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CISNET Junior Investigator Meeting

A Primer on Robust Decision Making for Health Policy

Pedro Nascimento de Lima

Assistant Policy Researcher, RAND Corporation

Ph.D. Candidate, Pardee RAND Graduate School

Visiting Student, Argonne National Laboratory

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Agenda

1. **What is RDM (10 minutes)**
    1. A brief primer on Robust Decision Making (RDM)
2. **RDM in Health: Early applications (5 minutes)**
    1. Robust Decision Making may be useful to Health modelers
        1. COVID-19 work: Stress-testing reopening strategies.
        2. Ongoing CRC Screening work: Evaluating Robustness to Assumptions.
3. **Ongoing and Future Work (5 minutes)**
    1. crcrdm package and ongoing work.

About Me

- Originally from **Brazil**., background in engineering and software. Before starting my PhD in the US, taught **Simulation modeling** for industrial engineering students.
- Used **Robust Decision Making on my master's dissertation**.
- Third-year **PhD candidate in Policy Analysis at RAND**.
- Working with **Carolyn Rutter (CRC Group CO-PI, IMABC, CRC-SPIN** creator)
- **Robert Lempert** (**RDM** creator) is my PhD advisor.
- Visiting student at **Argonne with Jonathan Ozik (HPC expert).**
- My CISNET work in one sentence: Leveraging HPC and RDM to inform CRC screening policy.

www.pedronl.com

Introduction to
Robust Decision Making

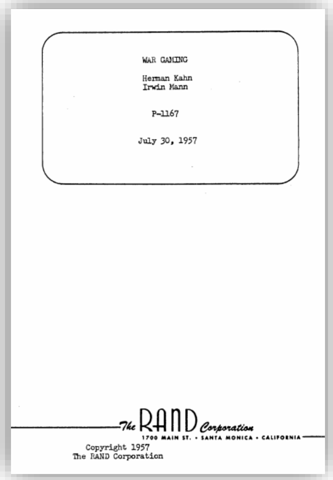
A Brief History of Robust Decision Making (at RAND)

1. RAND researchers were historically tasked to provide objective policy analysis for deeply uncertain problems.

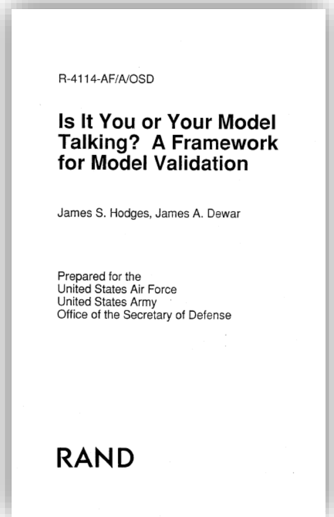
2. Most notably, these problems include **Nuclear strategy**, **military strategy / combat models**, **climate change, water resources management**, **coastal resilience**, etc.

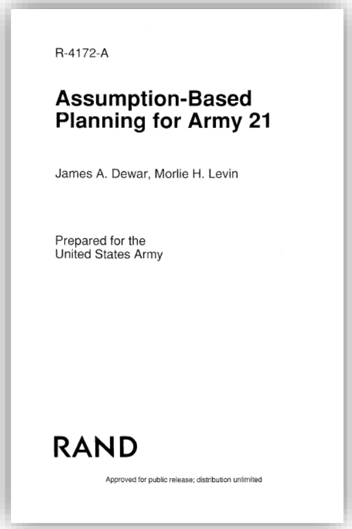
3. This demand for robust policy analysis led to the creation and refinement of a set of approaches for decision making under (deep) uncertainty. Many researchers have been associated with creating and refining methods for those conditions. They include:
    1. Herman Khan (Scenarios and US Nuclear Strategy)
    2. James Dewar (Assumption-Based planning)
    3. Robert Lempert, Steven Popper, and Steven Bankes (RDM)

A Brief History of RDM at RAND, cont'd



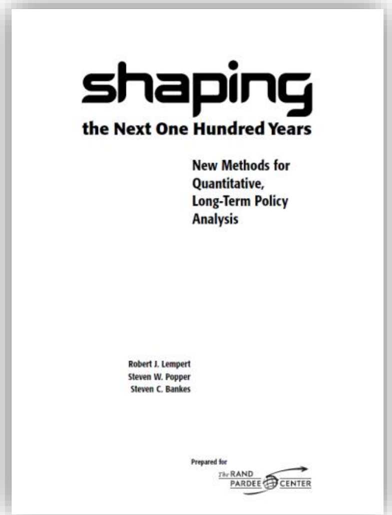
Khan (1957): "Military Planning in an Uncertain World" mentions the idea of "Real Uncertainty", later scenarios



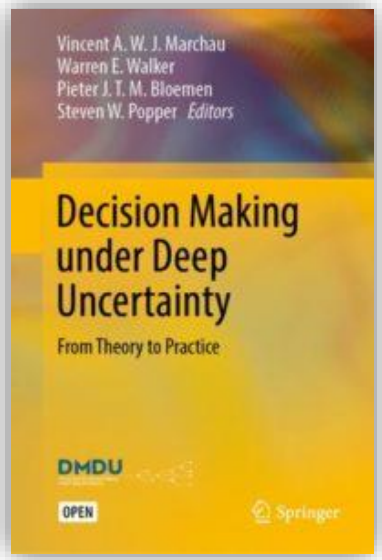


Dewar (1992): Assumption-Based planning, model validation and "validability"

Bankes (1993): Exploratory vs consolidative modeling



Lempert, Popper Bankes (2003): Robust Decision Making



DMDU Book (2019): RDM + other DMDU approaches

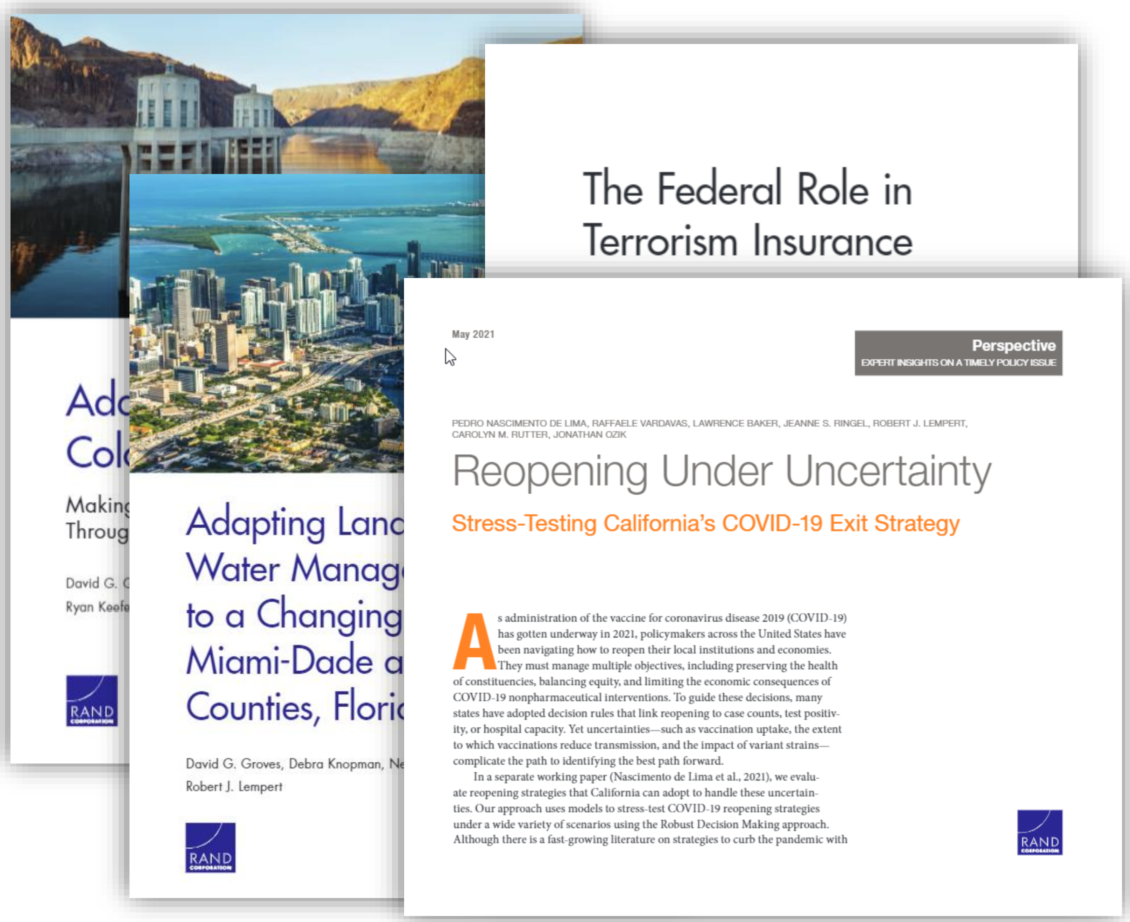
RDM has been used to inform decisions in many policy domains plagued with uncertainty

RDM has proven useful in policy areas as diverse as:

1. Water resources management
2. Coastal Resilience
3. Terrorism Insurance
4. COVID-19

List of RAND publications:

https://www.rand.org/topics/robust-decision-making.html



RDM draws from four frameworks to address uncertainty

1. **Decision Analysis**: RDM is a Decision Analytical approach. We use the same components of any DA analysis – a list of options, criteria for decision, and multiple uncertainties that define States of the World over which policies are evaluated.

2. **Scenarios:** RDM uses the idea of "multiple plausible futures" from scenario analysis. But scenario analysis techniques alone do not provide a quantitative basis for decision making.

3. **Assumption-Based Planning:** Provides a qualitative approach to "stress-test" strategies. RDM follows a process similar to ABP, but with quantitative analysis.

4. **Bankes' (1993) Exploratory Modeling:** RDM uses "exploratory modeling" to integrate 1, 2 and 3. We use models to investigate decisions under multiple plausible futures, seeking to characterize and improve the robustness of decisions.

Lempert (2019) discusses the reasons why RDM uses and complements these approaches.

When Uncertainties abound, relying critically on “best-guess” assumptions can be a dangerous bet

When uncertainties are significant, there are good reasons to be wary of analyses that rely critically on our “best guesses” of the future because:

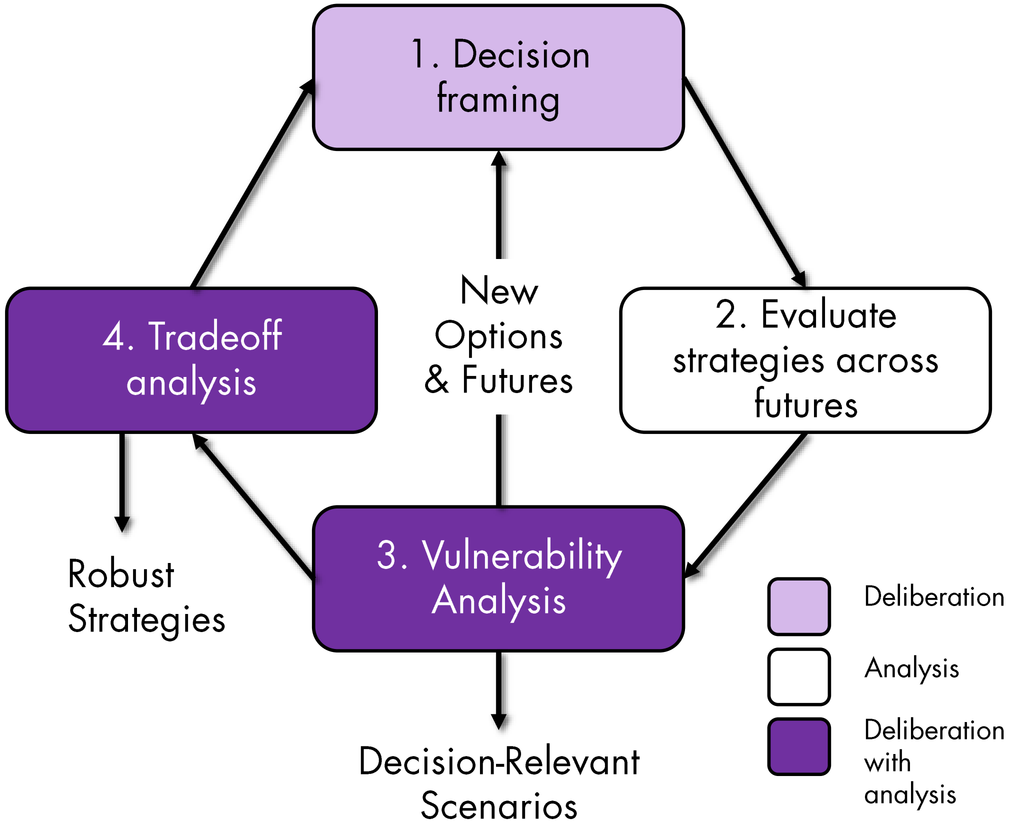
1. **They can be easily challenged.** Future modelers can always modify parameters and the parameter space and *may* find that prior studies results were not robust – ignoring uncertainty is a liability.
2. ***Strategies that are Optimal* in our best-guess definition of the world are not guaranteed to be *robust***.
3. **As our knowledge evolves and the future unfolds**, strategies based on our best-guess of the future can fail, ***sometimes* in predictable ways**.

The solution to these issues **is <u>not</u> to abandon or discredit model-based analyses**. Instead, modelers can be more proactive to confront uncertainty and find weaknesses of their model-recommended strategies ***before others do***. Doing so may reveal better, robust strategies when they exist.

The RDM Process

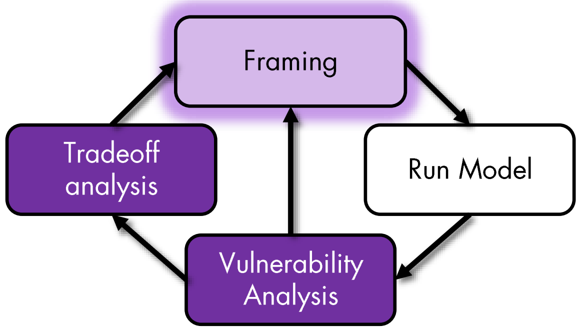
RDM is an ***iterative framework*** for evaluating and crafting policies under uncertainty. RDM work is often organized within four iterative steps:

1. **Decision Framing:** Defines the Policy Levers, Uncertainties, Outcomes of Interest and relationships involved in the decision-making problem.
2. **Evaluate Strategies across futures:** Perform a stress-test of each strategy in an ensemble of plausible states of the world.
3. **Vulnerability Analysis**: Characterize the robustness of strategies and identify conditions under which policies fail.
4. **Tradeoff Analysis:** Provide information on inescapable tradeoffs after robustness was characterized.



Clarifying RDM terminology

1. **A “Future” or “state of the world”**: Represents a set of assumptions we make about how the world works and will work over the course of the decision we need to make. A state of the world is codified as a single model structure together with values for each model parameter.
2. **An ensemble:** A collection of “states of the world”. Conceptually, it can include multiple models.
3. **Parameter Space:** The multi-dimensional space that represents the ensemble.
4. **Policy Lever or “lever”:** A single decision variable.
5. **A Strategy:** A strategy specifies how decision variables are combined to achieve one or multiple goals.
6. **A Robust Strategy:** A strategy that performs well compared to the alternatives across a specified ensemble.



1. Decision Framing - XLRM

Sampling from the "full" ensemble is impossible because we cannot feasibly evaluate policies across all plausible model structures, uncertainties and outcomes of interest. Decision framing is therefore an important step to constrain the analysis.

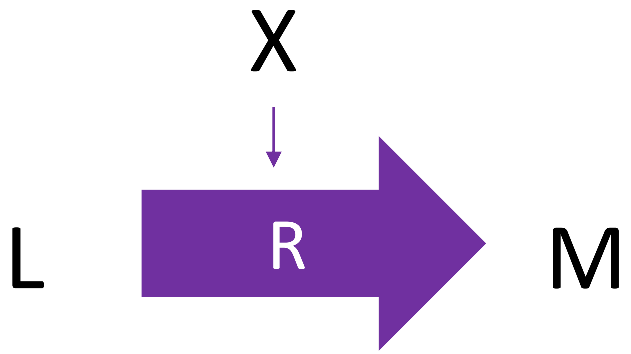
In this step, RDM studies often use an "XLRM" framework to define:

i. **X - The Uncertainties** relevant to a decision problem. These are factors outside of the control of decision makers.

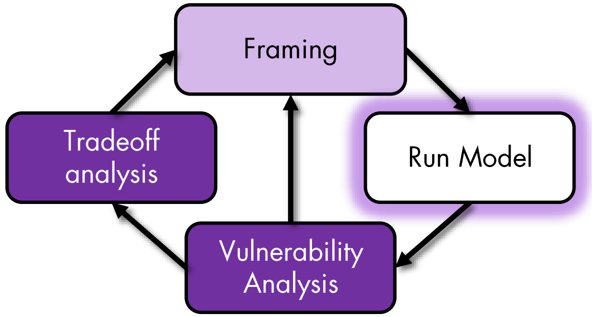
ii. **L – The Policy Levers**, and thus strategies to be evaluated.

iii. **M – The Outcome Metrics** to be used for decision making.

iv. **R – The relationships** that link X and R to M. RDM will often use models with a mechanistic link between levers and outcomes.

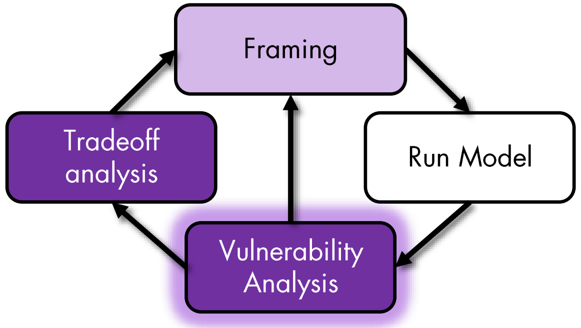


One can always tear apart an analysis with a poor or incomplete framing. Forecasting exercises ignore or confuse "L's" with X's. Any decision analysis **necessarily** includes the four elements even when it poorly represents one of those elements.



2. Evaluate Strategies across futures

1. Sample from “X” and create a list of strategies based on “L”.
2. Evaluate each strategy in each “future”. Compute outcomes of interest.
3. Choosing which “futures” are plausible can be hard and is done differently for different types of models.
4. Create a database of model runs that were used to stress-test policies.

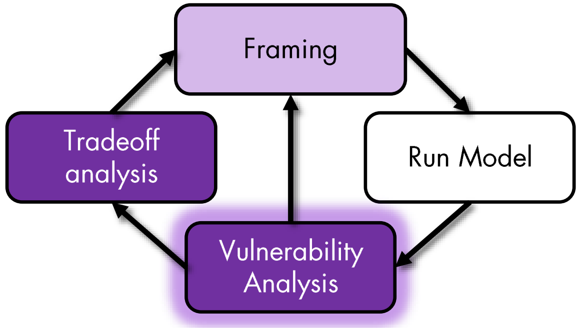


3. Vulnerability Analysis

1. RDM studies often use regret-based robustness metrics to characterize the robustness of policies (See Lempert 2009, box 2.2 for details).
2. This step allows us to characterize the **robustness** of strategies based on their performance across the ensemble.
3. If initial strategies are robust across the ensemble, that is a "good" finding.
4. When strategies are **not robust** across the ensemble, one can use "Scenario discovery" algorithms (e.g. PRIM) to:
    1. Determine if vulnerabilities can be attributed to specific ***regions*** of the parameter space.
    2. When they can, determine under which conditions strategies will fail.
    3. If this is the goal of the analysis, propose improved, robust strategies.

3. Vulnerability Analysis – Robustness Metrics

included here for completeness, read Lempert (2019)

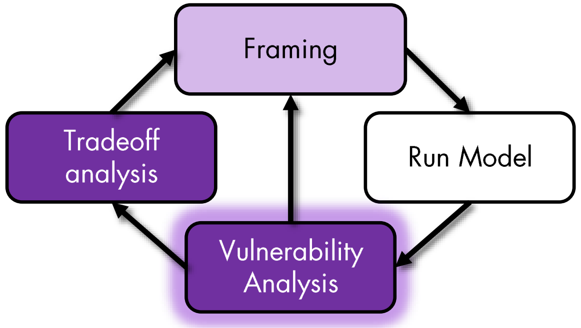


Consider a set of strategies s_i evaluated in states of the world f_j, resulting an outcome measure u_{ij}. Under the maximum expected utility framework, we would choose the strategy that $\max_i \sum_j p_j u_{ij}$. When we don't trust or lack these probabilities, one can just assume states of the world are equally likely (Laplace criterion) or other traditional decision analysis under uncertainty criteria:

1. Wald: Best Worse case: $\max_i \min_j \left(u_{ij}\right)$
2. Savage's Mini-max Regret: $\min_i \max_j \left[\max_i\left(u_{ij}\right) - u_{ij}\right]$
3. Hurcwicz (weighted average): $\max_i \left[\alpha \max_j\left(u_{ij}\right) + (1-\alpha) \min_j\left(u_{ij}\right)\right]$

We can rank and choose strategies according to those criteria. But the point of RDM is to discover *why* ***strategies fail and build better, robust strategies. So we do a little more work.***

3. Vulnerability Analysis – Robustness Metrics
included here for completeness, read Lempert (2019)

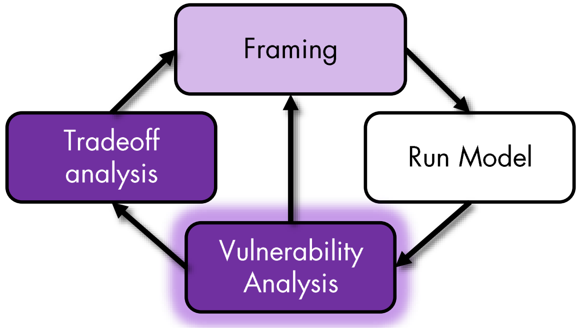


RDM studies often use extensions of these basic decision criteria depending on the question being asked.

For example, we can ask "which strategies result in low regret over most of the futures?". To answer this question, we can:

1. Compute **regret** for every strategy s_i in future f_j as $r_{ij} = \max_i(u_{ij}) - u_{ij}$. We can use a percentile of the regret distribution of strategies as a robustness metric.
2. Define a **high regret** indicator variable $R_{ij} = \begin{cases} 1, if\, r_{ij} > r_{max} \\ 0, \; otherwise \end{cases}$
3. Use the **high-regret** R_{ij} variable and/or the **regret** variable r_{ij} to **characterize vulnerability**.

Now, we look at the parameter space that defines f_j and investigate under which conditions strategies fail.



3. Vulnerability Analysis, continued

included here for completeness, read Lempert (2019)

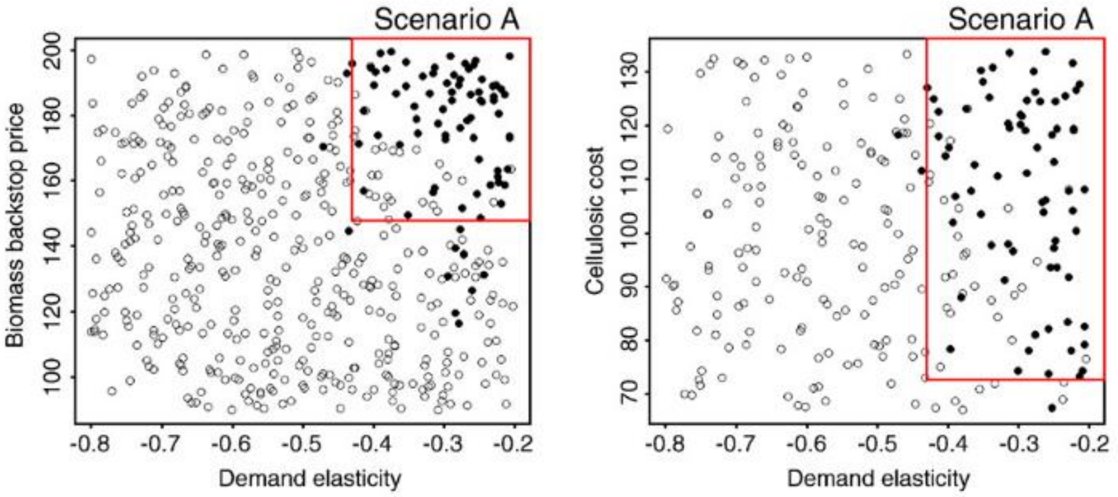
1. Scenario Discovery algorithms (e.g. PRIM) can be used to find clusters in the parameter space that explain the conditions under which strategies fail.

2. In the limit, you can use any classification algorithm to model $R_j = f(\boldsymbol{\theta}, s_j)$.

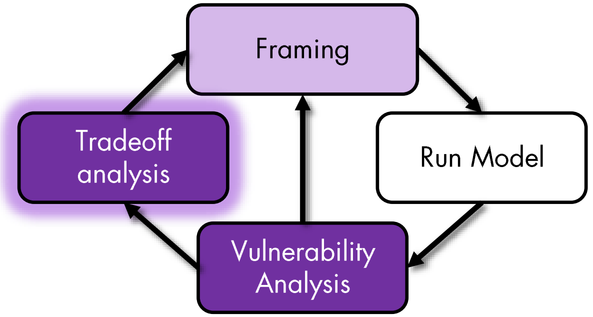
3. We tend to use algorithms that result in meaningful, interpretable statements (e.g., **CART** and **PRIM**): **E.g., if parameter a > *x* and b < *y, then the policy fails.***

4. This can be useful to bound conditions of concern – it can reveal **what needs to be true so that we would regret recommending a set of policies.**

5. ML can be used if we want to, but **the point is to explain in simple terms the conditions under which we will regret a certain decision**.



Bryant BP, Lempert RJ (2010)



4. Tradeoff Analysis

1. At some point, a decision needs to be made and the process needs to end.
2. Tradeoff analyses can demonstrate important remaining tradeoffs between outcomes of interest or states of the world.
3. Each RDM analysis emphasizes different types of tradeoffs. This step will often characterize:
    1. Tradeoffs arising from balancing multiple goals
    2. Tradeoffs arising from believing in different states of the world

RDM analyses will often refrain from offering a single-best option but will illuminate tradeoffs among strategies and seek to offer a menu of **non-dominated options.**

Back to the RDM Process

RDM is an ***iterative framework*** for evaluating and crafting policies under uncertainty

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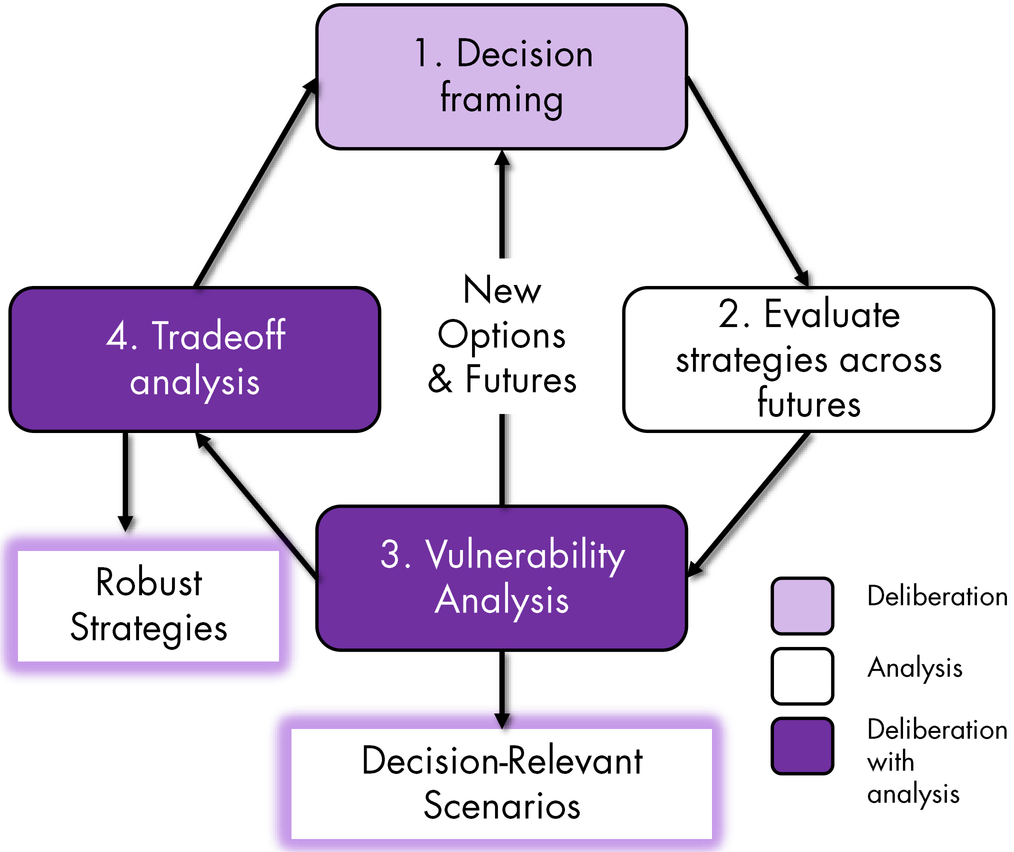
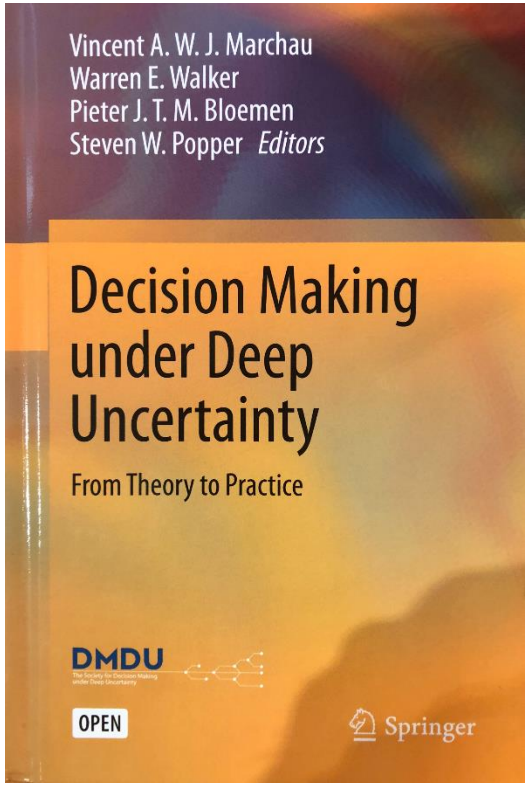


RDM is part of a family of methods called Decision making under deep uncertainty (DMDU) methods

Deep Uncertainty is the condition in which analysts do **not know** or the parties to a decision **cannot agree on**:

1. The **appropriate models** to describe the interactions among a system's variables;
2. The **probability distributions to represent uncertainty about key parameters**;
3. How to **value the desirability** of alternative outcomes.

Responsible decision support in those conditions **call for a thorough assessment of the robustness of alternative policies to those assumptions**.



DMDU Society: https://www.deepuncertainty.org/

RDM in Health Policy

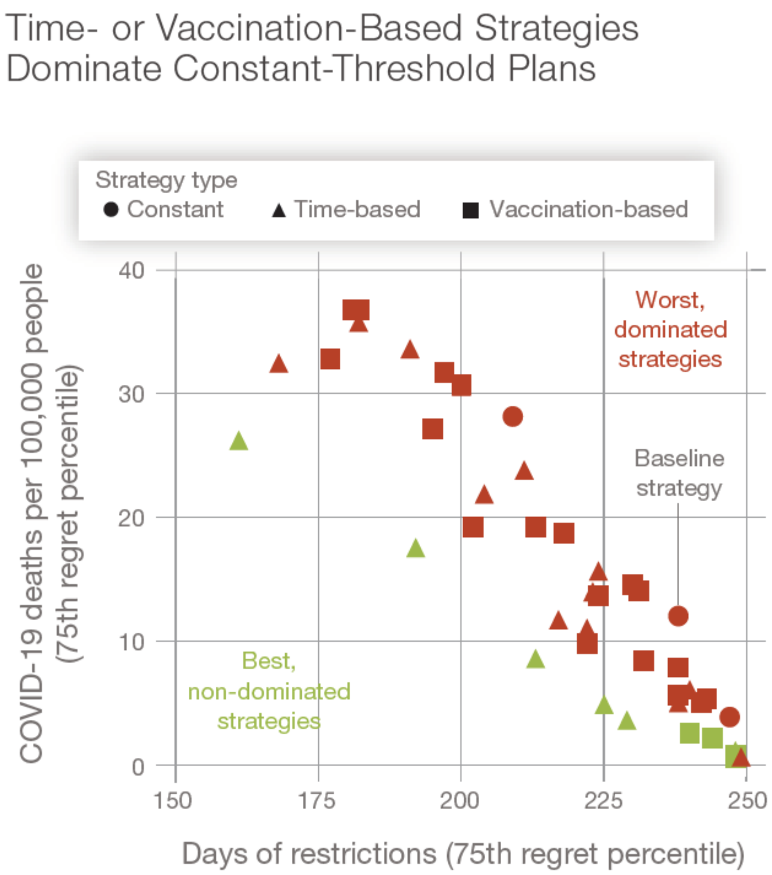
Recent Application:

Stress-testing COVID-19 reopening plans

1. We evaluated **78 COVID-19 alternative reopening strategies, each under 20,000 scenarios**
2. Our analysis revealed that some **strategies can be robust in terms of reducing deaths, but they could be dominated**.
3. Best exit strategies **combined high initial levels of stringency with relaxation rules contingent on vaccination**.
4. This approach **allowed us to account for uncertainties of concern** (e.g., new variant strains, loss of immunity, vaccine hesitancy, etc.).

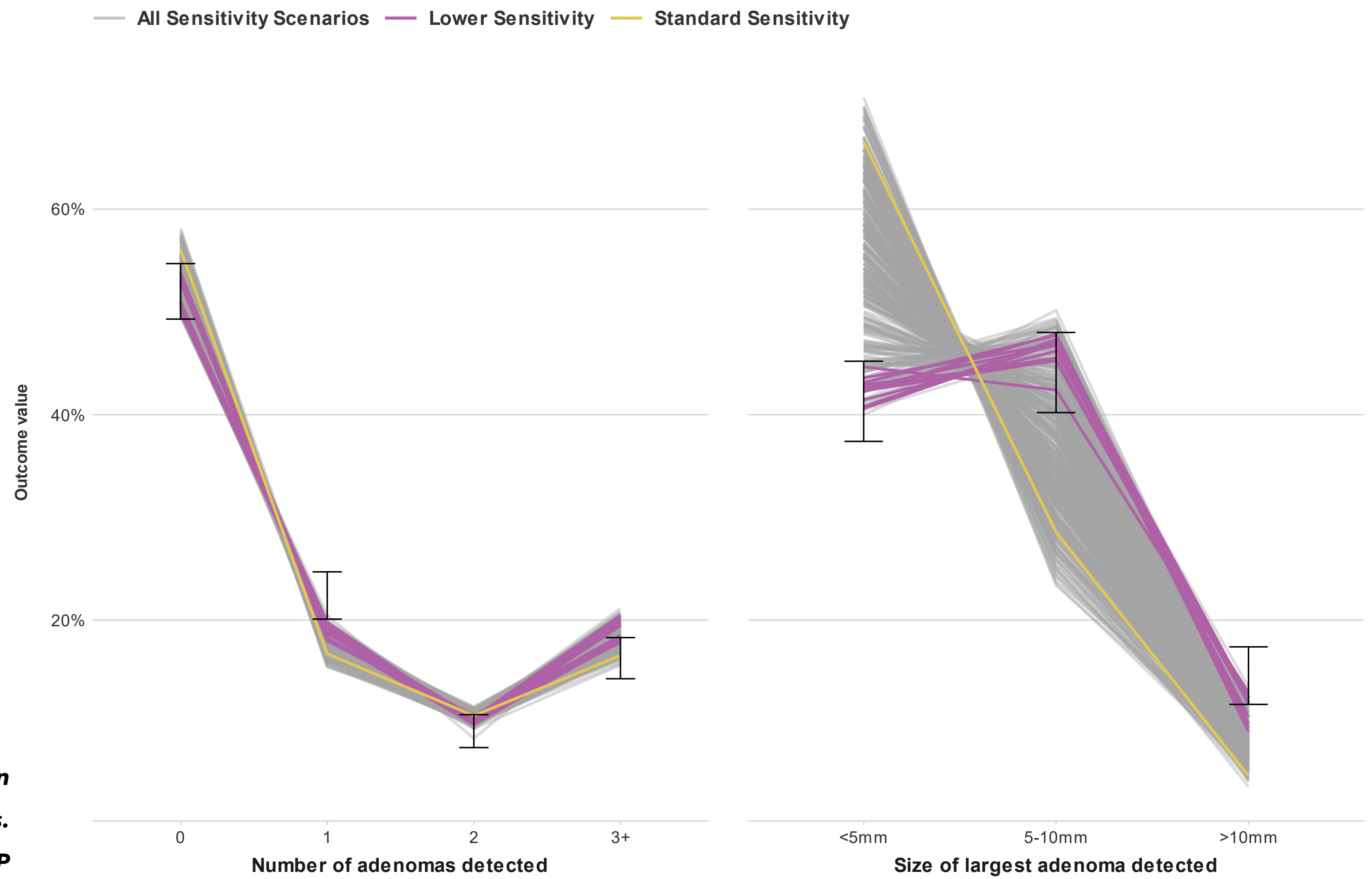
Nascimento de Lima et al, 2021. Reopening California: Seeking Robust, Non-Dominated COVID-19 Strategies. PLOS ONE.

https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0259166



Lack of confidence in your assumptions is likely a good reason to stress-test policies

1. **Outcomes from the Wheat Bran Fiber (WBF) is not compatible with commonly-used colonoscopy sensitivity assumption and CRC-SPIN.**
2. **Current model needs lower sensitivity to small adenomas to explain the data.**
3. We will further investigate these issues by evaluating the implications of uncertain assumptions.



Rutter, Nascimento de Lima, Lee, Ozik. Too Good to Be True? Evaluation of Colonoscopy Sensitivity Assumptions Used in Policy Models. Provisionally accepted in CEBP

RDM may be helpful to CISNET modelers, but there are a few hurdles in our way

1. Calibrating a model can be hard and time-consuming.
2. Credible microsimulation models that reflect heterogeneity are often memory-hungry and take a long time to run.
3. Addressing structural uncertainty can be a daunting process with little reward

Yes, there are a few hurdles in our way – but they are surmountable

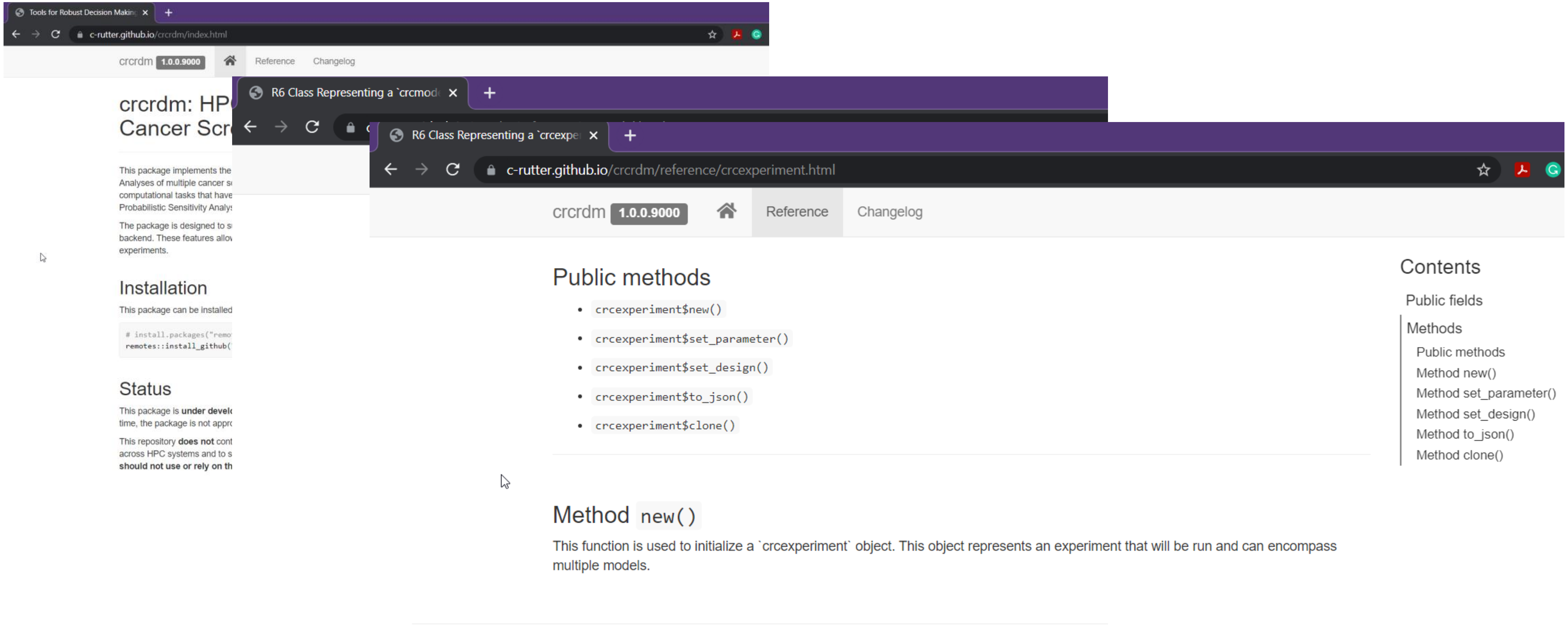
1. Calibrating a model can be hard and time-consuming
    1. **“Plug-and-play” Bayesian calibration approaches now exist and are increasingly used.**
2. Credible microsimulation models that reflect heterogeneity are often memory-hungry and take a long time to run.
    1. **Academic clusters and HPC resources can be efficiently employed if models are well-designed.**
3. Addressing structural uncertainty can be a daunting process.
    1. **This is still true, but structural uncertainties can be addressed if they are not an afterthought in the analysis. Comparative modeling mitigates this concern.**

crcrdm*: An R package to support cancer screening uncertainty analyses with HPC resources

1. Handles experimental designs with a natural history and a screening component
2. Handles results from Bayesian Calibration
3. Accommodates multiple models
4. Supports large-scale experiments on HPC systems with EMEWS
5. Efficiently handles long-running tasks

*dev. version, not ready for general use: https://c-rutter.github.io/crcrdm/

crcrdm*: An R package to support cancer screening uncertainty analyses with HPC resources



*dev. version, not ready for general use: https://c-rutter.github.io/crcrdm/

Opportunities for other modelers

1. RDM is closely aligned with the goals of other uncertainty analysis approaches, such as VOI.
2. The same infrastructure to **run** the model for an RDM analysis can be used for VOI analyses and vice-versa – but the approaches differ in their goals.
3. Modelers already have a wide range of approaches to tackle uncertainty – and computing power is no longer a constraint.

Key take-aways

1. RDM may offer contributions to cancer modelers.
2. RDM is not a substitute for VOI and other approaches, but it is a different framework and process that places more emphasis on robustness.
3. Using RDM requires large-scale computing and we are developing tools to support these large-scale experiments.
4. Key goal is to **evaluate and improve** the **robustness of strategies** by purposefully stress-testing strategies with models.

Short list of RDM publications

1. **Applications:**
   1. Nascimento de Lima, P., Vardavas, R., Baker, L., Ringel, J., Lempert, R. J., Rutter, C. M., & Ozik, J. (2021). *Reopening California: Seeking robust, non-dominated COVID-19 exit strategies.* https://journals.plos.org/plosone/article/comments?id=10.1371/journal.pone.0259166
   2. Nascimento de Lima, P., Vardavas, R., Baker, L., Ringel, J., Lempert, R. J., Rutter, C. M., & Ozik, J. (2021). *Reopening Under Uncertainty: Stress-Testing California's COVID-19 Exit Strategy*. https://www.rand.org/pubs/perspectives/PEA1080-1.html
   3. Groves, D. G., Fischbach, J. R., Bloom, E., Knopman, D., & Keefe, R. (2013). *Adapting to a Changing Colorado River Making Future Water Deliveries More Reliable Throught Robust Management Strategies*. https://doi.org/10.1214/07-EJS057
   4. Dixon, L., Lempert, R. J., LaTourrette, T., & Reville, R. T. (2007). *The Federal Role in Terrorism Insurance: Evaluating Alternatives in an Uncertain World.*

2. **Methods:**
   1. Lempert, R. J., Popper, S. W., & Bankes, S. C. (2003). *Shaping the Next One Hundred Years: New Methods for Quantitative, Long-Term Policy Analysis*. https://doi.org/10.7249/MR1626
   2. Lempert, R. J., Groves, D. G., Popper, S. W., & Bankes, S. C. (2006). A General, Analytic Method for Generating Robust Strategies and Narrative Scenarios. *Management Science*, *52*(4), 514–528. https://doi.org/10.1287/mnsc.1050.0472
   3. Lempert, R. J. (2019). Robust Decision Making (RDM). In V. A. W. J. Marchau, W. E. Walker, P. J. T. M. Bloemen, & S. W. Popper (Eds.), *Decision Making under Deep Uncertainty* (pp. 23–51). https://doi.org/10.1007/978-3-030-05252-2_2

Questions?

@PEDROLIMA_N

PEDRONL.COM

PLIMA@RAND.ORG