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PREVENT

D6.4 ADAPTATION AND RISK REDUCTION MATRIX OF THE CLIMATE EXTREME HOTSPOT REGIONS

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WP Lead Beneficiary:	FINRES
Authors:	Dan Xie
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1. Introduction

Climate change is causing tremendous impact on the economy sector. There is a need of taking decision on the best and most suitable adaptation options to mitigate these impacts. The question is, how to inform for these decisions, while the climate future is unknown or imperfectly known. Climate impact studies rely on projections that are based on various scenarios representing possible futures, depending on emission levels derived from different socio-economic pathways.

There is therefore a lot of uncertainties associated to decision making in the context of climate change mitigation. There is a growing field named **Decision Making under Deep Uncertainty** (DMDU hereafter), aiming on addressing these uncertainties while taking adaptation decision and climate mitigation policy. One of the most predominant DMDU technique is **Robust Decision Making** (RDM), which main goal is to take decision that works in all possible future types.

The main goal of this document is to provide an overview of RDM framework and discuss possible improvements for finres.

2. Different Types of Uncertainty

Uncertainty refers to a state of lack of knowledge or predictability regarding future events or outcomes. It implies a condition where the probabilities of different scenarios are unknown or difficult to quantify, introducing ambiguity, variability, and unpredictability into decision-making processes. In various disciplines, managing uncertainty involves acknowledging and addressing the inherent risks and unknowns associated with potential outcomes. For example, in the field of climate change, it refers to the fact we don’t know which scenario will play out, or it is not possible to assign a probability to them.

There is a difference between uncertainty and probability.

There are several levels of uncertainty, that calls for different approach types in term of decision making.

2.1. Complete Certainty

Complete certainty characterizes a state where the future is not only known but also precisely defined, offering a clear understanding of outcomes across various situations and variables. In financial markets for example, a contractual agreement with fixed terms and conditions reflects a state of complete certainty. The future cash flows and outcomes are explicitly known and defined.

2.2. Level 1 Uncertainty

At this level, knowledge exists regarding potential outcomes based on historical data, coupled with an exploration of the landscape through integration of sensitivity analysis. This additional layer allows delving into how outcomes may respond to subtle variations, enhancing understanding. As an illustration, consider a manufacturing process where historical data suggests a certain production yield. Through sensitivity analysis, the impact of minor variations in input parameters, such as raw material quality, can be explored to understand potential deviations in output.

2.3. Level 2 Uncertainty

Progressing to level 2, probabilities are assigned to known outcomes, constructing a probabilistic distribution for all potential future scenarios. Decision-makers then formulate policies based on these "expected" outcomes, incorporating a probabilistic perspective into strategic planning. In weather forecasting, meteorologists assign probabilities to different weather outcomes based on observed patterns. These probabilities, forming a probabilistic distribution, guide decision-makers in preparing for various potential weather scenarios.

2.4. Level 3 Uncertainty

Level 3 introduces a realm where the future is inherently unknown, but decision-makers utilize a set of parameters to construct scenarios. In this context, the emphasis lies on selecting outcomes that exhibit resilience across diverse scenarios, involving careful consideration of alternatives, weighting factors, and expected outcomes.

In urban planning for example, city officials may face Level 3 uncertainty when developing long-term infrastructure plans. Scenarios involving population growth, economic shifts, and environmental changes, decisions are made based on outcomes that demonstrate resilience across diverse future scenarios.

2.5. Level 4 Uncertainty

Level 4 represents a unique intersection where a future can be assumed in certain situations with scenarios, while acknowledging the presence of unknown, especially in the face of unprecedented events. Decision-making here involves navigating through a broad spectrum of potential outcomes, assigning weights judiciously, and considering various future scenarios.

To give some perspective, imagine a technology company planning for the release of a new product. While certain market trends can be assumed depending on different possible scenarios, Level 4 uncertainty arises in anticipating unforeseen events, such as a global economic downturn or a major technological breakthrough by a competitor. Decision-makers must navigate a broad spectrum of potential outcomes and prepare for a wide range of possible future scenarios.

2.6. Total Ignorance

Finally, in a scenario of total ignorance, no information about the future is available, presenting the utmost level of uncertainty. This underscores the significance of recognizing and addressing gaps in knowledge to inform decision-making.

In scenarios like the emergence of a novel virus, total ignorance prevails at the outset. Before comprehensive research and understanding, decision-makers lack information about the virus's behavior, transmission, and impact, underscoring the challenge of making informed decisions in the face of unknowns.

Level 4 is distinguished as Decision Making under Deep Uncertainty, a realm where even expert judgment reveals vulnerabilities, and the models employed in the preceding levels lack the robustness required for handling the intricacies of this level of uncertainty.

3. Possible DMDU Approaches

DMDU is an approach used to make decisions under different possible futures and pathways at a level 4 uncertainty. It could be based on 3 different approaches being: Robust Decision Making (RDM), Adaptative pathways (DAPP) and Decision scaling. Those follow a no regret approach and several indicators or objectives to be reach for the last one. The decision tree is one of the DMDU type of methods (Webber et al., 2022).

In climate science and decision-making, scientists face different level of uncertainty (at a level 4 magnitude) in the projections. Indeed, climate projections are outputs of a complex dynamic system and are applied to other complex dynamic systems (hydrology, agronomy, etc.). The level of the associate uncertainty is therefore important which makes decision complicated.

In other hands there is a need of implementing long term policy to mitigate the effect of climate change (Marchau et al., 2019; Murphy et al., 2011). This uncertainty grows with higher time horizon. However, waiting till a period from which the uncertainty is highly reduced will make the implementation of policies somehow irrelevant. It is then important to adapt regarding this uncertainty because the wait and see could make relevant policies irrelevant. The time span making the observations relevant for more accurate prediction will make the action unnecessary (Murphy et al., 2011).

It is then important to plan policies regarding the uncertainty of the future by simulating several possible futures and select the best outcomes in most of them: robust decision (Lempert, 2019).

There are multiple ways of addressing robustness in decision making. Certain follows a no regret approach, other a maximin, other an optimism-pessimism approach. All of those could result, regarding the sensitivity of the sector, into different outcomes. The type of robustness definition could therefore highly impact the type of decisions (Giuliani & Castelletti, 2016; Heltberg et al., 2009).

The three different DMDU tools and approaches respond to different context and sectors.

3.1. RDM

Robust Decision Making (RDM) serves as a comprehensive and adaptive approach to decision-making in the face of deep uncertainty. Positioned as a strategic planning framework, RDM seeks to pinpoint resilient strategies that can excel across diverse potential future scenarios, acknowledging the inherent complexities and uncertainties. This method entails the exploration of alternative strategies, incorporating scenario analysis to assess uncertainties, and identifying solutions capable of delivering favorable outcomes in various conditions. Grounded in quantitative analysis and scenario planning, RDM provides decision-makers with a structured approach to address complex problems within an uncertain and dynamic environment (R. J. Lempert, 2019; Robert J Lempert et al., 2013).

At its core, RDM represents a set of concepts, processes, and tools that leverage computation not for better predictions but for yielding improved decisions in conditions deep uncertainty conditions. It combines Decision Analysis, Assumption-Based Planning, scenarios, and Exploratory Modelling to stress-test strategies across numerous plausible future paths. The approach identifies policy-relevant scenarios and robust adaptive strategies, moving beyond predictive ranking to inform better decisions. Frontiers in RDM development involve expanding multi-objective capabilities, evaluating the impact of RDM-based decision support systems, and leveraging RDM's ability to incorporate multiple perspectives and ethical frameworks for addressing complex issues.

RDM fundamentally reimagines the role of quantitative models and data, shifting from predictive tools to vehicles for systematically exploring consequences, expanding the range of futures, and identifying crucial tradeoffs. Rather than making better predictions, RDM uses computer models and data to inform better decisions, emphasizing stress testing proposed decisions against a wide range of plausible futures. This iterative process allows decision-makers to identify key features distinguishing successful plans from those falling short of goals, enabling them to frame, evaluate, modify, and choose robust strategies that meet multiple objectives across diverse scenarios. Overall, RDM provides decision support under conditions of deep uncertainty, leveraging contemporary information technology for an operational and capable synthesis (Lempert et al., 2013; Marchau et al., 2019, n.d.).

3.2. Dynamical Adaptative Policy Pathways (DAAP)

Dynamic Adaptive Policy Pathways (DAPP) represents a tailored decision-making framework designed to navigate uncertainties and dynamic complexities, particularly in the realm of climate change adaptation and long-term planning. Departing from conventional static approaches, DAPP is characterized by its recognition of the evolving nature of challenges and its ambition to construct flexible policies capable of adapting over time. The core principle of DAPP involves iterative development and adjustment of policy pathways in response to changing conditions and emerging information. This adaptive approach not only acknowledges the inherent uncertainty in predicting future developments but also underscores the crucial need for continuous learning and adjustment. By providing decision-makers with the flexibility to adapt policies in real-time based on evolving insights and circumstances, DAPP offers a robust and effective strategy for navigating the intricacies of a profoundly uncertain world (Kwakkel et al., 2016; Kwakkel and Haasnoot, 2019).

DAPP explicitly incorporates decision-making over time, promoting proactive and dynamic planning in response to the unfolding future. Recognizing the uncertain design life of policy actions and the potential for reaching adaptation tipping points, DAPP visualizes multiple pathways in a metro map or decision tree, with time or changing conditions as key axes. It supports the design of a dynamic adaptive strategy encompassing initial actions, long-term options, and adaptation signals to guide when to implement long-term options or revisit decisions.

This approach to planning under deep uncertainty recognizes that decisions occur over time, dynamically interacting with the system of concern. DAPP integrates two complementary adaptive planning approaches—Dynamic Adaptive Planning and adaptation pathways—considering the sequencing and path dependencies of decisions over time. In the DAPP framework, a plan is conceptualized as a series of actions over time, including initial actions and long-term options. The proactive planning for flexible adaptation over time acknowledges that policies and decisions have a design life, requiring adjustment when operating conditions change. The preference for specific pathways is actor-specific and depends on trade-offs, such as costs and benefits, reflecting the dynamic and interactive nature of decision-making within complex systems (Lawrence and Haasnoot, 2017).

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3.3. INFO-GAP DECISION THEORY (IG)

Info-Gap (IG) theory provides a non-probabilistic decision-making framework designed to handle situations of deep uncertainty. Deep uncertainty arises when key factors influencing a decision are poorly known or beyond control. IG theory prioritizes alternatives and choices based on models, encompassing data, scientific theories, empirical relations, and contextual understanding. It has been applied across various fields such as engineering, biological conservation, economics, medicine, homeland security, and public policy.

The distinction between risk (where probability distributions are known) and true uncertainty (where they are not) is central to IG theory. Knightian uncertainty, representing ignorance about underlying processes, functional relationships, and future events, is quantified through info-gaps—the disparity between what is known and what is needed for a reliable decision. IG models uncertainty, particularly in the shape of a function, making it suitable for situations where estimates or predictions involve uncertain parameters or vectors.

The key concepts of IG theory are satisficing and robustness. Satisficing involves achieving an acceptable outcome based on explicitly stated criteria rather than pursuing the optimal outcome, which may be unrealistic under deep uncertainty. Robustness in IG theory assesses a decision's ability to satisfy critical goals over a wide range of uncertainties. The methodology involves evaluating the model, performance requirements, and uncertainty model, emphasizing the system's resilience, redundancy, flexibility, adaptiveness, and comprehensiveness.

IG robustness is crucial in decision-making under deep uncertainty, ensuring that decisions remain acceptable even if the situation evolves differently from expectations. The methodological outline involves assessing putative performance and robustness against uncertainty, with prioritization based on more robust decisions.

Info-Gap theory incorporates robust satisficing to guard against adverse surprises and achieve critical outcomes, while also employing opportune wind-falling to exploit favorable surprises and facilitate windfall outcomes in decision-making under uncertainty.

3.4. ENGINEERING OPTIONS ANALYSIS (EOA)

Engineering Options Analysis (EOA) is a process that evaluates the value of incorporating flexibility into the design and management of technical systems. It involves calculating the benefits of options, such as flexibility in timing, size, and location of changes, and presenting these benefits in terms of average expectations, extreme possibilities, and initial capital expenses. Drawing an analogy to chess, EOA develops a flexible strategy to maximize success in the face of deep uncertainties, exploring a wide range of possibilities and proposing opening decisions.

EOA is a distinct approach evolved from Real Options Analysis (ROA) and has found applications in various fields, including satellite deployment, oil field development, hospital design, factory implementation, military ship design, and facility renewal. It relies on computer simulations to model the interaction of uncertainties and managerial responses, efficiently organizing vast amounts of data generated during the analysis. Notably, EOA allows decision-makers to consider the value of multiple options simultaneously, a feature not typically present in financially based options analysis.

The methodology of EOA involves several steps, including formulating the problem, specifying objectives, developing a computationally efficient model, generating options, specifying uncertainties, calculating system performance across scenarios, reducing data for stakeholder consideration, supporting decision-making, and implementing a monitoring plan for future adjustments. EOA addresses the informational needs of stakeholders, providing insights into a range of possible outcomes, likelihoods, and value-for-money considerations. It embraces the reality of deep uncertainties in engineering systems and aims to fulfil the need for strategic decision-making in complex and uncertain environments.

3.5. Strengths and Limits of the Approaches

RDM approach excels in providing resilient strategies under conditions of deep uncertainty. Its strength lies in the identification of robust strategies that perform well across a wide range of possible futures. By systematically exploring various scenarios, RDM helps decision-makers uncover vulnerabilities and design strategies that are robust to uncertainties. However, a limitation of RDM is its tendency to focus on a predefined set of scenarios, potentially missing out on unanticipated events or evolving uncertainties that may arise.

DAPP approach emphasizes the ability to adapt policies over time in response to changing conditions. Its strength lies in its flexibility, allowing decision-makers to adjust strategies dynamically as new information emerges. DAPP considers the unfolding nature of uncertainties and provides a structured framework for adaptive decision-making. However, a challenge with DAPP is the complexity associated with implementing and managing dynamically adaptive policies, requiring a continuous monitoring system and the capacity to make real-time adjustments.

Info-gap is designed to handle severe uncertainty by explicitly embracing the limitations in knowledge. Its strength lies in the quantification of the degree of robustness against severe uncertainties, allowing decision-makers to prioritize strategies that can withstand worst-case scenarios. It acknowledges the inherent limits

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in information but provides a systematic way to make decisions robust to these limitations. Nonetheless, it may be criticized for its sensitivity to model assumptions and the potential oversimplification of uncertainties, leading to overly conservative decision-making.

EOA utilizes computer simulations to model the interactions of uncertainties and managerial responses in engineering systems. Its strength lies in efficiently organizing vast amounts of data and offering decision-makers insights into various strategic choices. EOA excels in handling the complexity of engineering problems and provides a structured methodology for evaluating options. However, a limitation is its dependence on computational resources, and it may not capture the full spectrum of uncertainties in cases where some aspects of the system are challenging to model accurately. Additionally, it may struggle to account for truly unforeseen events not included in the simulation space.

4. Foundation of DMDU

All Decision Making under Deep Uncertainty (DMDU) tools share a common foundation based on a specific set of four or five essential steps for making decisions amid uncertainty. The intricacies of these steps vary depending on the specific DMDU tool employed. The overall process can be divided into three key stages: Frame, Explore, and Choose.

Firstly, "Frame" involves defining the question at hand, gathering relevant information about the specific system, and compiling alternative options. Next, in the "Explore" stage, various potential futures are examined, and alternatives are tested within these scenarios. Finally, in the "Choose" phase, decision-makers navigate trade-offs and weigh policies before making a decision.

The iterative nature of this process encourages revisiting and refining the steps as needed. These steps are incorporated into the four subsequent techniques.

4.1. Decision Analysis

Decision Analysis (DA) stands as a systematic and structured approach within DMDU, contributing to informed decision-making processes. It is Utilizing expected utility approach. It uses the "agree-on-decisions" approach, embraced by RDM and similar methodologies. DA, particularly in DMDU contexts, involves breaking down complex decisions into manageable components, assessing uncertainties, and incorporating stakeholders' preferences. Leveraging quantitative models, scenario analysis, and sensitivity analysis, DA allows decision-makers to explore the consequences of various options across a range of plausible futures. It enhances the decision-making process by providing a transparent methodology to navigate uncertainty and make robust decisions in dynamic and complex environments.

4.2. Exploratory Modelling

It is crucial to differentiate between two types of models: consolidative models (CM) and exploratory models (EM). Consolidative models are designed to integrate all known facts into a comprehensive package that models the real world. On the other hand, exploratory models focus on linking a broad range of assumptions and their associated consequences without favoring any particular assumption. Exploratory models are particularly valuable when a model cannot be easily validated due to inherent uncertainty.

Consolidative models are most effective in supporting deductive reasoning, providing a structured approach to deriving conclusions based on known information. In contrast, exploratory models excel at supporting inductive reasoning, fostering an iterative cycle of questioning and responding to uncover insights in situations where uncertainties prevail, and traditional validation is challenging. This distinction underscores the diverse roles that these modelling approaches play in understanding and navigating complex systems.

4.3. Assumption Based Planning

Assumption-Based Planning (ABP) constitutes a crucial facet of stress-testing measures within the framework of RDM. This methodology goes beyond merely implementing a measure by proactively planning for potential failure conditions. ABP involves a meticulous examination of assumptions underlying a particular measure, aiming to identify circumstances that could lead to failure. Once potential failure conditions are identified, ABP facilitates the formulation of a comprehensive set of actions. These actions are designed to shape and prevent the occurrence of failure, incorporating preventive measures, hedging strategies, and a robust monitoring system. This integrated approach, embedded within RDM methodologies, underscores the proactive nature of decision-making, ensuring adaptability and resilience in the face of uncertainties and dynamic conditions.

4.4. Scenario Discovery

Scenario Discovery (SD) encompasses a collection of potential future scenarios devoid of explicit likelihood estimates. These scenarios are crafted by exploring how the future might unfold based on a defined set of uncertain parameters. In the realm of RDM, Scenario Discovery serves as a vital tool. RDM utilizes these approaches, often incorporating ABP to stress-test the scenarios and assign some degree of likelihood to each. This integrated approach allows decision-makers to explore and evaluate a spectrum of plausible futures, considering uncertainties and diverse parameters. By employing Scenario Discovery within RDM, the methodology gains a more comprehensive understanding of the potential landscape, enhancing its capacity to make robust decisions in the face of deep uncertainty.

5. RDM and Steps

Robust Decision Making (RDM) is an approach to decision-making designed to address complex challenges under conditions of deep uncertainty. Unlike traditional decision-making methods that rely on predicting the future, RDM acknowledges uncertainty and focuses on identifying strategies that perform well across a wide range of plausible future scenarios. This approach involves exploring various strategies, stress-testing them against different possible futures, and characterizing vulnerabilities and potential responses.

It addresses the inherent uncertainty and provide a framework to take safe decision regardless the uncertainty of parameters and future projections.

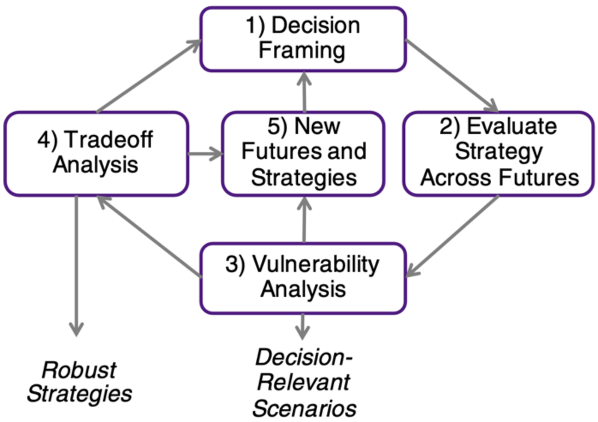

Figure 1. RDM steps, source: (Marchau et al., 2019)

RDM comprises four essential steps, ranging from decision framing to trade-off analysis and the evaluation of new futures and strategies. Each of these steps aligns with the foundational principles of DMDU.

5.1. Decision Building

The first step in RDM is to frame the decision. The decision depends on decision makers objectives and criteria. The framing should provide the impact of the actions as well as the alternatives, and identify the uncertainty associated, and the inherent relation between them. This step is consistent with the DA approach.

5.2. Iteration in Different Possible Future

In the second step, RDM involves a dynamic process of iteration across various possible futures. Utilizing simulation models, decision-makers evaluate the decision

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within a spectrum of scenarios and potential futures. This entails initiating the analysis with a broad array of possible strategies and subsequently refining them based on the evolving dynamics of the unfolding future. The iterative nature of this step follows the principle of EM.

5.3. Vulnerability Analysis

In this critical stage, the chosen strategies are stress tested to identify conditions and scenarios that could influence their effectiveness in achieving their goals. Given that strategies are contingent on specific parameters, the primary objective is to identify the combination of uncertain parameters that could render the strategy excessively risky or ineffective. Techniques such as Patient Rule Induction Method (PRIM) or Classification and Regression Trees (CART) are employed to unravel vulnerabilities and inform refinements. This step aligns with the rationale of Scenario Discovery (SD), enhancing the robustness of the decision-making process.

5.4. Trade-off Analysis

In this crucial step, the focus is on selecting and categorizing the refined set of strategies. A systematic criteria framework is established, enabling the assessment of one strategy in relation to another. This process might involve conducting a comprehensive economic and financial analysis to weigh the merits and drawbacks of each strategy. The objective is to discern the trade-offs inherent in each strategy, providing decision-makers with valuable insights into the multifaceted considerations that influence the ultimate decision.

6. Application and Case Study

At finres, the primary RDM seamlessly adopted approach integrates steps 2 and 3 through the application of a recursive decision tree. This approach streamlines the evaluation process, effectively linking the iteration in various possible futures with the subsequent vulnerability analysis. Furthermore, the trade-off analysis within this methodology encompasses a comprehensive economic and financial assessment, wherein key decision variables include the Internal Rate of Return (IRR) and Cost-Benefit Ratio (CBR).

This approach was applied for the agricultural sector: crop, livestock and aquaculture, and further expanded to wildfire management.

7. Sectoral approaches

7.1. Agriculture

Climate variability and hazards pose a significant threat to crop yield, with the extent of impact contingent on the specific local context, often defined by grid cells. It becomes imperative to judiciously select the most appropriate adaptation options in order to safeguard future yields for farmers. This strategic decision not only serves to mitigate risks associated with investments in the agricultural sector but also plays a crucial role in mobilizing private funding directed towards supporting farmers.

7.2. Overall Approach

As delineated earlier, climate projections come rife with uncertainties, particularly regarding the uncertainty of which scenarios will unfold. In response, finres employs the RDM approach to strategically identify robust adaptation measures capable of withstanding the diverse range of potential futures with a high probability of success. This aligns seamlessly with the "no regret" approach, emphasizing the selection of measures that yield benefits across a spectrum of plausible scenarios.

7.3. Decision Framing

At this stage, a comprehensive list of adaptation options is meticulously made through an exhaustive literature review. This list includes an assessment of each option's relative impact and its associated cost range at a country level. These adaptation options encompass diverse technologies designed to address various layers of risk, such as those related to temperature increase and high humidity events. Mathematical formulas are also employed to quantify their relative impact on increasing crop yield. Subsequently, a decision tree is elaborated, with the primary objective of selecting the most fitting adaptation option contingent on the principal risk drivers that contribute to yield reduction.

7.4. Recursive Selection and Vulnerability

In this phase, the decision tree is run across selected IPCC scenarios and models. Each SSPs/RCPs and model combination provides projections for temperature, humidity, precipitation, and other relevant factors. The impact of these diverse projections is evaluated for each specific crop, at the granularity of a specific grid cell and its associated soil phenology.

Following this assessment, the decision tree guides the selection of the most appropriate technologies to mitigate these impacts, unfolding along branches that align with the prevailing conditions. The outcome is an exhaustive list of measures, subject to stress testing based on uncertain parameters like future prices and soil erosion levels (randomisation). This stress testing refines the list, yielding a set of relevant technologies tailored to each time scale and grid cell.

This intricate process combines elements of RDM steps 2 and 3, integrating iteration across potential futures with vulnerability analysis. The impact on yield, both before and after implementing the selected measures, is then assessed, contingent on the risk reduction potential.

7.5. Trade-off Analysis

Within this framework, the selection of the most robust strategy is accomplished through an Economic Feasibility Assessment (EFA). Key considerations such as the relative price per hectare of the adaptation technique at the local level, coupled with the prevailing interest rate, form the basis for evaluating a series of Net Present Values (NPV) and payback periods. Subsequently, these metrics contribute to the assessment of an IRR, (also CBR in some cases).

The median IRR for a given technology is determined, and its probability of selection is evaluated based on its distribution. The level of maturity of each adaptation measure is also factored into this comprehensive assessment. The output is consolidated into a final table, serving as a decision tool, presenting a list of adaptation measures categorized by maturity level. The probabilities associated with the p50 and p90 percentiles (derived from distributions) are included, along with the corresponding median or average IRR over the specified period.

These lists consequently represent the adaptation options that exhibit optimal performance across a wide range of potential futures with a high probability and are financially viable. The framework's output aligns with the RDM objective, ensuring a robust and financially prudent selection of adaptation measures in the face of climatic uncertainties.

8. Possible Improvement

Is there another approach than decision tree?The main extension for the RDM framework developed in finres are at different level of the fundamental process.

8.1. Other Sectors

The main extension is to develop this framework in the different sector such as wildfire. The approach could vary depending on the sectoral context and level of uncertainty. For example, the uncertainty parameters for wildfire technologies are different from crop, and the decision tree branches, and selection condition should vary. Also at a seasonal level, provide more short term decision framing (implementable faster), and maybe at a DAP level.

8.2. Other Models

The second step of the RDM framework could imply (depending on the sector), not to run a decision tree but a model. For example, the (Sahlberg et al., 2021) article on selecting robust energy policy, used a simulation model testing all the technology and classifying them through their Levelized Cost of Electricity (LCOE), and further stress-testing them regarding the different parameters each technology encompasses.

So as an extension, different simulation model could be developed other than recursive decision tree, but model simulation across different model and scenario.

8.3. PRIM/CART for Vulnerability

Additionally, enhancing the existing framework by incorporating a dedicated vulnerability analysis step could prove valuable in expanding the spectrum of potential uncertain parameters. This analysis could involve the utilization of machine-based models like Patient Rule Induction Method (PRIM) and Classification and Regression Trees (CART). These models could be programmed to automatically generate several conditions that might lead to the failure of selected effective technologies or policies. The incorporation of a vulnerability analysis (SD) step contributes to a more comprehensive understanding of potential failure points and strengthens the robustness of the decision-making framework.

For a practical demonstration of the application of these concepts, a detailed case study employing this framework is available in the referenced article (Sahlberg et al., 2021).

8.4. Some Other Trade-offs

At this stage, it could be interesting to provide other metrics allowing the trade-off, maybe non-financial. This could widen the possibility of robust solutions, allowing decision-makers that have another preference than only financial to have a decision baseline.

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