[Robust Decision Making]

Summary

- Robust Decision Marking (RDM) is a methodology which aims to identify adaptation options or strategies which can perform well over a wider range of possible futures. The focus of RDM is on minimising regret rather than optimising utility.
- One of the biggest strengths of RDM is its capacity to help make informed adaptation decisions possible without relying on probabilistic predictions of future climate change.
- Applied with quantitative probabilistic modelling, RDM may rely on high volumes of data. Significant resources and expert knowledge may be needed for its application. More informal applications are possible but may suffer from subjective data inputs and stakeholders' perceptions.
- RDM is most useful under conditions involving high uncertainty. It can be particularly useful in near-term assessment for strategies that could enhance long-term resilience, and to identify low/no regret options.

What does Robust Decision Making do?

Robust Decision Making is based on the concept of "robustness" rather than "optimality", which emphasises an option's ability to be effective over a range of possible future conditions. Considering the characteristic of climate change and therefore adaptation objectives and measures, RDM is discussed as a very interesting method supporting adaptation decision making.

It can be considered as an alternative approach to more traditional economic assessment methods like cost-benefit analysis, as RDM seeks *robust* options ("good enough") instead of options deemed *optimal* in terms of economic efficiency. In other words, RDM seeks to minimise regret, instead of maximising expected utility.

RDM tests adaptation strategies across a large number of plausible future states, the main objective being to help decision makers anticipate or mitigate the impacts of a range of possible climatic changes. RDM can help integrate multiple sources of uncertainties, stemming from e.g. future climate and socio-economic conditions, in the analysis of the performance of adaptation options. . In particular, RDM allows decision makers to take robust or resilient decisions in the short-term, despite incomplete and uncertain information about the long-term.

When should I use Robust Decision Making?

RDM is useful in the adaptation context as it aligns strongly with the notion of adaptive management. In particular, the consideration of uncertainty in the application of RDM is seen as one of its most attractive features. RDM was developed to help policymakers make more effective decisions on near-term options which could have long-term consequences. For example RDM can examine the performance of large infrastructure investments as opposed to capacity-building, considering multiple potential futures. The RDM analysis would help identify trade-offs and synergies between a variety options and help build the best combination of options to reducing long-term vulnerability and build resilience.

The formal method provides the analytical power to test many strategies and sources of uncertainty and identify trade-offs, synergies and robust decisions. Since it highlights options which perform well against a wide range of possible futures, it is especially useful when climate model projections suffer from high uncertainty.

What are the key strengths and limitations of Robust Decision Making?

Key strengths

- Provides a structured approach to testing adaptation options or strategies against many possible futures.
- Applicable under situations of high uncertainty, e.g. climate change, where probabilistic information is low or missing.
- Can work with physical or economic metrics, enhancing potential for application across non-market sectors such as biodiversity or health.

Potential weaknesses

- Formal application using probabilistic modelling requires large amount of quantitative information, computing power, and a high degree of expert knowledge.
- More informal approaches can make the assessment of adaptation activities more subjective, influenced by stakeholders' perceptions.

What does it involve?

The formal application of RDM is computer-based, with a modelling interface presenting exogenous factors (outside the decision maker's control) and adaptation strategies and options (within their control). This computer based analysis allows RDM to evaluate how different strategies and options perform under large ensembles, often of thousands or millions of runs, which reflect different plausible future conditions. Iterative and interactive techniques are then applied to "stress test" different strategies, identifying potential vulnerabilities or weaknesses of proposed approaches. The performance of strategies and options is measured with metrics which can either be physical effectiveness or economic efficiency.

The formal application of RDM involves following a series of defined steps:

- Structure the problem by identifying key uncertainty parameters and performance indicators characterising the system under study and target adaptation;
- Propose one or more alternative adaptation strategies and options;
- Characterise uncertainties associated with the parameters defining the strategies and options, assigning a range of uncertainty values for each variable through stakeholder consultation or expert input;
- Assess each strategy over a wide range of plausible future scenarios;
- Summarize key trade-offs among promising strategies by identifying combinations of key uncertainty parameters.

Ideally, an RDM analysis concludes by identifying a robust adaptation option or strategy – one that performs well over a very wide range of possible future scenarios. In the event that a robust, well performing strategy is not identified, the iterative process of strategy reformulation begins again with stakeholders.

Informal applications of RDM forego the computer modelling interface, simply testing how different options or strategies perform against climate uncertainty. This approach also avoids the high data and resource needs required by the formal method. For example, where a formal RDM analysis may consider wide uncertainties such as socio-economic future and impact uncertainty, an informal application may involve analysis only of climate uncertainty.

Dessai and Helme (2007) carried out an informal application of RDM looking at climate uncertainty for water supply in one of the driest regions of England. Their analysis examined the implications of climate uncertainty on proposed local adaptation actions and assessed the robustness of the existing 25 year plan. Climate factors such as GHG emissions, climate sensitivity, carbon cycle, regional climate response and ocean diffusivity (among others) were considered one at a time.

To contrast with, Lempert and Groves (2010) undertook a study of the Urban Water Management Plan in Riverside County, California, using RDM. They selected key performance measures for the 25 year plan, and then developed alternative management strategies. The strategies were run through a computer model which examined multiple scenario futures and uncertainties and their interactions.

In Econadapt, RDM was applied using global-scale modelling (LINK TO WP4 INSIGHT).

Case Study: Robust decision-making in the Colorado river basin

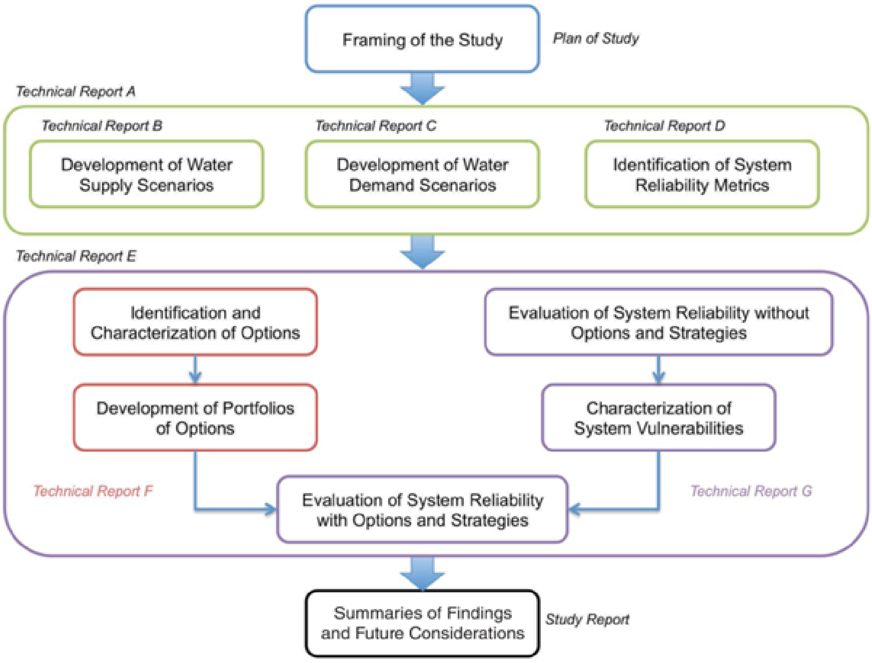
RDM was applied to water management in the Colorado River Basin (Groves et al, 2013). The approach developed a set of scenarios: four supply scenarios, six demand ones, and two reservoir operations scenarios (timeline: 2012-2060). 80 management options were considered by expert and stakeholders against a range of 19 performance criteria (e.g. cost, yield, availability, technical feasibility, legal risk, energy intensity). As result four portfolio strategies were developed.

Description of the four Portfolio

Portfolio	**Portfolio description**
Portfolio A (Inclusive)	Includes all options included in the other portfolios
Portfolio B (Reliability Focus)	Emphasizes options with high technical feasibility and high long-term reliability; excludes options with high permitting, legal, or policy risks
Portfolio C (Environmental Performance Focus)	Excludes options with relatively high energy intensity; includes options that result in increased instream flows; excludes options that have low feasibility or high permitting risk
Portfolio D (Common Options)	Includes only those options common to Portfolio B (Reliability Focus) and Portfolio C (Environmental Performance Focus).

The performance of portfolio strategies was evaluated against system performance criteria (e.g. water deliveries, electric power resources, flood control, water quality, ecological resources). The evaluation of each portfolio is dynamic: rules are included in the simulations that only implements specific options when thresholds of river basin conditions are crossed. Based on the simulation environment described above, the study considered the vulnerabilities of the system under different scenarios, which portfolio strategies may reduce those vulnerabilities, and their costs.

Figure: Steps followed for the RDM application



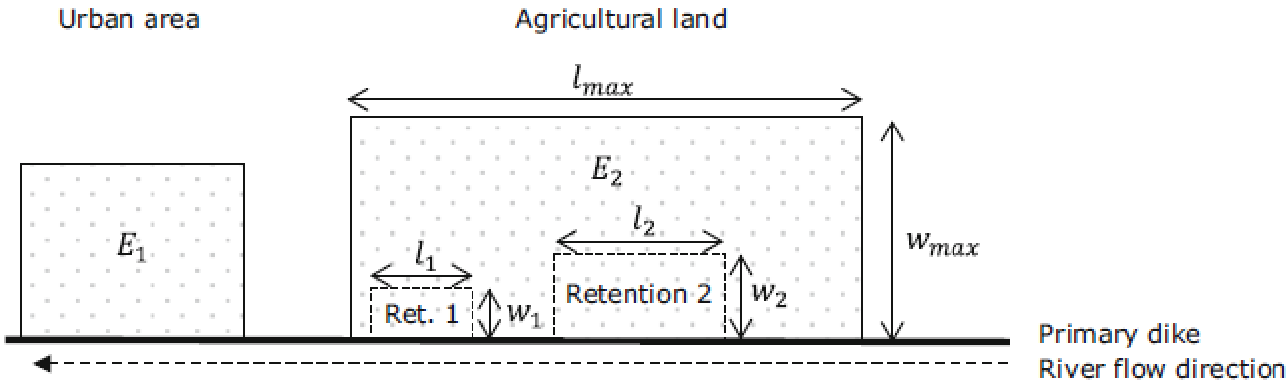
Overall, the study found that implementing any of the designed strategies increases the robustness of the river basin, and that, while the environmental strategy was cheaper than the reliability strategy for the upper and lower basin, it was only more effective than the reliability strategy in the upper basin. The method managed to present trade-offs against a large set of criteria and taking into account a large set of internal and external drivers to the river basin. In addition, the dynamic analysis helped to identify low regret options over time. For example, it was estimated that municipal water re-use and agricultural conservation should be implemented in the short term (<5 years) under all the presented scenarios.

Reference: 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 Through Robust Management Strategies. ISBN/EAN:9780833081797.

Case Study: Minimum maximum regret – A flood risk management application

Consider the problem of increasing river peak flows due to climate change and a river dike protecting agricultural land as well as urban area. The current river dike is expected to provide less flood protection in the future due to the impact of climate change on peak flows.

Robustness concepts are normative and to some extent arbitrary in nature. In this paper, a narrow definition of robustness is employed, i.e.: minimisation of maximum regret. As a decision rule it is possible to select and invest in a flood protection measure that minimizes maximum regret by comparing hypothetical outcomes with the best achievable outcome for various scenarios and investment choices. For the flood risk management application, two possible adaptation options are considered: either raising the existing river dike, or creating retention compartments on agricultural land in the upstream area. In the latter case, agricultural land can be deliberately flooded in order to attenuate peak flows to prevent flooding of the downstream urban area. However, damages arise from yield losses when the retention area is used (see following figure).



The study is based on a two-period investment problem. At two decision moments now (2015) and 2050 one can invest in either the primary dike or in retention storage. At the initial decision moment, three different peak flow projections are available (low, medium, high). Each scenario describes the development of an annual peak flow distribution, which is shifting over time due to climate change.

Under climate change, it is not only uncertain how peak flows will develop, but it is also hard to predict whether or not peak flow uncertainty will be reduced in the future. The future range of peak flow projections will depend on future peak flow observations and possibly also on new insights from improved climate models. Three possible learning scenarios are considered:

- ‘no learning’: the set of peak flow scenarios remains the same as today,
- ‘uncertainty reduction’: the set of peak flow scenarios becomes smaller, either the low or the high peak flow scenarios disappear from the original set,
- ‘uncertainty resolution’: complete knowledge on the development of the annual peak flow distribution is obtained.

Optimal investment strategies for the primary dike and the floodplain are developed. Not always all compartments of the floodplain will be used, when peak flows have to be reduced to prevent flooding of the urban area. The choice for either investment in the primary dike or in floodplain development follows from the cost differences between the flood protection measures given the optimal investment strategies under the different learning scenarios.

Furthermore, a **numerical implementation of the conceptual FRM Model** was considered. The results illustrate the effects of emerging information on optimal initial investment and on the optimal actions and costs after the emergence of new information.

Peak flow scenarios are based on literature sources and are adopted. Further different parameters e.g. about the cost of the investments are based on literature and assumptions.

Optimal dike height strategy for the uncertainty base case without learning, and optimal strategies for the specified learning scenarios was estimated, e.g. the optimal increment now is 55 cm for the uncertainty base case without learning, followed by an increment of 33 cm at 2050. Under *adaptive* minimisation of maximum regret for the learning scenarios, the initial optimal increment is 58 cm, with no increments to increments of another 58 cm as the optimal decisions at the second decision moment after emerging information (2050). **The optimal floodplain development** is to first invest in one retention compartment with a storage capacity of 250 million m^3. The reduction in damages from yield losses by the creation of a second retention compartment does not outweigh the investment costs to create it. The investment pattern is similar to the one found for the dike heightening problem. Under lower scenarios with less uncertainties no second investment would be required. For the other different learning and peak flow scenarios a second investment between 150 million m^3 and 400 million m^3, is needed.

The following table displays a comparison of the Net Present Values (NPVs) of the total costs under different learning and peak flow scenarios associated with both investment options. The regret values are estimated as the difference between the NPV for the dike and the floodplain investment for an individual scenario. The maximum regret value of both investment options are 7.3 for dike and 11.0 for the floodplain. The minimum of two maximum regret values is 7.3 for the dike. So that based on the dynamic application of the Minimax regret criterion, investment in the primary dike remains optimal.

Learning scenarios	Peak flow projections	NPV dikes (in Mio. Euro)	NPV floodplain (in Mio. Euro)	Regret value Dike (in Mio. Euro)	Regret value Floodplain (in Mio. Euro)
No learning	Low peak flow scenarios	288.7	285.1	3.6	0.0
No learning	Medium peak flow scenario	360.1	361.4	0.0	1.3
No learning	High peak flow scenario	420.2	428.2	0.0	8.0
Uncertainty reduction (low scenario disappears)	Low peak flow scenarios	287.2	271.2	6.9	0.0
Uncertainty reduction (low scenario disappears)	Medium peak flow scenario	366.5	359.2	7.3	0.0
Uncertainty reduction (high scenario disappears)	Medium peak flow scenario	360.7	362.2	0.0	1.5
Uncertainty reduction (high scenario disappears)	High peak flow scenario	411.2	422.2	0.0	11.0
Uncertainty resolution (complete knowledge)	Low peak flow scenarios	287.2	271.2	6.9	0.0
Uncertainty resolution (complete knowledge)	Medium peak flow scenario	359.5	359.2	0.3	0.0
Uncertainty resolution (complete knowledge)	High peak flow scenario	409.9	419.0	0.0	9.1

Further information: van der Pol, T.D., Gabbert, S., Weikard, H. et al. (2016) A minimax regret analysis of flood risk management strategies under climate change uncertainty and emerging information. Environ Resource Econ (2016). doi:10.1007/s10640-016-0062-y

Tool: Minimax regret analysis

A simple tool on the probabilistic extensions of CBA to identify welfare-maximising flood risk management strategies under climate change was developed by Thomas van den Pol & Ekko von Ierland. The tool evaluates the optimal investment for a range of scenarios.

Econadapt insights
Framing adaptation economics in decision-making: a policy-led framework
Integrated uncertainties and risk management for robust decision making
Uncertainties and causes of uncertainties in climate change adaptation
Uncertainties and risk analysis in climate change adaption
Sourcing and using climate information for economic assessments of adaptation