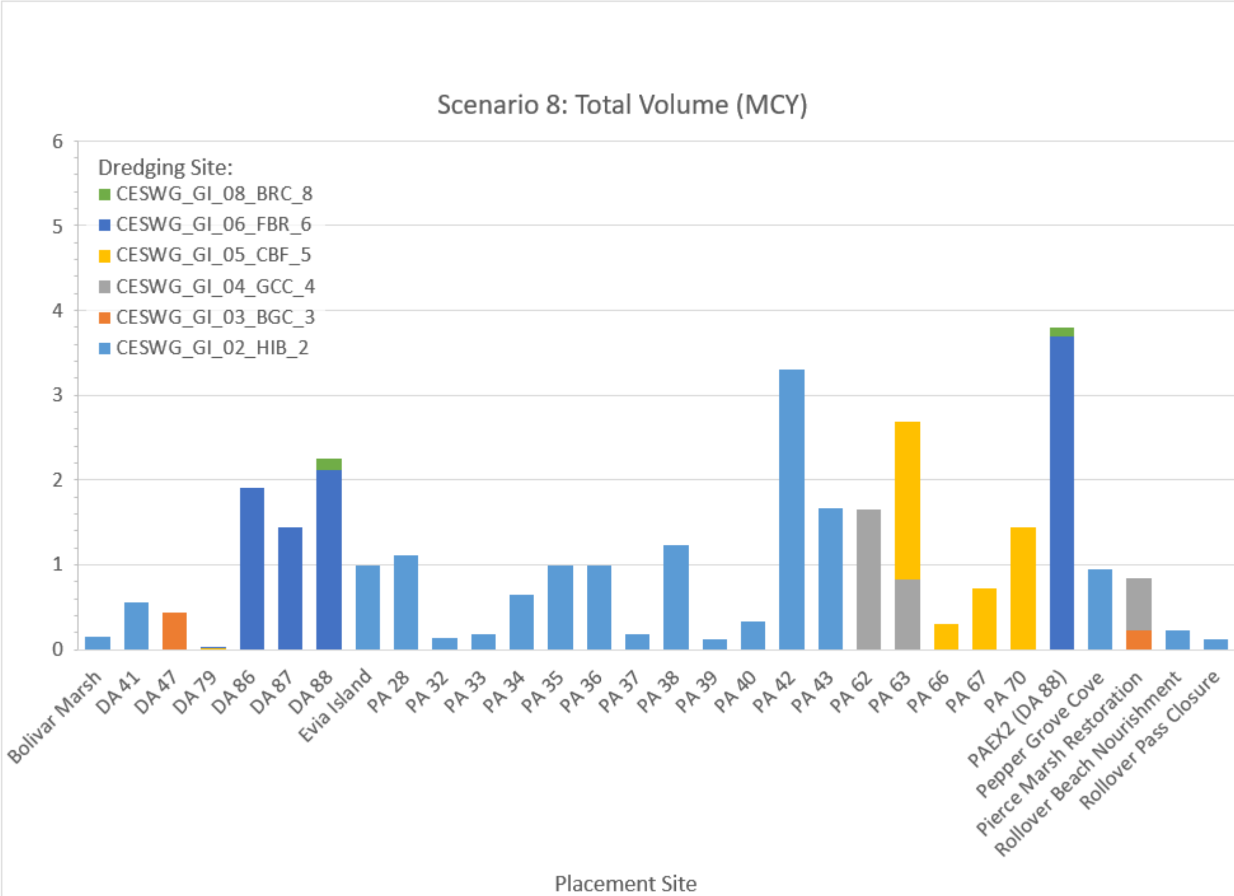
Appendix Figure 4.A9. *Detailed results for Scenario 5 showing the total volumes (millions of cubic yards) transferred between dredging and placement sites. Total volume is on the vertical axis, placement sites are on the horizontal axis, and dredging sites are in different colors. (Placement sites that received sediment from multiple dredging sites have total-volume bars of multiple color; placement sites that received the same total amounts of sediment have the same bar heights regardless of source(s); placement sites not used in this scenario are not shown.)*



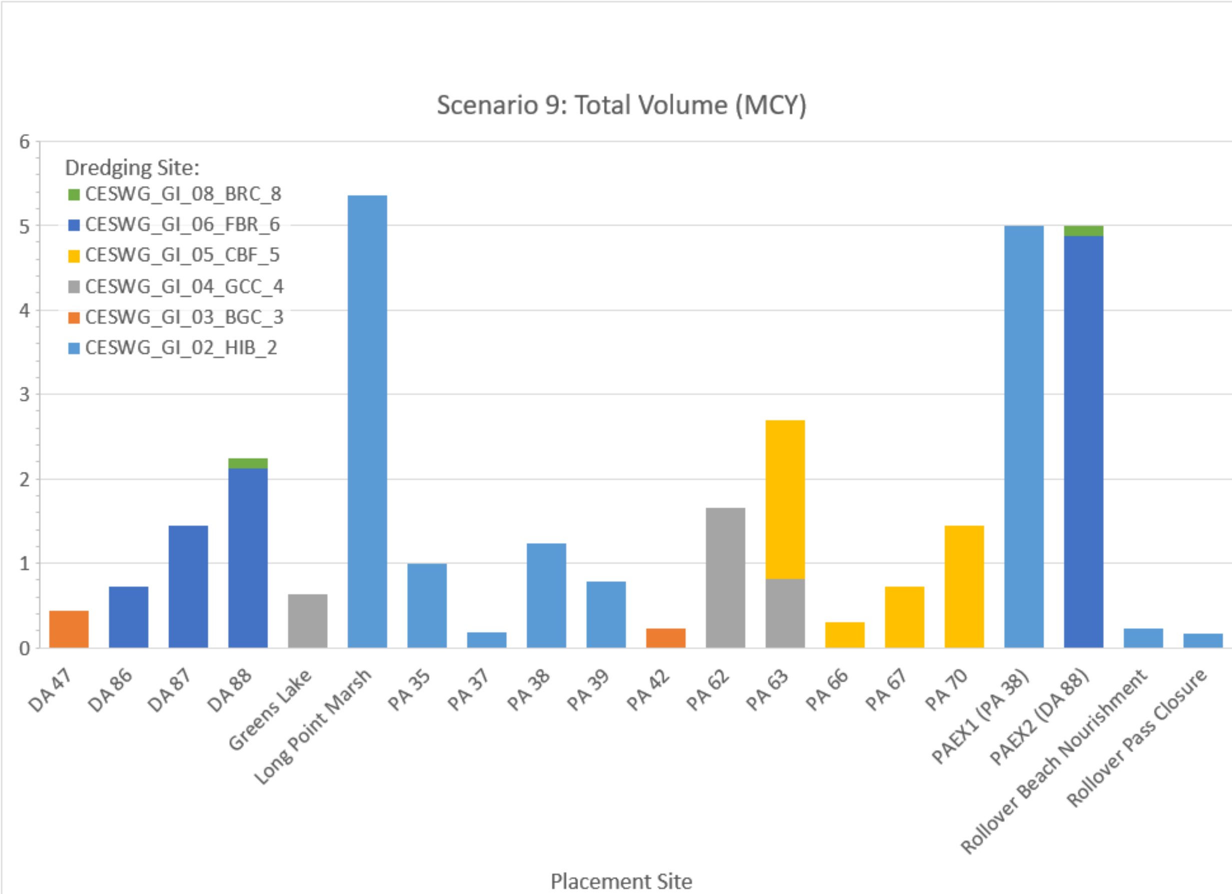
Appendix Figure 4.A10. *Detailed results for Scenario 6 showing the total volumes (millions of cubic yards) transferred between dredging and placement sites. Total volume is on the vertical axis, placement sites are on the horizontal axis, and dredging sites are in different colors. (Placement sites that received sediment from multiple dredging sites have total-volume bars of multiple color; placement sites that received the same total amounts of sediment have the same bar heights regardless of source(s); placement sites not used in this scenario are not shown.)*



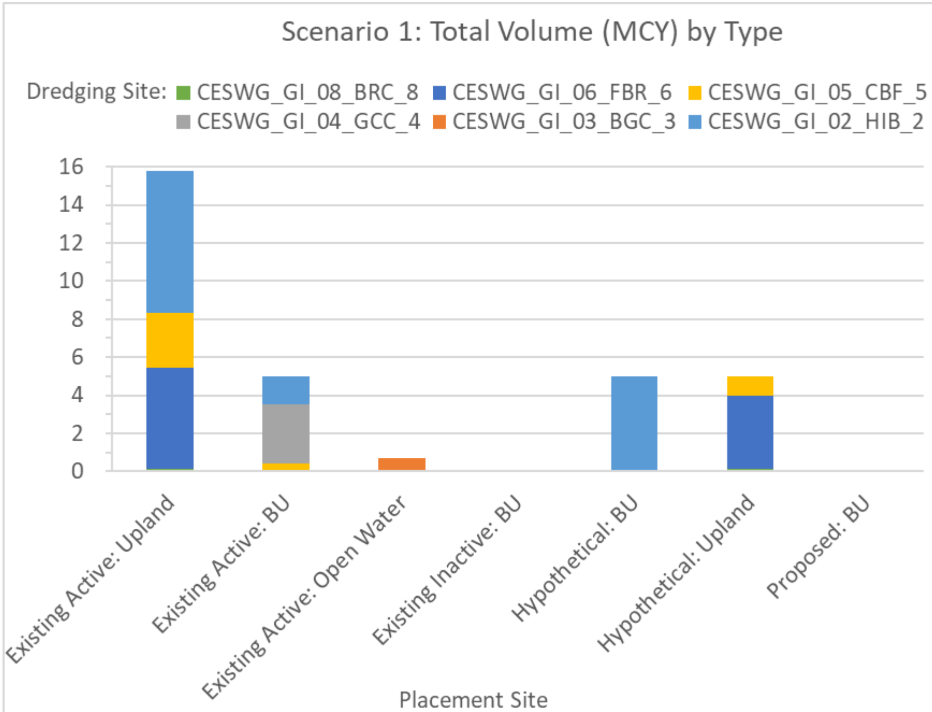
Appendix Figure 4.A11*. Detailed results for Scenario 7 showing the total volumes (millions of cubic yards) transferred between dredging and placement sites. Total volume is on the vertical axis, placement sites are on the horizontal axis, and dredging sites are in different colors. (Placement sites that received sediment from multiple dredging sites have total-volume bars of multiple color; placement sites that received the same total amounts of sediment have the same bar heights regardless of source(s); placement sites not used in this scenario are not shown.)*



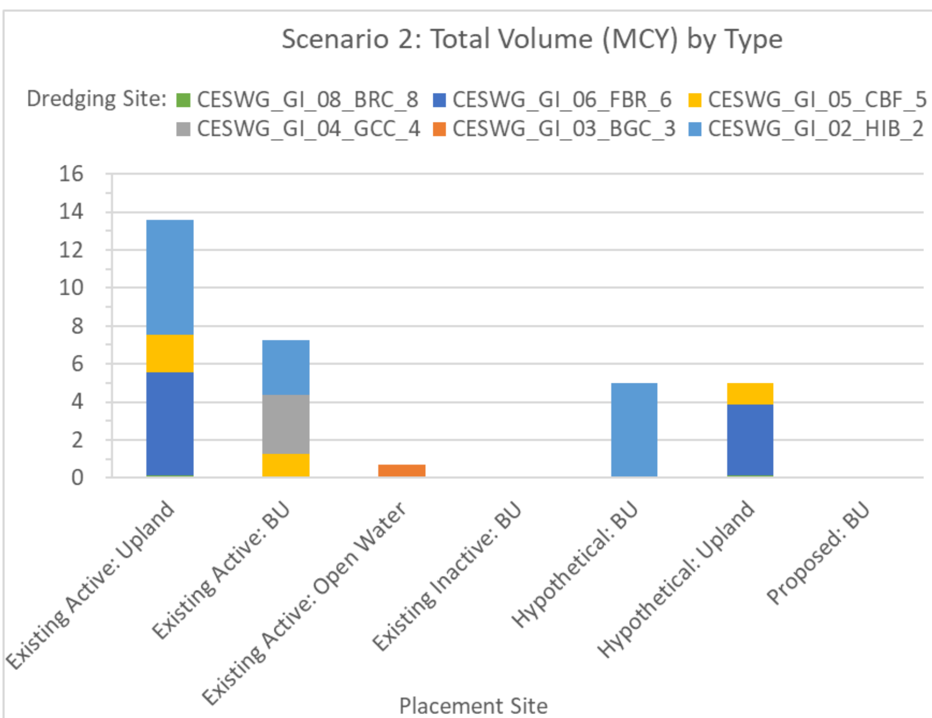
Appendix Figure 4.A12. *Detailed results for Scenario 8 showing the total volumes (millions of cubic yards) transferred between dredging and placement sites. Total volume is on the vertical axis, placement sites are on the horizontal axis, and dredging sites are in different colors. (Placement sites that received sediment from multiple dredging sites have total-volume bars of multiple color; placement sites that received the same total amounts of sediment have the same bar heights regardless of source(s); placement sites not used in this scenario are not shown.)*



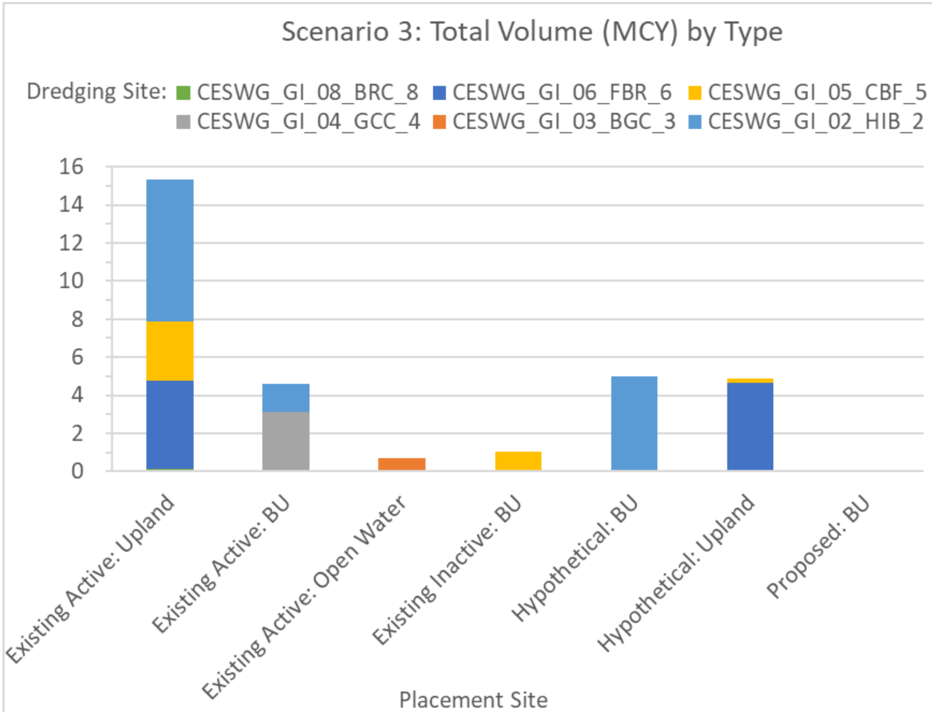
Appendix Figure 4.A13. *Detailed results for Scenario 9 showing the total volumes (millions of cubic yards) transferred between dredging and placement sites. Total volume is on the vertical axis, placement sites are on the horizontal axis, and dredging sites are in different colors. (Placement sites that received sediment from multiple dredging sites have total-volume bars of multiple color; placement sites that received the same total amounts of sediment have the same bar heights regardless of source(s); placement sites not used in this scenario are not shown.)*



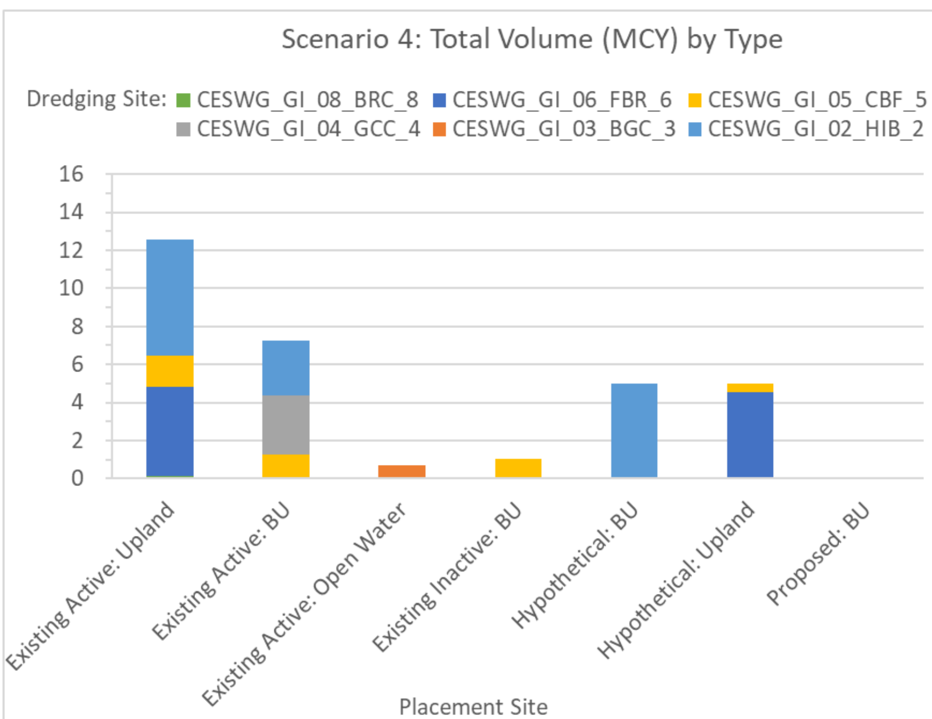
Appendix Figure 4.A14. *Detailed results for Scenario 1 showing the total volumes (millions of cubic yards) transferred between dredging sites and types of placement sites. Total volume is on the vertical axis, types of placement sites are on the horizontal axis, and dredging sites are in different colors.*



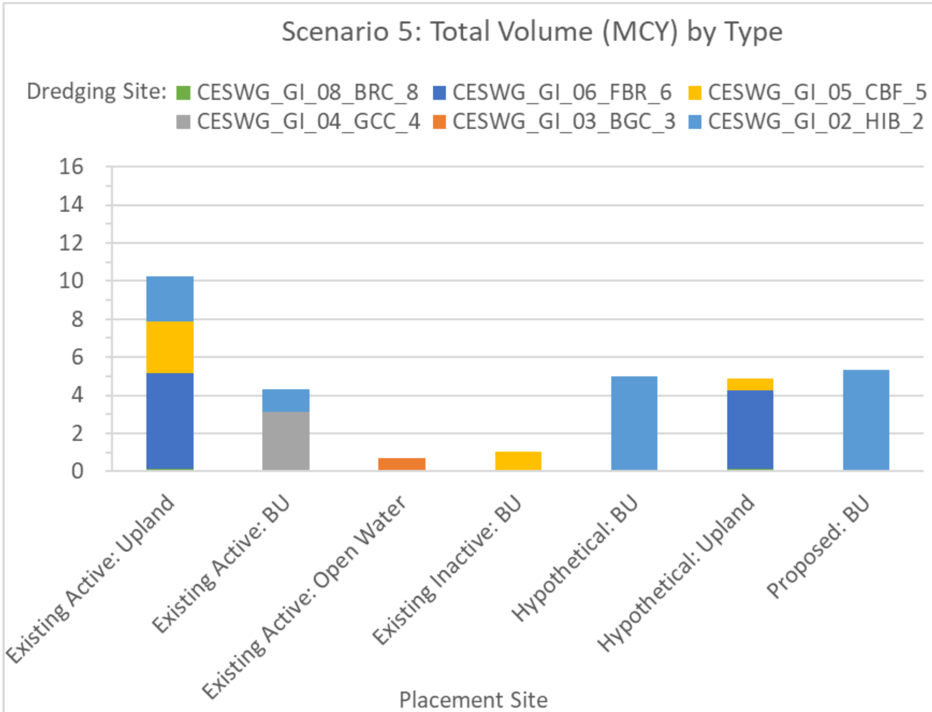
Appendix Figure 4.A15. *Detailed results for Scenario 2 showing the total volumes (millions of cubic yards) transferred between dredging sites and types of placement sites. Total volume is on the vertical axis, types of placement sites are on the horizontal axis, and dredging sites are in different colors.*



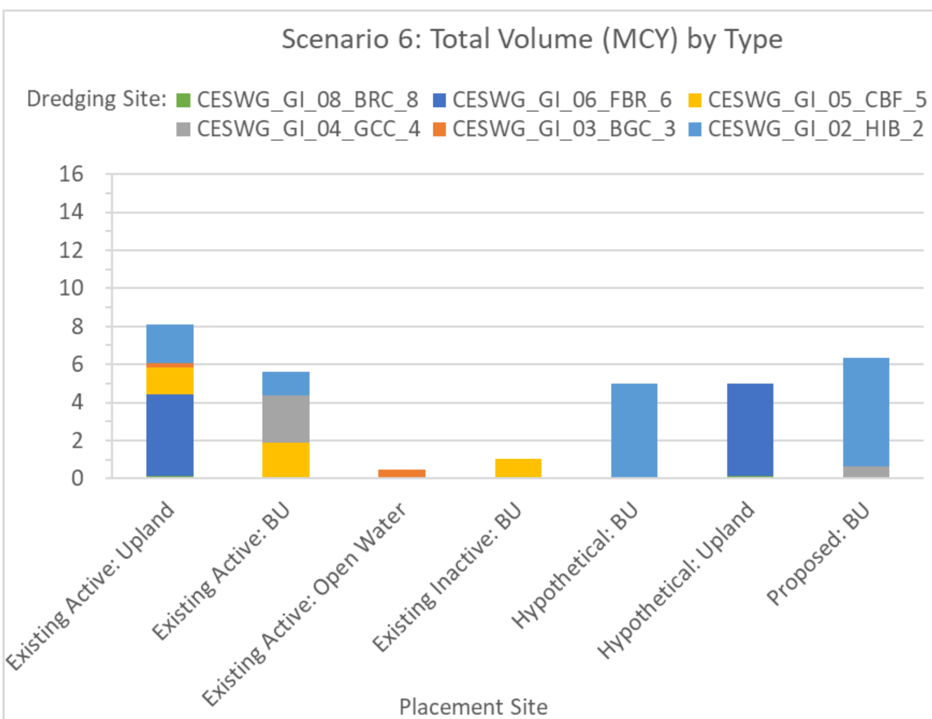
Appendix Figure 4.A16. *Detailed results for Scenario 3 showing the total volumes (millions of cubic yards) transferred between dredging sites and types of placement sites. Total volume is on the vertical axis, types of placement sites are on the horizontal axis, and dredging sites are in different colors.*



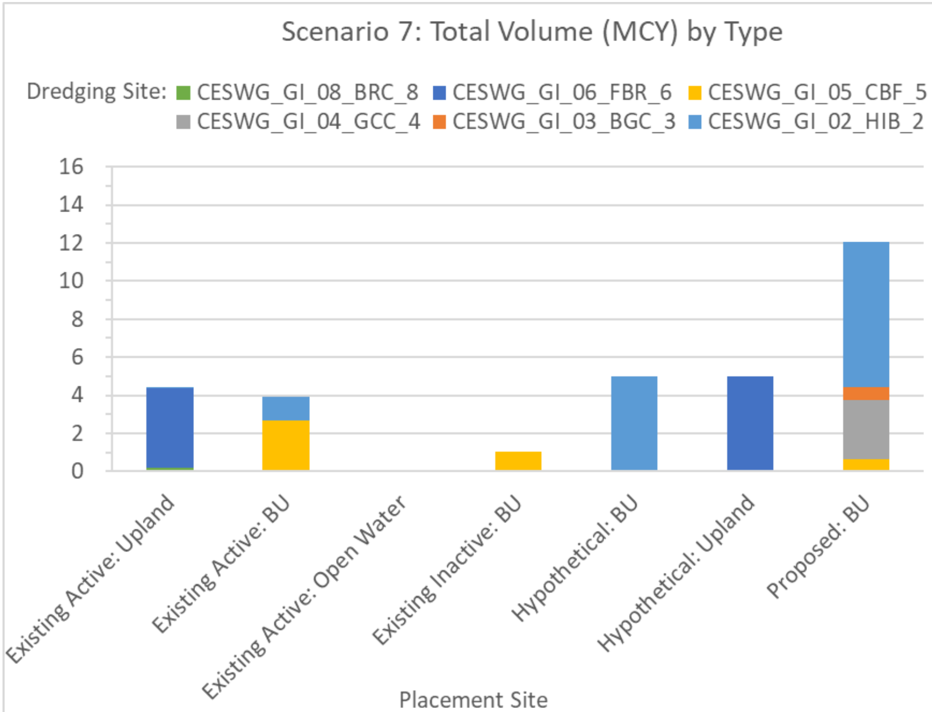
Appendix Figure 4.A17. *Detailed results for Scenario 4 showing the total volumes (millions of cubic yards) transferred between dredging sites and types of placement sites. Total volume is on the vertical axis, types of placement sites are on the horizontal axis, and dredging sites are in different colors.*



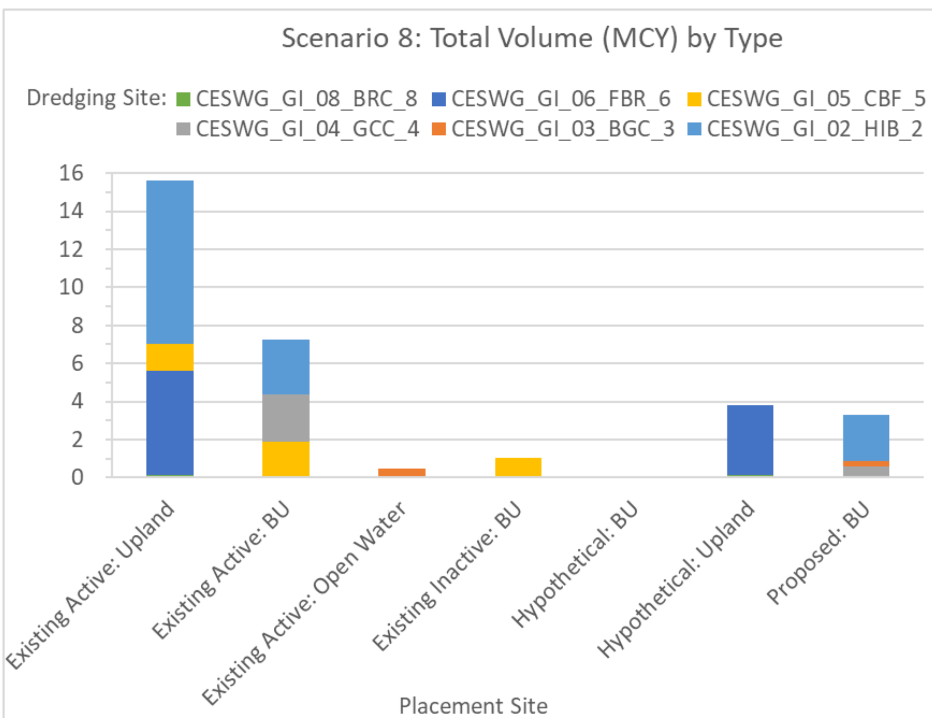
Appendix Figure 4.A18. *Detailed results for Scenario 5 showing the total volumes (millions of cubic yards) transferred between dredging sites and types of placement sites. Total volume is on the vertical axis, types of placement sites are on the horizontal axis, and dredging sites are in different colors.*



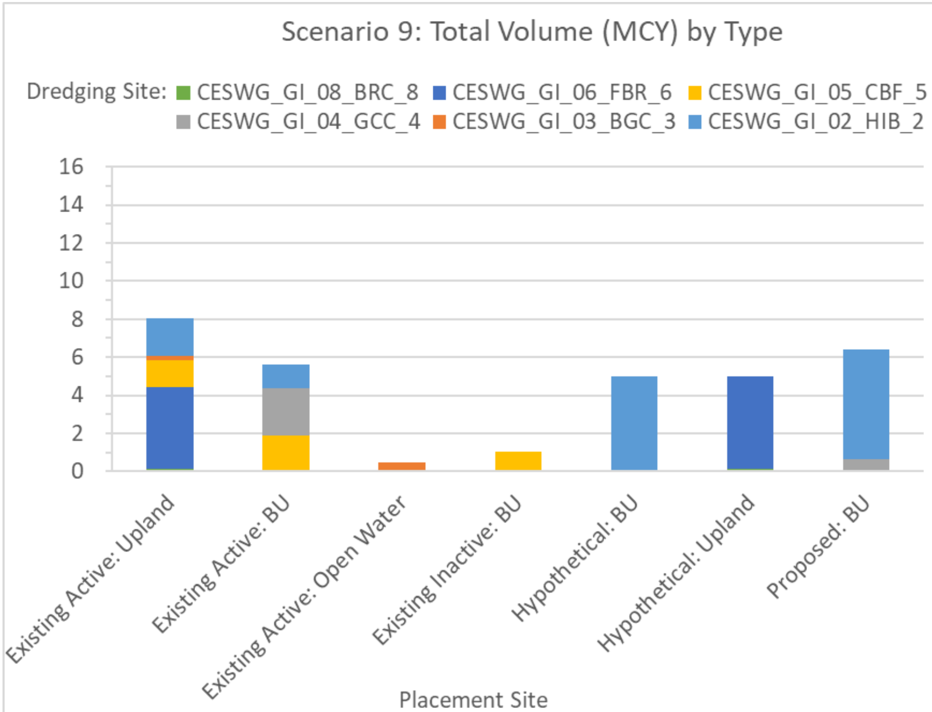
Appendix Figure 4.A19. *Detailed results for Scenario 6 showing the total volumes (millions of cubic yards) transferred between dredging sites and types of placement sites. Total volume is on the vertical axis, types of placement sites are on the horizontal axis, and dredging sites are in different colors.*



Appendix Figure 4.A20. *Detailed results for Scenario 7 showing the total volumes (millions of cubic yards) transferred between dredging sites and types of placement sites. Total volume is on the vertical axis, types of placement sites are on the horizontal axis, and dredging sites are in different colors.*



Appendix Figure 4.A21. *Detailed results for Scenario 8 showing the total volumes (millions of cubic yards) transferred between dredging sites and types of placement sites. Total volume is on the vertical axis, types of placement sites are on the horizontal axis, and dredging sites are in different colors.*



Appendix Figure 4.A22. *Detailed results for Scenario 9 showing the total volumes (millions of cubic yards) transferred between dredging sites and types of placement sites. Total volume is on the vertical axis, types of placement sites are on the horizontal axis, and dredging sites are in different colors.*