Appendix E

DMDU Overview and Approach

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Appendix E. DMDU Overview and Approach

E.1 Introduction

Uncertainty is a major challenge for the Post-2026 planning process. In the medium-to- long-term (e.g. 5 to 30 years), future streamflow conditions are the predominant driver of the impacts associated with each alternative (Smith et al., 2022). Future hydrology is expected to be drier (Lukas and Payton, 2020, p. 385, 2020; Salehabadi et al., 2022; Wang et al., 2025), but the magnitude and rate of drying is unknown. Not only are future streamflow conditions uncertain, but there is no scientific consensus on how to characterize the uncertainty probabilistically (i.e. the likelihood that a given hydrologic scenario will occur). This is known as deep uncertainty (Lempert, Popper and Bankes, 2003; Kwakkel and Haasnoot, 2019).

The analytical framework used in the Draft Environmental Impact Statement (DEIS), called Decision Making Under Deep Uncertainty (DMDU), is a non-probabilistic approach that seeks to provide reliable conclusions about robustness – the ability of an alternative to perform acceptably well across a broad range of future conditions (McPhail et al., 2018; Bonham et al., 2024) – and vulnerability – conditions associated with an alternative performing poorly (Bryant and Lempert, 2010; Bonham, Kasprzyk and Zagona, 2025).

The purpose of this appendix is to provide an overview of DMDU, document the specific implementation in the DEIS, and describe the collaborative process that enabled its implementation.

This appendix is structured as follows. **Section E.2**, Background, motivates the need for DMDU and provides an overview of key concepts. **Section E.3**, Methods, describes the specific methods used in the DEIS. **Section E.4**, Outreach and Collaboration, describes the training and collaborative efforts that were necessary to use DMDU in the DEIS. **Section E.5** provides a summary of previous sections.

E.2 Background

Uncertainty is often accounted for using probabilistic risk analysis, but risk analysis has several limitations for problems facing deep uncertainty. Risk analysis, in this context, uses a simulation model (such as the Colorado River Simulation System [CRSS]) to evaluate system outcomes over time (such as monthly reservoir elevations) across an ensemble of traces (Wheeler et al., 2022; Reclamation, 2024). Then, risk can be evaluated as the percent of traces in which a critical performance threshold is crossed, for example, percent of traces where Lake Powell elevation falls below minimum power pool (3,490 feet).

Each ensemble represents a narrative or a set of assumptions about the future, such as 'future hydrology has similar magnitudes to the past 30 years' (Lukas and Payton, 2020, p. 346) or 'future hydrology will continue to decline at current trends but with increased variability' (Salehabadi et al., 2025). Understanding this assumption is critical because risk percentages can be highly sensitive to the set of traces used. If there is uncertainty about the most appropriate set of assumptions, i.e., deep uncertainty, it is difficult to have confidence in any specific risk percentage, much less determine that it is sufficiently low. If the future proves to be more difficult than the assumed ensemble suggests, risk analysis can lead to a narrow view of what negative impacts are plausible and unintentionally steer decision-makers away from addressing them; if a future is more favorable than was assumed, the analysis can result in decisions that are unnecessarily expensive or austere.

As an alternative to risk-based decision making, Decision Making Under Deep Uncertainty (DMDU) is a well-established branch of decision science that seeks to provide reliable and actionable information about decision alternatives when faced with deep uncertainty (Kasprzyk et al., 2013; Herman et al., 2015; Maier et al., 2016; Marchau et al., 2019; Hadjimichael et al., 2020).

DMDU has three key elements: testing decision alternatives in a broad range of plausible future conditions, robustness analysis, and vulnerability analysis. This section explains these concepts in the context of the DEIS to provide concrete examples.

1) Each alternative (e.g., No Action, Maximum Operational Flexibility) is tested using simulation models in a large ensemble of streamflow traces. This ensemble is statistically designed to include a broad range of conditions, including those outside of the observed record, and the design also minimizes 'gaps' in the types of conditions being tested (See Appendix F, Approach to Hydrologic Uncertainty). The goal is to maximize the available information about how each alternative performs across a diverse set of traces, rather than predicting the likelihood of an outcome.

2) Alternatives are ranked according to their ability to maintain a specified performance level across a large percentage of traces (robustness). Robustness differs from risk because a) the set of traces being evaluated explores a much broader set of conditions and b) the emphasis is relative comparison of the alternatives (i.e. ranking from most to least robust) rather than a likelihood of success or failure.

3) Vulnerability analysis discovers the conditions in which an alternative is likely to satisfy or fail to meet a given performance level. Here, 'conditions' refer to the values of statistics describing annual natural flow at Lees Ferry in each streamflow trace. Example streamflow statistics include average annual streamflow during the worst 10-year drought and the driest single year (see **Section E.3**). An example conclusion from vulnerability analysis is that the Supply Driven alternative is likely to fall below 3,500 feet if there is a 10-year drought drier than 11.9 MAF/year, on average (see **Figure TA 3-8**). This is powerful information because it does not depend on any single hydrology ensemble being the 'correct' representation of the future (recall, deep uncertainty means there is no consensus on what future hydrology is 'correct'). And, when compared to historical extremes, it provides actionable insights. For example, the worst 10-year drought on record averaged 11.8 MAF/year (2012-2021). So,

unless future conditions are wetter than recent hydrology, it can reasonably be expected that the Supply Driven alternative will result in Lake Powell falling below 3,500 feet.

E.3 Methods

DMDU begins by evaluating each decision alternative in a large set of traces using simulation models. The set of traces used in this study includes 400 hydrologic traces (see **Appendix F**, Approach to Hydrologic Uncertainty) combined with 3 sets of initial reservoir storage conditions (see **Appendix G**, CRSS Initial Conditions Conditions) for a total of 1,200 simulations per alternative per model. Each combination of a hydrologic trace and initial condition is called a future. Because the DEIS covers many resources, many models were used, such as CRSS (hydrologic and water deliveries resources), GTMax (electrical power resources), temperature models (water quality and fish resources), smallmouth bass models, and dust emission models (air quality), to name a few (see the technical appendices in **Volume III** for more information). The modeling period covers January 2027 to December 2060. These model runs produce large datasets describing how each alternative performs over time across various streamflow conditions. These datasets are then analyzed in the robustness and vulnerability analyses.

In the DEIS, robustness is defined as the percent of futures where a performance goal is satisfied (called the satisficing metric in DMDU literature) (McPhail et al., 2018; Bonham et al., 2024). Various other robustness metrics exist, but satisficing was chosen because the performance criteria can be tailored to each resource based on expert input (see **Section E.4**), and because it provides a clear connection to vulnerability analysis. Performance goals are defined using four components: a timeseries, a threshold, a preferred direction, and a frequency. For example, **Figure TA 3-7** evaluates the percent of futures in which monthly Lake Powell elevation (the timeseries) stays above (the preferred direction) 3,500 feet (the threshold) in 100% of months (the frequency). Robustness is evaluated for each alternative, and the resulting scores are used to rank the alternatives from most to least robust.

Next, vulnerability analysis applies a machine learning algorithm to accomplish two tasks (Bryant and Lempert, 2010; Bonham, Kasprzyk and Zagona, 2025). First, it identifies the streamflow statistic that is the most skillful predictor of whether a given alternative will satisfy or fail to meet a performance criteria. Second, it identifies the specific values of that statistic associated with achieving/failing the criteria. The subsequent paragraphs describe the streamflow statistics, the machine learning algorithm, and the method for evaluating accuracy.

Table E-1 lists the streamflow statistics included in the vulnerability analysis. Each streamflow statistic is calculated for each of the 1,200 futures. It is important that the statistics examine short (1- and 2-year), medium (5- and 10-year), and long-term (20- and 34-year) windows because the ability or inability to satisfy different performance levels can be more strongly associated with different durations than others. Likewise, conditions that describe both dry and wet conditions are included because some resources are prone to failure under dry conditions (e.g., Lake Powell elevation below 3,500 feet) while others are prone to failure under wet conditions (e.g., use of Glen Canyon Dam spillway). In addition to statistics that describe dry and wet conditions, the median of the 2-, 5-, 10-, and 20-year moving average natural flows were also tested to describe 'normal' conditions, but statistics in the dry or wet categories proved to be more skillful predictors for all analyses shown in **Volume III**.

Table E-1
Streamflow statistics tested in vulnerability analysis

Streamflow Statistic	Category
Minimum 1-year natural flow volume	Dry conditions
Average Lees Ferry natural flow during the driest 2-year period	
Average Lees Ferry natural flow during the driest 5-year period	
Average Lees Ferry natural flow during the driest 10-year period	
Average Lees Ferry natural flow during the driest 20-year period	
Maximum 1-year natural flow volume	Wet conditions
Average Lees Ferry natural flow during the wettest 2-year period	
Average Lees Ferry natural flow during the wettest 5-year period	
Average Lees Ferry natural flow during the wettest 10-year period	
Average Lees Ferry natural flow during the wettest 20-year period	
Median of the moving 2-year average Lees Ferry natural flow	Normal Conditions
Median of the moving 5-year average Lees Ferry natural flow	
Median of the moving 10-year average Lees Ferry natural flow	
Median of the moving 20-year average Lees Ferry natural flow	
2027-2060 Average Lees Ferry natural flow	Long-term average

The machine learning algorithm chosen for this analysis is the Patient Rule Induction Method (PRIM) (Bryant and Lempert, 2010). PRIM identifies values of the streamflow conditions that accurately separate the modeled futures into two categories (those that satisfied and those that failed to meet criteria). Although PRIM can test multiple streamflow statistics simultaneously, it was applied to one statistic at a time to maximize interpretability of the results.

Accuracy was evaluated with a two-step criteria. First, for each streamflow statistic, PRIM was used to identify the value such that at least 90% of futures that are predicted to satisfy the performance criteria actually do satisfy it (based on modeling output). Because the goal was to standardize the accuracy of results between alternatives and across resources as much as possible, the value that resulted in an accuracy closest to 90% was chosen[1]. This first step defines the value for each streamflow statistic and each alternative. In the second step, the streamflow statistic is selected that, on average across alternatives, has the highest accuracy at predicting a future will fail to meet the performance criteria.

[1] To standardize results as much as possible, the values of the streamflow statistics for all 1,200 futures were tested when evaluating accuracy. In PRIM literature, this implementation would be considered maximally 'patient'. The patience of the PRIM algorithm, as implemented in existing programming libraries, is controlled by the alpha parameter. To ensure all 1,200 futures were evaluated for the D EIS, a custom implementation of PRIM was programmed rather than using existing programming libraries.

E.4 Outreach and Collaboration

DMDU is a widely accepted branch of decision science in academic research (Bonham, Kasprzyk and Zagona, 2022; Gold et al., 2022), and it has been applied in several non-academic decision support studies (Dixon and RAND Center for Terrorism Risk Management Policy, 2007; Molina-Perez et al., 2019). Reclamation applied DMDU in the 2012 Colorado River Basin Water Supply and Demand Study (Reclamation, 2012; Groves et al., 2013) and has funded multiple research-oriented applications investigating annual operations at Lake Powell and Lake Mead (Alexander, 2018; Smith et al., 2022; Bonham et al., 2024).

The DEIS, however, is the first use of DMDU in a decision-making process in the Colorado River Basin where numerous resources are explicitly evaluated. This is a challenge that affords tremendous opportunity for Basin-wide, cross-discipline collaboration. It was necessary for Reclamation to provide education and training so that interested parties (e.g., Basin States, Tribes, partner federal agencies, Mexico) could interpret results and incorporate them into their planning activities. Further, it was necessary for Reclamation to collaborate with subject matter experts to define performance criteria. This section describes three key efforts towards achieving broader familiarity with DMDU in the Basin.

First, Reclamation developed the Integrated Technical Education Workgroup (ITEW) 'to ensure that Colorado River partners have a common and accurate understanding of the underlying tools and concepts needed to meaningfully participate in the development of Post-2026 operating alternatives' (Reclamation, 2023). The Research and Modeling team gave six educational and training webinars on topics including CRSS, hydrology, DMDU, and reservoir operations from May 2023 to November 2023 (www.usbr.gov/ColoradoRiverBasin/post2026/itew.html). Participants included Tribes, Basin States, municipalities, water and irrigation districts, non-governmental organizations, other federal agencies, researchers, and Mexico.

Second, Reclamation, in partnership with Virga Labs, developed and published the 'Colorado River Post-2026 Operations Exploration Tool' (hereafter, 'web tool'). The web tool is an interactive website (www.crbpost2026dmdu.org), launched in November 2023, that immerses the user in a guided, customizable DMDU analysis with a low barrier to entry. It is loaded with hundreds of operational strategies for Lower Basin reductions and releases from Lake Powell. The user can also create their own strategies using a variety of operational paradigms, which are then modeled in thousands of future scenarios using CRSS and cloud computing. The user defines performance requirements for the resources they are interested in, and the tool calculates robustness and vulnerability.

The web tool has been an important part of building familiarity with DMDU in the Basin. As of November 2025, 791 users have registered to use the web tool and 356 custom operational strategies have been created. It played a major role in shaping the Lower Basin shortage and Lake Powell release operations in the Maximum Operational Flexibility alternative. Further, the tool supported extensive collaboration between Reclamation, National Park Service, and Fish and Wildlife Service to define the performance goals that shaped the Lake Powell operations in the Enhanced Coordination alternative. Given the number of users and consistent use of the web tool over two years, it is assumed that many others gained valuable knowledge about how to use DMDU to evaluate creative operations in the Basin.

Third, Reclamation, in partnership with AECOM, has led a major collaborative effort with resource experts to define performance thresholds and perform the DMDU analyses presented in the DEIS. The DEIS includes over 100 total robustness and vulnerability analyses across 17 different resources. While Reclamation has the subject matter expertise to define the performance requirements for some resource categories, e.g., water deliveries and hydrology, many resources required input from subject matter experts beyond Reclamation. The collaborative process launched in May 2024 and has required 3 to 6 meetings per resource. Participants in the collaboration include the cooperating agencies, the USGS Grand Canyon Monitoring and Research Center, AECOM, SWCA, Hazen and Sawyer, among others (see List of Preparers, Chapter 6).

E.5 Summary

Due to the long-term planning horizon and deeply uncertain nature of hydrology, DMDU is the preferred analytical framework for the Post-2026 DEIS. The main elements of DMDU, as applied in the DEIS, are a hydrology ensemble that considers a broad range of hydrologic conditions, robustness analysis that ranks operational alternatives, and vulnerability analysis that discovers the streamflow conditions where alternatives satisfy or fail performance criteria. Reclamation has led several efforts leading up to the publication of the DEIS to build basin-wide familiarity with DMDU, including educational webinars, an interactive web tool, and numerous collaborative meetings with resource experts. The concrete product of these efforts is the analysis contained in the technical appendices in **Volume III** of the DEIS.

These collaborative efforts have also contributed to critical but difficult to quantify areas. This process has strengthened basin-wide, inter-agency and cross-discipline relationships. It has challenged people to grow in their understanding of the resource models this basin relies on for decision-making. And, it has created quantitative measures of performance for numerous resources where they may not have existed previously. Collectively, these 'growing-pains' have paved the way for DMDU as the analytical framework used in the DEIS, the first such multi-resource, basin-wide, decisional application in the Colorado River Basin.

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