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Deciding how to decide under uncertainty: A methodology map to address decision-making under uncertainty

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Abstract
This paper presents a methodology map built on a thorough comparison of approaches that can be used to address decision-making under uncertainty based on the level of uncertainty considered. The methodology map is provided to help researchers and practitioners on the selection of the most convenient approach for their specific context. An overview of different approaches for decision-making under uncertainty is provided. Approaches are then compared to each other, where requirements, limits, pros, cons and different circumstances under which each approach is more appropriate are discussed. Four different approaches are studied, the cost-benefit analysis (CBA), Probabilistic decision tree (PDT), Robust decision-making (RDM), and Dynamic adaptation policy pathway (DAPP).
Results show that different considerations are expected to rule the selection process. It should depend on the problem in-hand (e.g. type of uncertainty, the number of alternatives) and enclose a rationale that addresses its limitations (e.g. available time, fund).
The developed work is expected to support researchers and practitioners in the selection of convenient approaches to inform decision-making based on available knowledge, with awareness of the implications of the selected approach over the final output that will support holistic decisions.

Keywords: Decision-making, deep uncertainty, cost-benefit ratio, probabilistic decision tree, robust decision making, dynamic adaptive policy pathway

1. Introduction

Making decision under uncertainty is a challenge that can be addressed using systematic decision-making approaches. The complexity of identifying the most adequate approach for specific problem settings can result in a sub-optimal decision or require large efforts if aspects such as problem's complexity (e.g., uncertainty, number of alternatives, flexibility), limitations (e.g., time), and resources (e.g., budget) are not considered.

So far, several different approaches for decision-making under uncertainty have been developed, studied, and applied such as robust decision making, dynamic adaptation pathways, and Bayesian network. A particular topic of interest in this regard is to address decision making under climate change's uncertainty (Ryu et al. 2017; Norton et al. 2019; Williams et al. 2020; Linquiti and Vonortas 2012; Zheng, Egger, and Lienert 2016). Decision-makers need to find the most suitable adaptive strategy to be able to adapt their systems to climate change. However, the uncertainties of climate change and the number of possible adaptive strategies are a challenge to decision makers. Having a systematic approach in this regard is of interest. The present work studies different approaches to address the decision-making under uncertainty that are adequate to adapt infrastructure systems to climate change. While comparing methodologies is not exclusively new, and works can be found that compare approaches in a case study (Bartholomew and Kwakkel 2020; Kwakkel, Haasnoot, and Walker 2016), the current work pursues to go a step ahead by establishing guidance in this regard. For such, climate change-related uncertainty is discussed in Section 2; Sections 3, 4 and 5 discuss different approaches and their implementation in a representative case study; and Section 6 draws the conclusions of this analysis.

2. Uncertainty associated with climate change

Uncertainty due to climate change can be categorized in different forms, and in the present work and context of implementation, uncertainty is classified into two main categories:

- Probabilistic uncertainty: applied when future circumstances are uncertain, but it is possible to project possible scenarios and assign a probability to each.
- Deep uncertainty: applied when decision makers cannot predict or agree on possible future scenarios or their probabilities.

In a broad sense, uncertainty may be defined simply as state of limited knowledge. According to the IPCC (IPCC 2014) there are five main sources of uncertainty in climate change:

- Climate response to greenhouse gas (GHG) emissions, and their associated impacts.
- Stocks and flows of carbon and other GHGs.
- Technological systems. Deployment of technologies as a driver of GHG emissions.
- Market behavior and regulatory actions.
- Individual and firm perceptions to climate change.

These are complex, and it is challenging to assign probabilities and predictions to each; which makes decision-making schemes also complex. According to the IPCC (IPCC 2018), providing different probable scenarios to uncertainty is approach-dependent. In the literature some studies considered it as probabilistic (Ekholm 2018; Farber 2015; Nassopoulos, Dumas, and Hallegatte 2012; Rabl and van der Zwaan 2009) and other as deep (Buurman and Babovic 2016; Shortridge, Aven, and Guikema 2017; Walker, Marchau, and Swanson 2010; Lawrence, Haasnoot, and Lempert 2020; Helmrich and Chester 2020; Workman et al. 2020).

3. Implementation

A simple virtual case study was developed in the context of the main objective of comparing and discussing how uncertainty considerations merge with decision-making schemes.

A municipality's water distribution system obtains its water supply from a surface-water reservoir. Municipal demands include residential demand for 100,000 Households (constant over time). The reservoir receives inflow from the natural watershed and is operated to maintain flows downstream. Fig. 1 shows an illustrative model of the system.

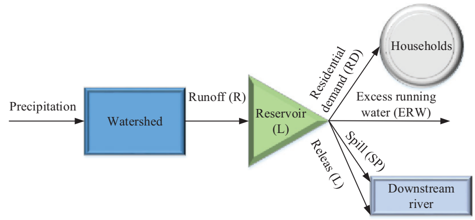

Fig. 1. Illustrative model of the system.

Watershed runoff (R_t) at time t is given by:

$$R_t = C_t \frac{(P_t - 0.2 \times S_t)^2}{P_t + 0.8 \times S_t} \text{ (Berglund 2015)} \quad (1)$$

where R_t is the runoff (thousand m^3), P_t the average monthly precipitation (cm), S_t the average monthly watershed coefficient (cm) and C_t, the runoff coefficients (thousand m^3/cm). The volume of water in the reservoir is based on demands, runoff, spill, and release, Eqs. (2)-(4). Release (L_t) is the monthly volume of water released to maintain flow in the river downstream of the reservoir.

$$L_t = 6 \times 10^{-10} \times V_{t-1}^{2.8478} \quad (2)$$

with V_t being the volume in the reservoir at time t and V_{t-1} is that at the previous time period (it is previous year in this study). Spill (Sp_t) is the amount of water released to ensure that the reservoir does not overtop. It is given by:

$$Sp_t = \max(V_{t-1} + R_t - RD_t - L_t - MV, 0) \quad (3)$$

where maximum reservoir's volume (MV) is 239 million m^3 and RD_t, residential demands, is the average monthly demand (μ_d) times the number of households. Maximum volume of spill (MSP) is 12 million m^3. Any quantity larger than it will result in excess running water (ERW),

$$ERW = \max(Sp_t - MSP, 0) \quad (4)$$

The reservoir volume, V_t, in each time t is

$$V_t = \max(V_{t-1} + R_t - RD_t - Sp_t - L_t, 0) \quad (5)$$

The initial reservoir volume is 177 million m^3 and the average monthly values at the starting year are:

- $P_{t=0}$ (cm) = 8.9.
- μ_d (L/Household) = 23,940
- $C_{t=0}$ (thousand m^3/cm) = 18,970.
- $S_{t=0}$ (cm) = 7.1.

Future rainfall increase uncertainty: It is assumed that due to climate change the average monthly rainfall might increase between 0.1% and 1% per year. Adaption is required for a period of 50 years.

Adaptation measures: Four different adaptation measures are considered, Table 1. These adapt the system to withstand a maximum amount of ERW that if exceeded will cause damage to it.

Table 1. Adaptation measures information.

Adaptation measure	Cost (Billion €)	Implementation time (years)	ERW threshold (million m^3)
M1	9	1	10
M2	21	3	30
M3	58	5	55
M4	89	8	100

It is noted that if two measures are implemented, ERW will increase by the largest number. In case of exceedance of the threshold, every extra m^3 will damage the system by €100,000. It is assumed that the budget will be spent equally each year and the implementation t=0; e.g., M2 will cost 3M€ in 3 years, i.e., 1M€ per year.

4. Decision-making

The four different approaches considered are now discussed.

4.1. Cost-benefit analysis

Cost-benefit analysis (CBA) estimates monetary costs and benefits of pursuing a course of action by translating non-monetary costs and benefits into monetary units. Optimal decision is the one that maximizes a cost-benefit ratio. It can appear in literature as a methodology or decision criterion, and is generally used to assess profitability of investments (Williams et al. 2020). Costs and benefits include financial, environmental, and social effects. Its implementation goes as follows:

1: Describe problem settings, uncertainties, and objectives. In the present implementation, the setting is the case study, uncertainties include future's climate, and objectives include deciding on ERW protection. In practice, different possible scenarios with assigned probability are assumed; five are considered (Table 2).

2: Find every alternative action. Implementation should find every possible action that can help to reach the project objectives under the uncertainties considered (Table 1).

Table 2. Future possible scenarios.

Scenario no	Rainfall increase (%/year)	Rainfall increase after 50 years (%)	Probability (%)	ERW (million m^3)
Sc1	0.1	5.1	45	3
Sc2	0.4	22.1	25	25.9
Sc3	0.6	34.9	15	43.7
Sc4	0.8	48.9	10	63.9
Sc5	1	64.5	5	86.7

3: Describe and calculate benefits and costs for each action. In CBA it is necessary to monetarize costs and benefits. To account for time in a fair comparison, costs should be transferred to their present value. The present value of the implementation cost (IC_p) and damage cost (DC_p) are weighted using Eqs. (6) and (7), respectively.

$$IC_p = \frac{IC}{(1+r)^{t/2}} \quad (6) \qquad DC_p = \frac{DC}{(1+r)^y} \quad (7)$$

where r is the annual inflation ratio, and y is the year of the ERW event. The total present cost of each adaptation measure (TC_p) is therefore:

$$TC_p = \sum_i IC_p^i + \sum_f DC_P^f \tag{8}$$

where all the investments (i) for adaptation and expected ERW event (f) are considered at present *t*. The benefit of an adaptation strategy is the improvement achieved by the applied action, i.e., potential damage by an ERW event that was prevented:

$$B_P = \sum_f \frac{B_f}{(1+r)^{y_f}} \tag{9}$$

where B_p is the present value of benefit and B_f is its value of at the time of ERW (at year y_f). Finally, the cost-benefit ratio (CBR) is,

$$CBR = \frac{B_p}{TC_p} \tag{10}$$

4: Find the most suitable action. The simplest way to make a decision in this regard is to weigh CBR by the probabilities, obtaining a PCBR. The adaptation decision will have the highest PCBR.

According to Fig. 2, M2 has the highest PCBR, followed by M4. Moreover, it is interesting to infer the lower robustness of M2 in comparison with M4 regarding the CBR for different scenarios, which remarks the need to discuss adaptation decision-making on a more holistic and probabilistic form.

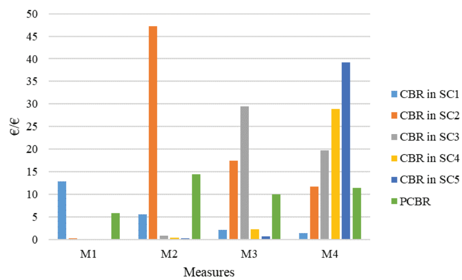

Fig. 2. Adaptation measures' performances.

4.2. Probabilistic decision tree

A decision tree is a decision support tool that uses a tree-like model of decisions and consequences, including event outcomes, resource costs, and utility (Cartwright et al. 2013). It uses a diagram of options and assigned probabilities to identify optimal actions. It is implemented as follows:

1: Describe problem settings, uncertainties, and objectives. Multiple time periods are required to enable its capability of identifying a flexible outcome (two 25-year time spans are assumed, with an increase of ERW threshold by half of the original value, see Table 3 for adaptation measures). It demands assumption of future scenarios and two are considered for such in this section (lowest and highest rainfall increase).

2: Build the decision tree: it consists of three elements (see Fig. 3). Decision nodes: show a decision to be made; illustrated by squares. Chance nodes: show a group of possible outcomes; illustrated by circles. Each possible alternative flows from a decision node to a chance node. Outcomes: represents the sum of the costs and benefits of each path through the tree and are shown by triangles.

3: Eliminate unrealistic outcomes: Measures that do not have an acceptable performance should be crossed off.

Table 3. Adaptation measures.

From year 0 to year 25		
Measures	Cost (billion €)	ERW threshold increase (million m^3)
M1,1	4.5	5
M2,1	10.5	15
M3,1	29	27.5
M4,1	44.5	50
From year 25 to year 50		
Measures	Cost (billion €)	ERW threshold increase (million m^3)
M1,2	4.5	5
M2,2	10.5	15
M3,2	29	27.5
M4,2	44.5	50

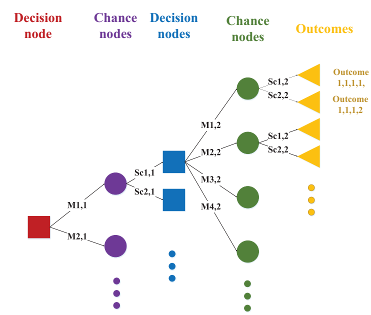

Fig. 3. Example of decision tree structure.

4: Select the most suitable outcome. Each outcome represents a possible adaptation pathway that can be chosen by the decision-makers. There are different methods to choose the most suitable combination of measures, being the simplest finding outcomes with most probable combination of scenarios and choose the outcome with the optimum measures' combination (lowest cost) amongst them. The most probable in this Case Study is scenario Sc1,1 and Sc1,2 with probability of 72.25%, and the optimal adaptation for this scenario is the combined M1,1 and M1,2.

4.3. Robust decision-making

RDM is an iterative decision analytic framework that aims identifying potential robust adaptation strategies, characterizes their vulnerabilities, and evaluate the trade-offs among them (Croskerry 2009; Lempert and Collins 2007). RDM will usually identify a robust alternative within 1 or 2 iterations. It evaluates the performance of options under a range of future occurrences to determine which options perform in multiple. The goal of it is not to find the optimum alternative, but to find the alternative that has the lowest sensitivity to changes. RDM is implemented as follows:

1: Define strategy and context: In this step any involved parties fill a so-called XLRM matrix, Fig. 4. The performance metric (M) aims to making the system resistant, in the present case that would be protecting against ERW. The uncertain factor (X) addresses future rainfall increase. There are four different adaptation measures, which are policy levers (L). Finally, Eqs. (1)-(5) define the relationship (R).

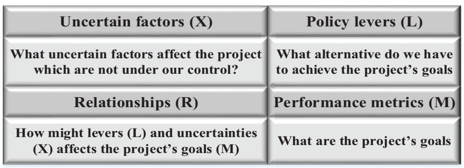

Fig. 4. XLRM matrix.

2: Stress tests: based on the information from the previous step, the system will be evaluated under multiple representative different potential future scenarios. Larger numbers of possible scenarios improve the implementation. For representative purposes, 10 different future scenarios are considered that include rainfall increases in [0.1%, 0.2%, … 1%]. Results of the stress test in the example studied are shown in Fig. 5.

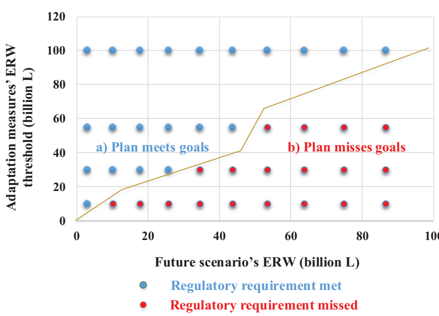

Fig. 5. Case study's summarized stress test.

3: New and revised strategies: this step involves making the decision and choosing the robust alternative. To do so clusters (a) "plan meets goals" and (b) "plan misses goal" are discussed for ERW resistance and cost of adaptation (see Table 4).

Table 4. RDM Adaptation measures in a) and b).

Measure	a)Plan meets goals		b)Plan misses goals	
	Resist?	Cost	Resist?	Cost
M1	Yes	Low	No	High
M2	Yes	> M1	No	Slightly <M1
M3	Yes	High	No	Low
M4	Yes	V. high	n/a	<M3

As defined, M3 resists in the first cluster with a high cost and fails in the second cluster with a low cost. According to Fig. 5, possible future area that M3 fails in, around 40% of possible future area, is smaller than the area that it resist in, which means it fails only if extreme events occurs in the future. M4 does not fail in any cluster, however, its cost is very high in the first cluster and lower than M3 in the second cluster. Therefore, M4 can be chosen in projects that resistance is the most important factor, and M3 can be chosen in projects that try to avoid overspending their budget while trying to be as much resistant as possible. In conclusion, M3 and M4 can be chosen as the robust alternatives.

4.4. Dynamic adaptive policy pathway

DAPP aims to support the development of an adaptive plan to deal with deep uncertainties. This approach identifies potential actions and thresholds at which actions should be taken or future decisions made. It identifies pathways, monitors their evolution and when thresholds are met, triggers a new pathway (Haasnoot et al. 2013). DAPP is implemented as follows:

1: Describe problem settings, objectives, and uncertainties. Problem setting (current situation) is described in Section 3, the only objective is making the system resistance against ERW, and the only uncertainty is in the rainfall increase. Rainfall is assumed to increase from 0.1% to 1% per year for the next 50 years. In a form of deep uncertainty, two different scenarios should be considered: the optimistic and pessimistic that use respectively the 0.1% and 1% range limits.

2: Identify and assess all actions: that is, the adaptation measures of Table 1. Adaptation tipping points are identified, i.e., the time at which the action can no longer be useful to ensure its goals and there is a need to implement another action. With the total rainfall increase (TRI_y) and average monthly rainfall precipitation (P_t) in each year defined as:

$$TRI_y = (1 + IPY)^y - 1 \qquad (12)$$

$$P_t = P_0 \times (1 + TRI_y) \tag{13}$$

where IPY is the rainfall increase per year, y is the year that the calculations are for, and P_0 is the average monthly rainfall precipitation in Year 0 (8.9 cm). Other parameters are calculated using the equations in the previous sections. The year that each measure will fail (i.e., adaptation tipping points) should be found for the two defined scenarios, the low rainfall increase (LRI) and the high rainfall increase (HRI). Results in Table 5

Table 5. Adaptation tipping points.

Adaptation measures	ERW threshold (million m^3)	LRI				HRI			
		year	TRI (%)	Pt (cm)	ERW (million m^3)	year	TRI (%)	Pt (cm)	ERW (million m^3)
M1	10	>50	n/a	n/a	n/a	10	10.5	9.8	10.12
M2	30	>50	n/a	n/a	n/a	23	25.7	11.2	30.9
M3	55	>50	n/a	n/a	n/a	36	43.1	12.7	55.5
M4	100	>50	n/a	n/a	n/a	>50	n/a	n/a	n/a

shows that in LRI, none of the measures reaches its tipping point. In HRI, M1, M2, and M3 reach their tipping points in year 10, 23, and 36, respectively, while M4 does not reach its tipping point.

3: Develop adaptation pathways and subway map: Different pathways are assembled using the information provided in step 2 and a dynamic adaptive pathways map is established (Fig. 6). There are multiple pathways that can be chosen by the system's decision-makers.

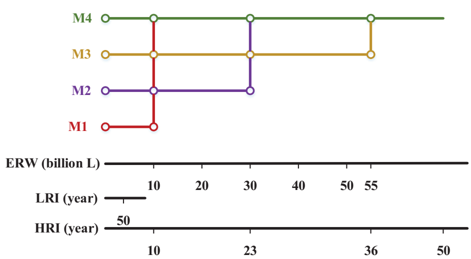

Fig. 6. Dynamic adaptive pathways map.

Therefore, it should be explained why a decision-maker may choose to start measures that reach a tipping point. Although starting with M1, M2, or M3 reaches a tipping point much sooner than M4, choosing those less costly alternatives grants enough time to observe the future, freeing budget for planning alternatives with higher resistance, or to overcome other potential problems.

4: Evaluate different pathways: After establishing all pathways, these should be analyzed and evaluated by their performance. Some pathways will dominate other, and all the non-dominated pathways are used to develop a set of promising pathways. For instance, if M2 is selected at the start, when reaching its tipping point, other alternatives may be implemented based on the updated information about the climate, the project's expected budget at the moment, and any other relevant information. M2 raises the ERW threshold three times more than M1 and helps the system resist much longer in HRI, admitting that the cost of M2 is not a problem, it can be said that M2 dominates M1 in Year 0. Hence, the set of promising pathways include: M2→M3→M4, M2→M4, M3→M4, and M4), see Figure 7.

5: Select the preferred pathways: a specified number of pathways should be kept for reference. The preferred pathways require different perspectives to be evaluated. If a decision-maker pursues a large resistance pathway and budget is not a limitation at the start, M4 is the preferred choice (First perspective). If there is a limitation in budget or will to postpone implementing M3 or M4, hence, gaining more information about the future trends, M2 should be chosen in Year 0. After M2 reaching its tipping point, the pathway should continue with M2, M3 if the updated predictions about the future are closer to LRI. If M3 is implemented and then identified to reach a tipping point, M4 should be implemented (Second perspective). And, so on for M2, M4 if closer to HRI (Third perspective). Finally, if budget is not a limitation it is decided that at start the most expensive measure is not of interest, M3 should be chosen in Year 0 and if it reaches a tipping point, M4 should be implemented (Fourth perspective).

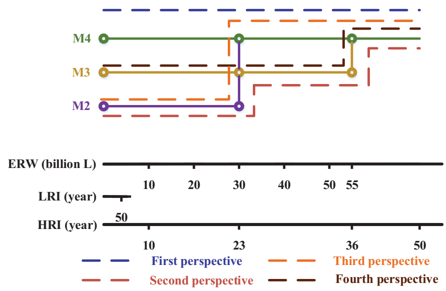

Fig. 7. Preferred pathways from four different perspective.

5. Comparative overview

Application of CBA demands the quantification of the probability of future events. It is highly efficient when the problem settings are clear and well characterized. The same applies to PDTs if probabilities are assigned to each outcome. PDTs are visual, simple to understand and interpret, which is of interest to inform stakeholders and all parties involved in the decision processes. Moreover, these can determine worst, best and expected scenarios. However, small changes in the data can lead to a large change in the structure of the tree. In this regard, CBA is less onerous in terms of effort, and is easily changed in systematic way (just needs to reassess the analysis metrics). A comprehensive RDM requires a significant amount of work and time to access expertise in relevant fields, constructing questionnaires to minimize cognitive biases, and administering and applying consistency checks (Kwakkel, Haasnoot, and Walker 2016). Computational costs may also be large. It avoids assigning probabilities to scenarios, and it is expected to perform under deep uncertainty. DAPP results in an adaptation pathway that can be changed conditional on the future. The outcome is not a static optimal plan. It works well under deep uncertainty (Haasnoot et al. 2013). DAPP emphasizes dynamic adaptation over time, and thus offers a natural way for handling the identified vulnerabilities (Kwakkel, Haasnoot, and Walker 2016). However, DAPP takes more time than other approaches that use a static adaptation strategy as the outcome.

6. Conclusion

Different adaptation approaches perform in different circumstances. These depend on the characteristics of the alternative actions being considered, the data available, and the time and skills available. Incorrect implementation of an adaptation approach may lead to bad management of resources.

Considering climate change as probabilistic or as deep uncertainty depends on the amount of information available, the approach to decision and loss (i.e. risk), and its limitations. Table 6 summarizes scenarios that were found to suit each approach. Different strategies are identified as optimal based on the approach.

To select a decision-making approach, first there is a needed to consider the type of uncertainty. It depends on accessible resources (budget, time, expertise), importance of the project, and other potential considerations. Then, required flexibility in the outcomes should be considered. In other words, the decision-makers need to decide if rigid or flexible implementation is of interest attending the resource available. It is noted that CBA and RDM can suggest flexible pathways as well, but check points need to be set up in a period for such. DAPP and PDT are intrinsically suggestive in terms of establishing flexible paths.

If uncertainty is to be considered probabilistic CBA is of interest. Moreover, if the outcome is to be accessed and analyzed by local officials or citizens, then PDTs are of interest. However, if the uncertainty is considered deep and there are no limits on the time of the decision-making process, budget, and hiring experts, RDM or DAPP can be of interest. Nonetheless, if flexibility is required as well, then the most suitable approach is DAPP.

Table 6. Considerations and properties of each approach.

Approaches	Uncertainty	Flexibility	Input parameters	Outcome	Understandable for	Suggested measure
CBA	Probabilistic	No	Monetary	Single	Experts	M2
PDT	Probabilistic	Yes	Several	Single and multiple	Non-experts	M1
RDM	Deep	No	Several	Single	Experts	M3 or M4
DAPP	Deep	Yes	Several	Multiple	Experts	Pathways

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