CTCN assistance in Uganda

Adaptation to climate change through improved information and planning tools for Lake Victoria

Decision-making guidelines

Report / Technical Note

April 2018

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1 Introduction

This report presents guidelines for decision making in the water and energy sectors. The focus of the guidelines is on providing advice for decision making under uncertainty.

The guidelines are appropriate for use in two different, but related, contexts. The first is seasonal planning, where decisions are made based on forecasts of conditions up to one year in the future. The second is long-term planning, where decisions are made based on forecasts of conditions up to 50 years ahead.

The seasonal planning context is relevant for operational decision making. Operators of reservoirs, hydropower facilities, and irrigation systems must make decisions about how to operate their systems based on forecasts of supplies and demands over the coming months. Farmers must make decisions about which crops to plant and how to allocate inputs based on forecasts of rainfall and irrigation water availability. The seasonal planning context may also be relevant for government agencies responsible for responding to drought conditions.

The long-term planning context is relevant for planning, including planning of both infrastructure and policy measures. Large-scale water resources infrastructure projects, including dams, hydropower plants, and irrigation schemes, have long design lifetimes, and estimating performance over these lifetimes is important for performing a reasonable project assessment. Some policy measures may also have long-term impacts that may be important to understand before the policies are implemented. For example, policy reforms of the energy and agriculture sectors can having lasting impacts on the water sector, and the success of failure of these policies may be impacted by hydrological conditions.

Decisions in both the seasonal and long-term contexts must be made given uncertainty about future conditions. Uncertain conditions affecting decision outcomes can include uncertainty about climate and weather, economic conditions, demographic projections, and other factors. The focus of these guidelines is on characterizing this uncertainty and using this information to help make good decisions.

These guidelines organize approaches for decision making using the “agree on assumptions” and “agree on decisions” dichotomy introduced by the World Bank (Kalra et al., 2014). The two types of approaches describe two different ways to use data, models, and assumptions to support a decision-making process.

When using “agree on assumptions” approaches, decision makers and stakeholders begin by identifying data sets, models, and other assumptions that will be used to estimate how a decision will perform in the future; having “agreed on assumptions”, the decision is then assumed to follow from resulting analysis. Most decision support exercises in water resources planning use “agree on assumptions” approaches, and these are likely to be more familiar to readers of these guidelines.

“Agree on decisions” approaches argue that it may be unproductive to agree on assumptions at the outset of a decision-making process. Assumptions about the future can be wrong, and stakeholders may not be able to agree. In either case, the resulting decision will be vulnerable, either because the future turns out differently or because the decision lacks stakeholder support. “Agree on decisions” approaches focus on building stakeholder engagement and support through a comprehensive analysis of how different assumptions may impact on a decision outcome.

The guidelines are demonstrated using two case studies from Uganda. The first case study is a seasonal planning problem encountered by dryland farmers, and was formulated based on feedback from stakeholders involved in the CTCN assistance. The second case study is concerned with long-term planning for hydropower and irrigation development.

2 Background

2.1 Uncertainty and water resources planning

Managers and operators of water resource systems have to make decisions without full knowledge of the consequences of those decisions. Reservoir operators need to make release decisions without knowing whether reservoir inflows in the coming months will be sufficient to meet demands. Water system planners and managers must make decisions about expensive new infrastructure without knowing how these investments may perform over long design lifetimes. Policy-makers in the water sector must decide on appropriate measures for managing and distributing water to various uses without knowing how these measures will impact on the livelihoods of water users and other stakeholders.

Uncertainty in water resources management results from external factors including meteorological, demographic, and economic factors. Uncertain meteorological variables including rainfall, evaporation, and temperature affect the quantity and timing of river runoff and groundwater recharge, impacting water supplies. These variables can also have significant impacts on water demand, as irrigation and hydropower demands are partly a function of meteorological variables (for example, irrigation demand is a function of evaporation). Water use in the irrigation, energy, and other sectors is linked to economic activity, so economic growth and changes in the economy can also have impacts on water use. Demographic factors influence water use directly (for example, by changing domestic water demand) and indirectly, through impacts on economic activity.

In addition to external factors, uncertainty related to the implementation of a decision can also affect a decision outcome. For example, the cost and time schedule for completing a hydropower facility are uncertain, and some aspects of the long-term operation, such as sedimentation, may be uncertain as well. New policy measures, such measures to increase uptake of water saving technologies, may also have uncertain outcomes depending on how water users respond to incentives or other measures meant to motivate uptake.

2.2 Alternatives and scenarios

This document uses the terms *scenario* and *alternative.* Because these terms are sometimes defined differently in different contexts, we provide the following precise definitions:

- **Scenario:** A scenario is a representation of future conditions that affect the outcome of a decision. For example, a scenario could consist of a single seasonal rainfall forecast time series.
- **Alternative:** An alternative is a possible course of action, and decision makers must decide among two or more alternatives. For example, an alternative could consist of a crop and a planting date.

2.3 Representing uncertainty in models and other decision support tools

Computer simulation models are used in water resources planning to estimate how decisions will perform, at both seasonal and long-term time scales. For example, in the seasonal context, a model may be used to predict runoff, irrigation demand, and hydropower demands, and how different reservoir operations may perform given assumptions about the future. In the long-term context, models can be used to estimate how infrastructure and policies will perform over design lifetimes, given inter-annual variation in rainfall and other drivers. In addition, models are often used to estimate performance given projections of climate change. In both the seasonal and long-term contexts, optimization tools are sometimes used to help identify projects and policies that best meet the objectives of decision makers.

The role of uncertainty should be considered when using models and other analytical tools to predict future performance. The most common approach is to develop scenarios. A scenario is an internally consistent and plausible representation of future conditions. In many planning exercises, a number of scenarios (usually 2-4) will be developed to capture a plausible range of futures. For example, a long-term planning exercise might include two representations of future climate: one based on an average of climate model projections and one representing a worst-case scenario.

While the scenario approach is straightforward, it is difficult to incorporate more than about four scenarios in a coherent evaluation exercise. For example, if three different planning alternatives are under consideration and three scenarios of future conditions have been developed, then nine sets of results must be compared. This practical limit on the number of scenarios that may be considered constrains the extent to which uncertainty can be investigated in the exercise. In addition, there is no way to guarantee the sample of the uncertainty space included in the scenario set is representative, or includes the future scenarios that are most relevant for decision making.

To include a broader sample of uncertainty, some planning approaches use a probabilistic approach to summarize information from an ensemble representation. For example, if an ensemble of 20 rainfall forecasts is available, and we can assign a probability to each ensemble member, then it is possible to make inferences about the likelihood of different outcomes (e.g., average, 90% percentile). Decision makers can then use this information to make decisions based on their own risk preferences.

2.4 Agree on assumptions vs. agree on decisions

The scenario and probabilistic approaches described above both require decision makers and stakeholders to agree on assumptions, including:

- A modeling approach, and choice of model(s).
- Input data to the model(s).
- Other assumptions informing the decision process (for example, assumptions about uptake of water efficiency measures).

If uncertainty is considered in the decision making process, then it is also necessary to make further assumptions.

- If a scenario approach is being used, then stakeholders must agree on the number of scenarios to be developed, and which type(s) of uncertain information should be varied in each scenario.
- If a probabilistic ensemble approach is being used, then stakeholders much agree on which type(s) of data should be varied using ensembles, and how to assign probabilities to each ensemble member.

If a decision making process requires agreeing on assumptions, the process may be vulnerable to failure. If stakeholders are unable to agree, then the process may stop or the resulting decision may be undermined by a lack of stakeholder support. In addition, even if it is possible to agree on a decision, the decision may be vulnerable to failure if assumptions about the future turn out to be wrong.

To address some of the weaknesses in “agree on assumptions” approaches, a literature has developed over the past 15 years on alternative approaches to water sector planning. These efforts originated at the RAND Corporation in California, and applied the Robust Decision Making (RDM) framework (Bryant & Lempert, 2010; R. Lempert, 2013; R. J. Lempert, Groves, Popper, & Bankes, 2006) to water planning.

The Robust Decision Making approach addresses the weaknesses of “agree on assumptions” approaches by beginning with a comprehensive analysis of sensitivity to assumptions. In this step, uncertain factors affecting a decision are sampled and the performance of the decision is estimated for each combination of uncertain factors. As an example, a 2008 analysis of a water agency plan in California, USA identified six uncertain factors likely to impact the performance of the plan, and developed ensembles to represent the uncertainty in each factor (Groves, Knopman, Lempert, Berry, & Wainfan, 2008). Table 2-1 displays the six types of uncertainty, along with the number of ensemble members developed for each uncertainty type.

Table 2-1 Uncertainty ensemble developed to support Robust Decision Making, California planning example

Uncertainty type	Number of ensemble members
Climate (rainfall and evaporation)	90
Effectiveness of implementing water recycling	3
Effectiveness of implementing artificial groundwater recharge	3
Effectiveness of household water savings	4
Effectiveness of efforts to reduce the area of impermeable surface	5
Reliability of water imports from other basins	4

An ensemble of 900 random combinations of the six uncertainty factors was developed, and performance under each set of assumptions was estimated using a simulation model.

In the next step of the RDM framework, the resulting database of model results is searched to identify combinations of uncertain factors that result in unacceptable performance. Critical to this step is a definition of unacceptable performance, which must be agreed upon by stakeholders. It is possible to define unacceptable performance according to multiple metrics if stakeholders cannot agree on a single metric. In the California example, supply-demand balance was used at the performance metric, with supply shortages and excess supply characterized as unacceptable outcomes. A search of the database of model runs then identified subsets of uncertain factors likely to result in each of the two unacceptable outcomes. Uncertain factors linked to the supply shortage outcome are displayed in Table 2-2.

Table 2-2 Ranges of uncertain factors resulting in supply shortages, California planning example

Uncertainty type	Range of values causing unacceptable performance
Climate (rainfall and evaporation)	Drier climate
Effectiveness of implementing water recycling	Recycling goals met or missed, but not exceeded
Effectiveness of efforts to reduce the area of impermeable surface	Increase in impermeable surfaces due to urbanization

The other uncertain factors were not found to be linked to the supply shortage outcome (i.e., the performance of the decision was not found to be sensitive to these factors).

In the final step of RDM, the subset of uncertain factors causing unacceptable performance is used to evaluate planning alternatives. Decision makers and stakeholders then have the option of selecting an alternative that performs reasonably well in this subset, or of developing a new alternative. Because such an alternative appears likely to perform well regardless of how the future turns out, it is referred to as a “robust” alternative. In the California example, a subset of 203 of the original 900-member ensemble was found to be associated with three uncertain factor ranges displayed in Table 2-2, while a set of 131 ensemble members was associated with oversupply. These subsets were then used in the planning process to help identify planning alternatives unlikely to result in shortage while, at the same time, reducing the likelihood of overinvestment in new supplies.

The focus of RDM is on understanding how uncertainty will affect a decision, motivated in part by the hypothesis that better understanding of the impact of assumptions will help stakeholders agree on decisions. In the 2014 policy paper, the World Bank characterized this as a shift in focus from agreeing on assumptions to agreeing on decisions (Kalra et al., 2014). The World Bank has since promoted the use of RDM and related frameworks (e.g., Ray and Brown (2015), Kwakkel, Haasnoot, and Walker (2015)), and has mainstreamed these approaches into its own analytical activities (e.g., Hallegatte, Bangalore, Fay, Kane, and Bonzanigo (2015)).

3 Seasonal case study description

Application of the decision making guidelines to a seasonal planning problem is illustrated using a case study example from Uganda. The case study addresses decision making by farmers involved in dryland agriculture.

Most farmers in Uganda practice dryland irrigation, and are dependent on rainfall to meet crop evapotranspiration requirements. Therefore, predicting the onset of the rainy season is important for planning labour activities and other inputs to production. In addition, other properties of the rainy season, such as the magnitude of rainfall and the extent of dry periods can affect crop yields and agricultural livelihoods. Because crops respond in different ways to water stress, seasonal forecast information is also relevant for crop selection.

Many farmers in Uganda are interested in seasonal rainfall because these predictions can help them decide which crops to plant, when to plant, and how to allocate resources during the growing season. A number of government agencies are involved in providing seasonal forecasts and/or giving advice to farmers based on forecast information, including the Uganda National Meteorology Authority, the Ministry of Agriculture, and the Ministry of Water and Environment. There is considerable interest in Uganda how best to use seasonal forecast information to inform decision making.

The case study focuses on two decisions that are made by farmers prior to the onset of each of the two rainy seasons that occur each year (March-May and October-December):

- Which crop(s) to plant
- When to plant

The case study makes use of the following information from the data portal to provide advice about the two decisions:

- Ensemble rainfall data, including ensemble forecasts
- Historical potential evapotranspiration.

In addition, the case study makes use of a crop yield model, AQUACROP. AQUACROP is used to make estimates of crop yields based on forecasts of rainfall and potential evapotranspiration, and is also available as part of the data portal.

More details about available data and the crop yield model are provided in the following sections.

3.1 Ensemble rainfall forecasts

To predict the performance of a planting decision (with respect to both crop date and planting date), we need to predict the onset of each rainy season, along with the timing and magnitude of rainfall over the course of the season. Two options are provided in the data portal for making these predications: historical data and a seasonal forecast.

Because it is impossible to predict rainfall exactly at a seasonal time scale, we use an ensemble approach to make predictions. In other words, we use an ensemble of predictions, each of which represents a different possible rainfall pattern over the coming months. Information about how to use ensemble information in decision making is provided in Section 5.

3.1.1 Rainfall ensembles based on historical data

The data portal provides rainfall ensembles based on historical data. To construct these ensembles, each year of a historical rainfall time series is treated as a separate ensemble member. In the data portal, two historical data sets are available in ensemble format:

- **CHIRPS** (Climate Hazards Group InfraRed Precipitation with Station data): This is a global, gridded data set that is based on a mix of satellite and station data. The time step is daily and the spatial resolution of the grid is 0.05°. The data set covers the period from 1 January 1981 to 31 December 2017, and each year is available as part of the historical ensemble, for a total of 37 ensemble members.
- **TRMM** (Tropical Rainfall Measuring Mission): This is a global, gridded data set that is largely based on satellite data. The time step is daily and the spatial resolution of the grid is 0.25°. The data set covers the period from 1 January 2000 to 31 December 2017, and each year is available as part of the historical ensemble, for a total of 18 ensemble members.

3.1.2 Ensemble seasonal forecast

A seasonal rainfall forecast is available in the data portal that forecasts daily rainfall at a nine-month lead time. The seasonal forecast is produced by the US National Centers for Environmental Prediction’s Climate Forecast System, version 2 (CFSv2). The time step of the forecast is daily, and forecasts are available on a 0.5° grid.

CFSv2 is a global model that simulates atmospheric, ocean, sea ice, and land processes , along with accompanying feedbacks between the four process models. CFSv2 runs on an ongoing basis, providing forecasts four times daily. CFSv2 is also integrated with data assimilation routines that are used to update initial conditions.

Two versions of the CFSv2 forecast are available from the data portal. The first version, called “Seasonal forecast”, consists of direct output from the forecast. The second version, called “Seasonal forecast (corrected)” consists of forecast output that have been downscaled and bias-corrected.

In this context, downscaling is the process of differentiating coarse gridded data over a finer grid, while bias correction refers to processing that removes systematic errors from climate model outputs. In the data portal, both downscaling and bias correction are accomplished in a single step, using the "delta-change" method.

To apply the delta-change method, we computed average monthly precipitation simulated by a CFSv2 model during a historical reference period from 1 January 2001 to 31 December 2010. We repeated the same calculation using the TRMM data set. We then estimated a scaling factor for each month by dividing the average observed (TRMM) rainfall by the average simulated rainfall:

$$SF_i = \frac{\overline{observed_i}}{\overline{simulated_i}}$$

$$\begin{aligned}
&Where \\
&SF = monthly\ scaling\ factor \\
&i = month\ index \\
&\overline{simulated_i} = average\ simulated\ rainfall\ for\ month\ i, 2001-2010 \\
&\overline{observed_i} = average\ observed\ rainfall\ for\ month\ i, 2001-2010
\end{aligned} \tag{3.1}$$

The appropriate monthly scaling factor is then applied to each value of the seasonal forecast. Because the spatial scale of TRMM is finer than the CFSv2 forecast, this serves as a downscaling step. In other words, each single CFSv2 grid value is adjusted by four different scaling factors to obtain a forecast aligned with the TRMM grid.

The CFSv2 ensemble consists of 20 ensemble members and a new ensemble is retrieved from CFSv2 once a week. Each ensemble consists of the 20 most recent CFSv2 forecast runs. Because the CFSv2 forecast runs every six hours this means that the start and end dates for each forecast in a single 20-member ensemble can differ by anywhere from 6 hours to five days. The ensemble members differ only in terms of initial conditions, which are updated using data assimilation routines.

The CFSv2 forecasts may not have sufficient forecasting skill to be useful for advising farmers in Uganda. The skill of the CFSv2 forecast has been evaluated globally, for sub-Saharan Africa, and for East Aftrica. However, we are not aware of any assessments of forecast skill targeting Uganda. In addition the other skill assessments have focused on rainfall indicators that may not be useful for farmers (e.g., none assess forecast skill for predicting the onset of the rainy season). In addition, the corrected version uses an observed timeseries, TRMM, that may not be consistent with on-the-ground measurements (see Section 3.1.1). The CFSv2 forecasts should be evaluated for skill in predicting rainfall variables relevant for agriculture in Uganda before being applied to real-world decision making.

3.2 Potential evapotranspiration

Two potential evapotranspiration (PET) data sets are available through the data portal:

- **MOD16** (MOD16 Global Terrestrial Evapotranspiration Data Set): This is a global, gridded data set based on satellite measurements. The time step is once every 8 days, and the spatial resolution of the grid is 5 km. The data set covers the period from 1 January 2000 to 27 December 2014.
- **CRU** (Climate Research Unit): This is a global, gridded data set based on ground station measurements. The station measurements have been interpolated on to a global grid with a spatial resolution of 0.5°. The time step of the data set is monthly, and it covers the period from January 1901 to December 2013.

At the time of writing, only the CRU PET data set is available in the AQUACROP model that is used to estimate crop yields as a function of soil water stress (see Section 3.3). The AQUACROP model uses average monthly values.

3.3 AQUACROP model

AQUACROP is a model that simulates crop water use and crop yield response to water stress (Steduto, Hsiao, Raes, & Fereres, 2009). AQUACROP was developed by the Food and Agriculture Organization of the United Nations (FAO) and is available through the data portal.

To run the AQUACROP model through the data portal, users are prompted to provide the following information:

- Rainfall input (either historical or forecast)
- Crop type(s)
- Planting date(s)
- Soil type(s)
- Crop area(s)

Based on this information, AQUACROP then simulates crop yields and other parameters as a function of accumulated soil water stress.

3.4 Summary of seasonal case study

The seasonal case study can be summarized as follows:

- Decisions:
  - Planting date
  - Crop

- Uncertain factor affecting decision:
  - Rainfall

- Method for evaluating decision performance:
  - Crop yield model (AQUACROP)

- Metric used to evaluate performance:
  - Crop yield

4 Long-term case study description

Application of the guidelines to a long-term planning problem is illustrated using a second example from Uganda. The long-term example is hypothetical and concerns decision-making about whether to invest in large-scale infrastructure, including hydropower facilities and irrigation schemes.

While Uganda has already approved a number of major projects along the Nile River, further investment may be possible in the future.

Because most famers in Uganda practice dryland irrigation, the government is also considering investment in irrigation infrastructure. Irrigation development could reduce vulnerability to drought and expand agricultural production to marginal lands that are not suited to dryland farming.

The performance of both hydropower and irrigation infrastructure is uncertain in the long term. Hydropower generation capacity is affected by hydrological conditions, which may change as a result of climate change. In addition, the economic performance of hydropower facilities is affected by uncertain economic factors like the cost of alternative energy supplies. Irrigation system performance is also affected by uncertain hydrologic and economic conditions. In this context, evaluation of proposed projects may benefit from investigating how different assumptions about hydrological and economic conditions might affect the performance of decisions.

The rest of this section presents tools and data sets available as part of the data portal that can be used to investigate the performance of hydropower and infrastructure projects in the long term.

4.1 Basin planning application

The basin planning application is a modeling and analysis tool located in the data portal that can be used to evaluate water resource management plans, including plans that include new infrastructure.

Underlying the basin planning application is a model of the Nile River and Lake Victoria that was developed using the software package MIKE HYDRO Basin. The model simulates rainfall-runoff processes, lakes, reservoirs, water uses (including irrigation), and hydropower. The model can be used to investigate how changes to rainfall and evaporation resulting from climate change may affect water availability and the performance of water infrastructure.

The basin planning application also includes post-processing functionality that can be used to explore the sensitivity of model performance to economic conditions. The functionality includes a net present value (NPV) calculator that estimates NPV based on a discount rate and an expected annual return. The annual return can be linked to other indicators to become a function of hydrological conditions.

4.2 Climate change scenarios

Climate change scenarios are used to estimate the impact of long-term changes in climate on meteorological variables including precipitation and potential evapotranspiration. Climate model scenarios are developed from global and regional climate models, which simulate the Earth's climate into the future using different assumptions about greenhouse gas emissions.

The data portal provides climate change projections from ten regional climate models (RCMs). Regional climate models simulate a portion of the Earth's surface (usually a continent) using output from a global climate model (GCM) as boundary conditions. RCMs simulate climate on a finer grid scale than is computationally feasible using global models. Because some of the physical processes that drive precipitation, such as orographic effects, are not resolved by GCMs, RCMs are more useful for projecting changes to rainfall. Each of the ten RCMs uses different assumptions about the physical processes driving climate, so the models make different projections about how the climate will change.

Four climate change scenarios are available in the data portal for each of the ten RCM simulations. The four scenarios provide estimates for two points in the future, near-term and end-of-century, each with two sets of assumptions about anthropogenic activities will affect the climate.

The near-term and end-of-century climate change estimates are developed by comparing climate model outputs from the two future periods (2016-2035 and 2081-2100) to a 1986-2005 baseline. Average monthly changes are estimated by comparing average monthly values from the baseline period to the average for the same month in the future. The resulting set of 12 monthly “change factors” can be used to modify inputs to the basin planning application’s MIKE HYDRO Basin model by modifying each value in an input time series using the appropriate monthly change factor.

The two sets of assumptions about anthropogenic activities are from the Representative Concentration Pathways (RCP) scenarios developed by the Intergovernmental Panel on Climate Change as part of its fifth Assessment Report (Pachauri et al., 2014). The RCP 4.5 scenario assumes that greenhouse gas emissions will peak in 2040, and then decline slightly. The RCP 8.5 scenario assumes that greenhouse gas emissions will continue to rise throughout the 21st century.

The four scenarios are summarized below:

- **rcp45 2016-2035**: This scenario estimates near-term climate changes based on the RCP 4.5 greenhouse gas concentration scenario
- **rcp85 2016-2035**: This scenario estimates near-term climate changes based on the RCP 8.5 greenhouse gas concentration scenario.
- **rcp45 2081-2100**: This scenario estimates end-of-century climate changes based on the RCP 4.5 greenhouse gas concentration scenario.
- **rcp85 2081-2100**: This scenario estimates end-of-century climate changes based on the RCP 8.5 greenhouse gas concentration scenario.

Figure 4-1 presents monthly rainfall change factors for the rcp45 2016-2035 scenario. Each ensemble member is based on output from a different RCM. The change factors are multiplicative. The table provides an example of the range of variation predicted by different climate models.

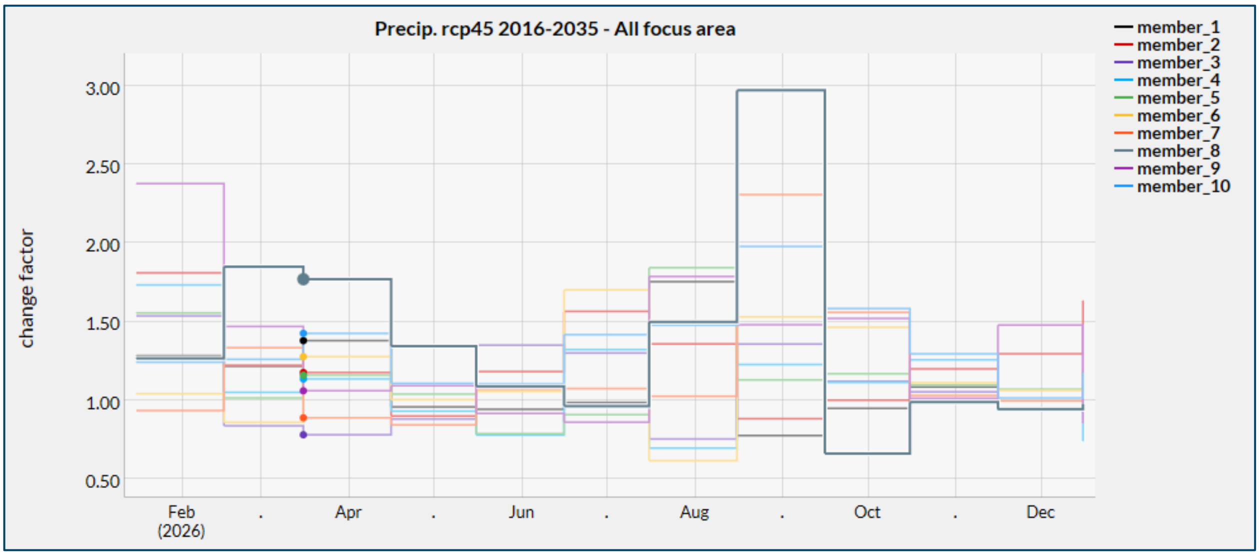

Figure 4-1 Precipitation change factors for the rcp45 2016-2035 scenario

4.3 Irrigation demand scenarios

When irrigation infrastructure is built, irrigation water demands may be uncertain. Contributing factors include uncertainty about:

- Evapotranspiration and rainfall.
- Types of crops that will be grown.
- Irrigation methods.

To account for uncertainty in irrigation demands, the basin planning application allows users to provide three demand estimates at each irrigation location. A baseline estimate is given as a time series of average monthly demands, while upper and lower bounds can be specified as fixed fractions of the baseline estimate.

4.4 Economic scenarios

Uncertainty about economic conditions in the future affects estimates of the economic benefits of new hydropower and irrigation infrastructure. Economic uncertainty results from many factors including uncertainty about population growth, infrastructure development, security, trade relationships, political stability, and changes to the structure of the economy.

The basin planning application can estimate the NPV of a proposed investment, such as a new dam, hydropower plant, or irrigation scheme. The NPV is estimated based on an annual return and a discount rate. The annual return can be linked to become a function of other indicators.

To account for economic uncertainty, the basin planning application allows users to provide three annual return estimates for each investment. A baseline estimate must be provided, while upper and lower bounds can be specified as fixed fractions of the baseline.

4.5 Summary of the long-term planning case study

The seasonal case study can be summarized as follows:

- Decisions:
  - Which new infrastructure schemes should be built?

- Uncertain factors affecting decision:
  - Climate
  - Irrigation demands
  - Annual return for irrigation schemes
  - Annual return for hydropower facilities

- Method for evaluating decision performance:
  - MIKE HYDRO Basin model in basin planning application
  - Economic post-processing in basin planning application

- Metric used to evaluate performance:
  - NPV
  - Reliability

5 Comparison of approaches to decision making

This section demonstrates different approaches to decision making using tools available in the data portal. The demonstration shows how to use “agree on assumptions” and “agree on decisions” approaches using the data portal tools.

The section demonstrating “agree on assumptions” approaches uses two methods: scenario analysis and probability-weighted decision analysis. The section demonstrating “agree on decisions” approaches introduces robust decision making.

5.1 Agree on assumptions

Two “agree on assumptions” approaches are demonstrated: scenario analysis and probability-weighted decision analysis. In scenario analysis, 2-4 scenarios are developed to represent a range of conditions that may occur in the future, and information from the scenarios is used to inform a deliberative decision-making process. In probability-weighted decision analysis, we develop an ensemble of future conditions and assign a probability to each ensemble member. The resulting information can then be used to inform a decision process based on the risk preferences of decision makers.

The scenario analysis approach is demonstrated using the long-term planning case study, while probability-weighted decision analysis is demonstrated using the seasonal case study.

5.1.1 Scenario analysis

In the scenario analysis, we develop two scenarios of future conditions and two decision alternatives. We then analyse each scenario/alternative combination using functionality available in the basin planning application and compare results.

5.1.1.1 Future scenarios

Two scenarios of future conditions are developed and compared to a third baseline scenario.

In the first scenario, called the “Pessimistic” scenario, we assume that greenhouse gas concentrations will rise throughout the 21st century (i.e., the RCP 8.5 assumptions). We further assume that a combination of rising temperatures and weak adoption of water saving technologies in irrigation will lead to a rise in irrigation demands.

In the second scenario, called the “Optimistic” scenario, we assume that greenhouse gas concentrations will decline after 2040 (i.e., the RCP 4.5 assumptions) and further assume that strong adoption of water saving technologies will lead to a decline in irrigation demands.

Assumptions used in the scenarios are summarized in Table 5-1.

Table 5-1 Assumptions used to develop scenarios of future conditions.

Scenario	Climate change	Irrigation demand	Irrigation annual return	Hydropower annual return
Baseline	Historical	Baseline	Baseline	Baseline
Pessimistic	rcp85 2081-2100	High	Baseline	Baseline
Optimistic	rcp45 2081-2100	Low	Baseline	Baseline

In the Pessimistic and Optimistic scenarios, we use an average of the ten sets of change factors available for each climate scenario (i.e., we do not use results from individual climate model runs). We use results from the end-of-century period (2081-2100) instead of the near-term because of the focus on long-term planning.

5.1.1.2 Decision alternatives

Two decision alternatives are developed and compared across the three future scenarios described in Section 5.1.1.1. The first alternative is called “Existing HP w/environmental flows” and includes three existing hydropower facilities that are simulated together with environmental flow requirements. The second is called “New irrigation” and consists of the first alternative with a new irrigation scheme added.

5.1.1.3 Overview of workflow

An overview of the scenario analysis workflow is given in Figure 5-1.

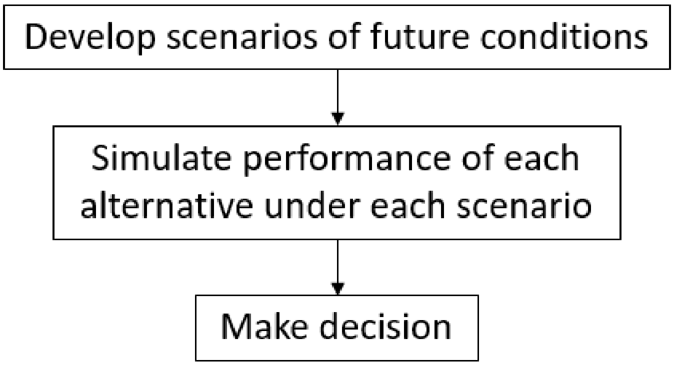

Figure 5-1 Overview of scenario analysis workflow

5.1.1.4 Case study example

The application to the long-term planning case study is now presented following the workflow given in Figure 5-1.

Develop scenarios of future conditions

Projected average monthly changes in rainfall for the 2081-2100 end-of-century period are presented in Figure 5-2 and Figure 5-3. Each change factor is equal to the ratio of average monthly rainfall in the end-of-century period to a 1986-2005 baseline. Because each scenario includes ten different ensemble members, ten sets of change factors are presented in each plot. However, an average of each 10-member ensemble is used to create the climate scenarios.

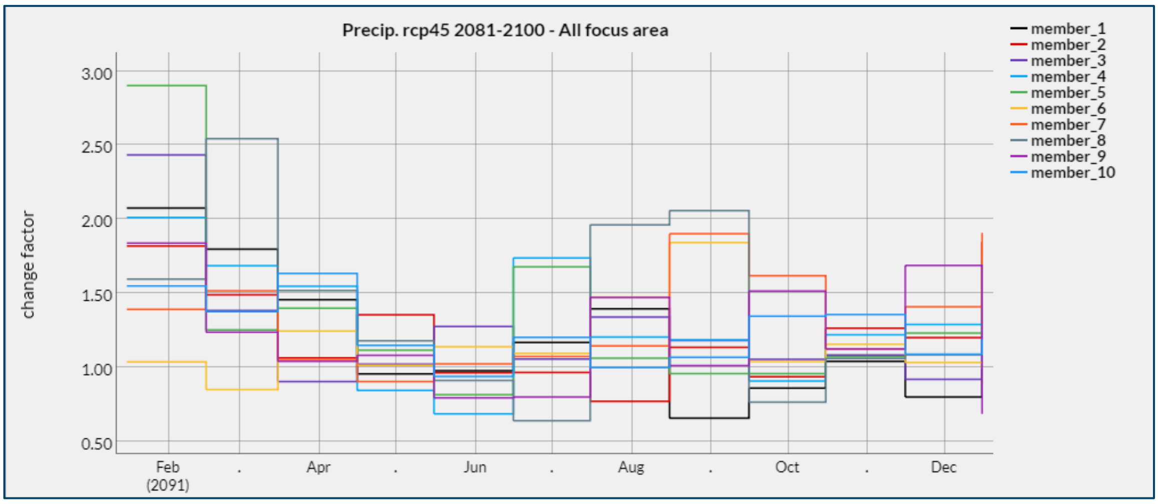

Figure 5-2 Change factors for the rcp45 scenario

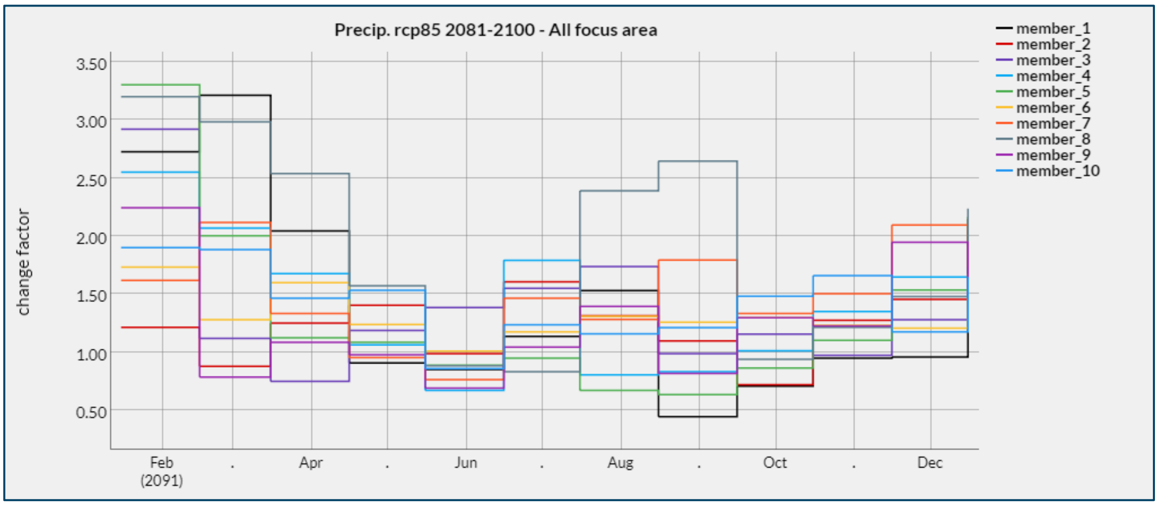

Figure 5-3 Change factors for the rcp85 scenario

Baseline, high (pessimistic) and low (optimistic) irrigation water demands are presented in Table 5-2.

Table 5-2 Irrigation water demand assumptions (values are in m^3/s)

Month	Baseline	Pessimistic	Optimistic
January	12.01	14.412	9.608
February	67.34	80.808	53.872
March	34.77	41.724	27.816
April	6.61	7.932	5.288
May	0.64	0.768	0.512
June	2.37	2.844	1.896
July	0.44	0.528	0.352
August	26.28	31.536	21.024
September	6.06	7.272	4.848
October	17.43	20.916	13.944
November	8.07	9.684	6.456
December	8.55	10.26	6.84

Simulate performance of each alternative under each scenario

5.1.2 Probability-weighted decision analysis

In the probability-weighted decision analysis, we apply an ensemble simulation approach to a set of decision alternatives. We assume a probability distribution for the ensemble and use information from the ensemble simulation to inform decision rules. In this example, we present two decision rules: one appropriate for a risk-neutral decision maker and the other appropriate for a risk-averse decision-maker.

5.1.2.1 Ensemble representation of future uncertainty

In the seasonal case study application, we use an 20-member ensemble to represent the expected range of uncertainty in seasonal rainfall forecasts. We assume that each of the 20 rainfall scenarios is equally likely or, in other words, we assume that the probability of any rainfall scenario is equal to 0.05.

5.1.2.2 Decision alternatives

In the seasonal application, we assume that we need to make decisions about a crop type and planting date at a lead time of about one month. We focus on the March-May rainy season and assume that the decision is made on 1 February. We consider three crop types and three planting dates, for a total of nine decision alternatives as summarized in Table 5-3.

Table 5-3 Decision alternatives under consideration in seasonal planning example

Alternative	Crop type	Planting date
1	Maize	01-Aug
2	Maize	08-Aug
3	Maize	15-Aug
4	Beans	01-Aug
5	Beans	08-Aug
6	Beans	15-Aug
7	Tomatoes	01-Aug
8	Tomatoes	08-Aug
9	Tomatoes	15-Aug

5.1.2.3 Decision rules

In this section, we present the two decision rules: one for a risk-neutral decision maker, and the other for a risk-averse decision maker.

Rule for risk-neutral decision maker

We assume that a risk-neutral decision maker wants to maximize the expected value of a decision. In other words, a decision maker following the risk-neutral rule will select the alternative with the highest expected value.

The expected value of an alternative is:

$$\begin{aligned}
&E[r(a_1,\theta)] = p(\theta_1) * r(a_1,\theta_1) + p(\theta_2) * r(a_1,\theta_2) + \cdots + p(\theta_n) * r(a_1,\theta_n) \\
&Where \\
&n = number\ of\ scenarios \\
&a = alternative \\
&\theta = scenario
\end{aligned} \tag{5.1}$$

$$r(a_1, \theta) = reward\ from\ alternative\ a_1\ given\ scenario\ \theta$$
$$p(\theta) = probability\ of\ scenario\ \theta$$

A risk-neutral decision maker is indifferent between two alternatives if the expected values of the alternatives are equal. For example, a risk-neutral decision maker is indifferent between the following alternatives:

- An alternative for which the probability of a $500 reward is 100%
- An alternative for which the probability of a $1000 reward is 50% and the probability of no reward is also 50%

Rule for risk-averse decision maker

We assume that risk-averse decision maker wants to maximize the probability that a decision will not result in failure.

Application of the rule for the risk-averse decision maker requires defining failure thresholds. A failure threshold is minimum crop yield, crop value, or other indicator value, where any value below the threshold would have serious consequences for the decision maker. The risk-averse decision maker would like to maximize the probability of avoiding this outcome.

After one or more failure thresholds have been defined, the probability of an alternative not resulting in failure is defined as follows:

$$\begin{aligned}
&p(a_1) = p(\theta_1) * \Lambda[r(a_1, \theta_1)] + p(\theta_2) * \Lambda[r(a_1, \theta_2)] + \cdots + p(\theta_n) * \Lambda[r(a_1, \theta_n)] \\
&Where \\
&n = number\ of\ scenarios \\
&a = alternative \\
&\theta = scenario \\
&r(a_1, \theta) = reward\ from\ alternative\ a_1\ given\ scenario\ \theta \\
&\Lambda[r(a_1, \theta)] = 1\ if\ reward\ r\ exceeds\ failure\ threshold, 0\ otherwise \\
&p(\theta) = probability\ of\ scenario\ \theta
\end{aligned} \tag{5.2}$$

The decision maker then selects the alternative that maximizes this value.

The risk-averse decision maker is willing to forego an alternative with a higher expected value in order to minimize the probability of an unacceptable outcome.

5.1.2.4 Overview of workflow

An overview of the workflow for probabilistic decision analysis is given in Figure 5-4.

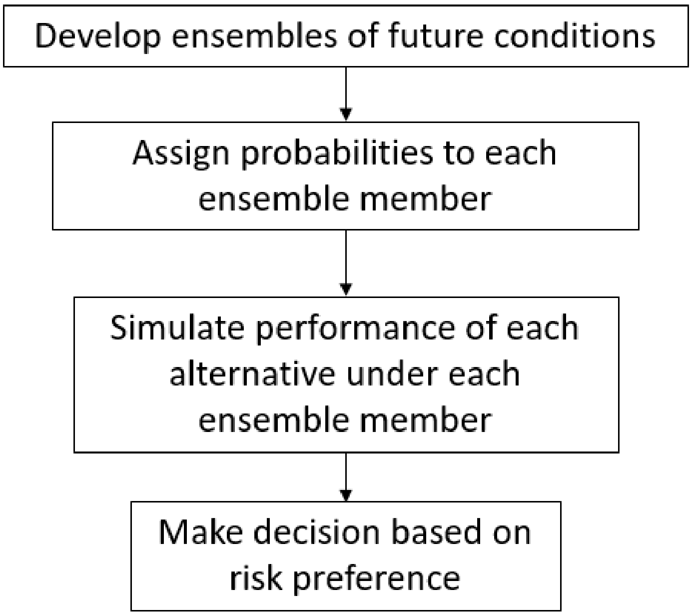

Figure 5-4 Workflow for probabilistic decision analysis

5.1.2.5 Case study example

The application to the seasonal planning case study is now presented following the workflow given in Figure 5-4.

Develop ensembles of future conditions

In the first step, we use an ensemble rainfall forecast to represent uncertainty in future conditions. The ensemble rainfall forecast is taken from the data portal and consists of the corrected CFSv2 seasonal forecast described in section 3.1.2. A plot of the 20-member ensemble retrieved on 25 May 2018 is shown in Figure 5-5. The plot consists of values over the Lake Kyoga area.

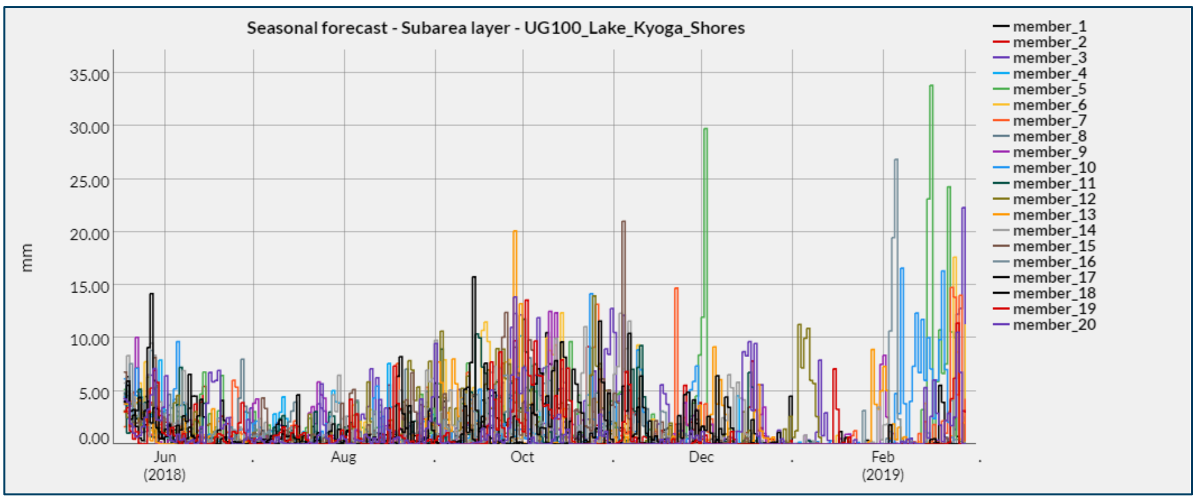

Figure 5-5 CFSv2 seasonal forecast for Lake Kyoga area

A screen capture from the data portal shows the area over with the averaging takes place (Figure 5-6).

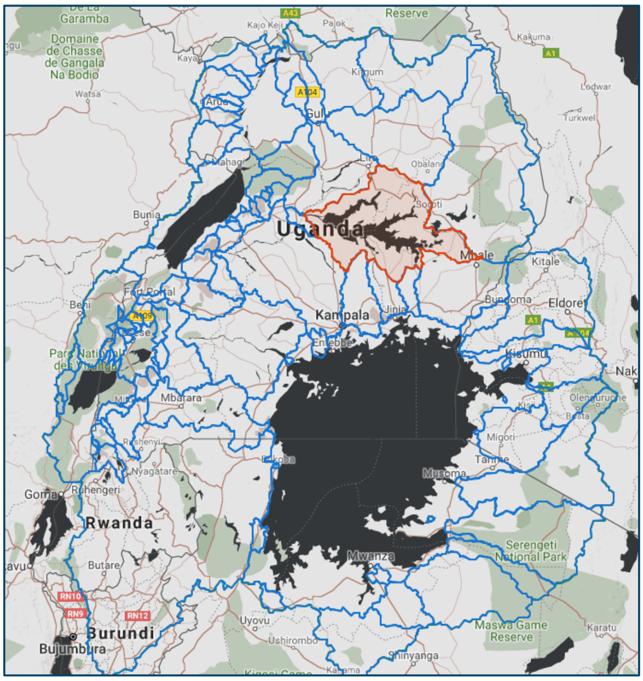

Figure 5-6 Area used to average seasonal forecast values (red)

Assign probabilities to each ensemble member

We assume that each member of the input ensemble is equally likely. In other words, the probability of each ensemble member is equal to 0.05.

Simulate performance of each alternative under each ensemble member

We simulate nine different alternatives, each of which is a combination of a crop type and a planting date. The nine combinations are summarized in Table 5-4.

Table 5-4 Summary of planning alternatives

Alternative	Planting date	Crop type
1	01-Aug-2018	Maize
2	08-Aug-2018	Maize
3	15-Aug-2018	Maize
4	01-Aug-2018	Tomatoes
5	08-Aug-2018	Tomatoes
6	15-Aug-2018	Tomatoes
7	01-Aug-2018	Beans
8	08-Aug-2018	Beans
9	15-Aug-2018	Beans

The performance of each alternative is simulated using the AQUACROP model, as described in section 3.3. Because the seasonal forecast information was retrieved on 25 May 2018 and the planting dates are in August 2018, the resulting performance estimates are equivalent to forecasting performance at a 2-2.5 month lead time.

Make decision based on risk preference

We assume that a decision maker will evaluate each decision based on the relative crop yield indicator (the simulated yield as a percentage of the maximum potential yield).Values of the ensemble average and the percentage of ensemble members exceeding a minimum performance threshold are presented in Table 5-5. We assume that minimum acceptable relative yield is 80%.

Table 5-5 Ensemble simulation results for relative yield indicator

Alternative	Planting date	Crop type	Expected value (%)	% of ensemble exceeding minimum threshold
1	01-Aug-2018	Maize	93.4	95
2	08-Aug-2018	Maize	93.35	90
3	15-Aug-2018	Maize	92.7	90
4	01-Aug-2018	Tomatoes	69.1	40
5	08-Aug-2018	Tomatoes	68.8	40
6	15-Aug-2018	Tomatoes	68.15	40
7	01-Aug-2018	Beans	87.2	65
8	08-Aug-2018	Beans	86.9	60
9	15-Aug-2018	Beans	86.05	60

According to the simulation results, the decision with the highest expected value is Maize, 01-Aug-2018. This decision also results in the highest percentage of ensemble members that exceed the 80% threshold for the relative yield indicator. Therefore, both a risk-averse and a risk-neutral decision maker would select this alternative.

A different perspective can be provided by estimating the unit value of each decision. We assume that the unit value is equal to the crop yield provided by the price. Expected unit values are provided in Table 5-6. A risk-neutral decision maker prioritizing the unit value indicator would still select Maize, 01-Aug-2018.

Table 5-6 Expected unit values of decision alternatives

Alternative	Planting date	Crop type	Expected yield (tonnes/ha)	Price* (USD/tonne)	Expected unit value (USD/ha)
1	01-Aug-2018	Maize	13.813	292.5	4040
2	08-Aug-2018	Maize	13.783	292.5	4032
3	15-Aug-2018	Maize	13.706	292.5	4009
4	01-Aug-2018	Tomatoes	4.877	605	2951

5	08-Aug-2018	Tomatoes	4.858	605	2939
6	15-Aug-2018	Tomatoes	4.797	605	2902
7	01-Aug-2018	Beans	3.52	744.2	2620
8	08-Aug-2018	Beans	3.506	744.2	2609
9	15-Aug-2018	Beans	3.476	744.2	2587

*Based on 2016 producer prices obtained from FAOSTAT database. Producer prices for Uganda were unavailable, so prices for Kenya were used instead.

5.2 Agree on decisions

An "agree on decisions" approach is presented using the example of Robust Decision Making (RDM). In the RDM application, we select a decision alternative according to a robustness metric. We then perform a vulnerability analysis to identify future conditions that could cause the selected alternative to fail. We then re-evaluate alternatives against this subset of future conditions and use the information to inform decision making.

The RDM approach is demonstrated using the long-term planning case study.

5.2.1 Future scenarios

In the RDM approach, we estimate how decision alternatives may perform under a wide range of future conditions in order to find out where decisions may be vulnerable to failure. Table 5-7 summarizes options for varying assumptions about future conditions in the basin planning tool. Because we would also like to understand how different uncertain factors affect performance in combination, the planning tool can sample each possible combination of uncertain factors.

Table 5-7 Options for representing uncertainty in the basin planning tool

Uncertain factor	Number of scenarios	Comments
Climate	10	Each greenhouse gas concentration scenario and projection period (e.g., rcp85, 2081-2100) consists of ten scenarios. Not possible to view results from different green greenhouse concentration scenarios and/or projection periods in the same group of simulation outputs.
Irrigation demand	3	Possible to specify a baseline estimate, and two additional scenarios as a multiplier of the baseline.
Irrigation annual return	3	Possible to specify a baseline estimate, and two additional scenarios as a multiplier of the baseline.
Hydropower annual return	3	Possible to specify a baseline estimate, and two additional scenarios as a multiplier of the baseline.

5.2.2 Identification of failure thresholds

The RDM approach requires definition of failure thresholds. In other words, stakeholders and decision makers need to identify minimum acceptable values of the metrics used to measure plan performance. In the planning tool, thresholds may be applied to any of the output indicators produced by the tool.

5.2.3 Identification of the robust alternative

In the next step of the robust decision making methodology, we identify a “robust” alternative using a robustness metric. The robustness metric is similar, but not identical, to the formulation of probability of avoiding failure given in Section 5.1.2.3.

$$
\begin{aligned}
&\mathrm{RM} = \frac{1}{n}\sum_{i=i}^{n} \Lambda[r(a_1, \theta_i)] \\
&Where \\
&RM = robustness\ metric \\
&n = number\ of\ scenarios \\
&a = alternative \\
&\theta = scenario \\
&r(a_1, \theta) = reward\ from\ alternative\ a_1\ given\ scenario\ \theta \\
&\Lambda[r(a_1, \theta)] = 1\ if\ reward\ r\ exceeds\ failure\ threshold, 0\ otherwise \\
&i = scenario\ index
\end{aligned}
\qquad (5.3)
$$

The robust alternative is the alternative with the highest value of robustness metric. In other words, the robust alternative is the alternative for which the reward exceeds the failure threshold in the largest number of scenarios.

A decision formulated using robust decision making is similar to a decision formulated using the rule for the risk-averse decision maker in the probability-weighted decision analysis. Both decision methodologies seek to identify an alternative that is unlikely to fail, rather than an alternative that maximizes the potential reward. The methodologies differ in the approach used to identify this alternative.

5.2.4 Vulnerability analysis

In the vulnerability analysis step, we examine the conditions that could cause the alterative identified in the previous step to fail.

It is also possible to enter the robust decision making methodology at this step, in the case that only one alternative is under consideration. The vulnerability analysis step is then used to identify conditions that could cause failure, and to modify the alternative if necessary.

In the vulnerability analysis step, we begin by examining the subset of scenarios that caused the alternative identified in the previous step to fail. In the case study example, this would be a combination of climate, irrigation demands, and annual return values resulting in NPV values below the failure threshold.

After identifying this subset, the vulnerability analysis then proceeds by examining the properties of the subset, comparing to conditions that have occurred in the past, and engaging in a dialogue with decision makers and stakeholders about whether these conditions could occur again. If it is thought to be reasonably likely that these conditions could occur again, then the decision is considered vulnerable to failure, and should be modified. This process will be different for every decision-making context, and an example is provided in the case study description that follows.

5.2.5 Overview of workflow

An overview of the workflow for robust decision making is given in Figure 5-7.

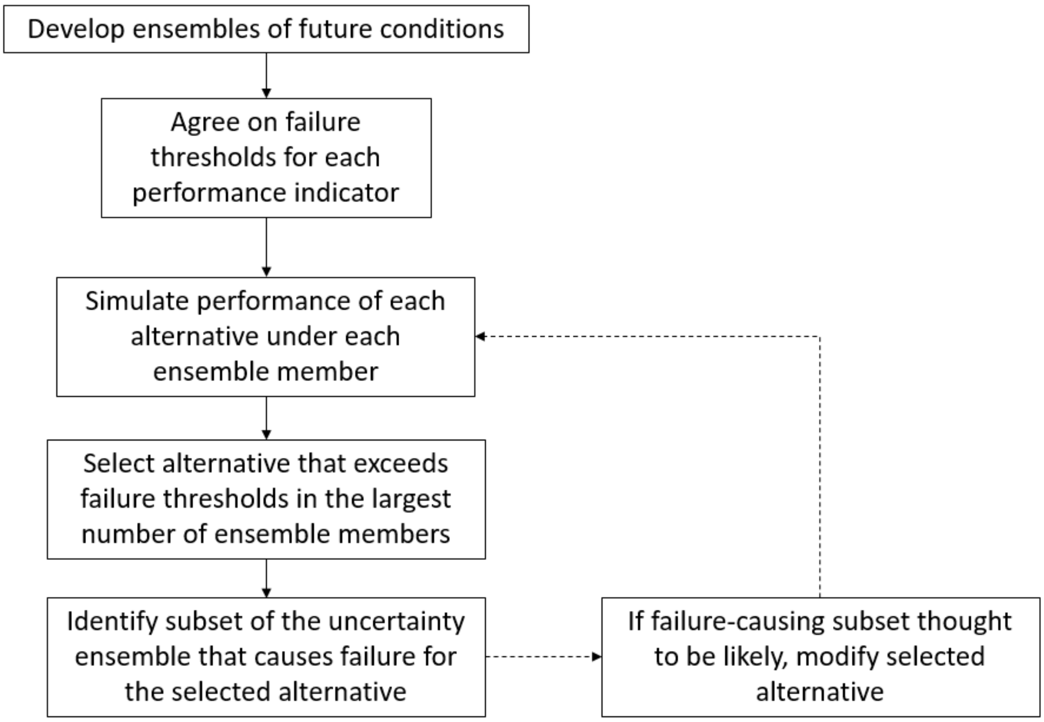

Figure 5-7 Overview of workflow for robust decision making. Dashed lines represent optional steps.

5.2.6 Case study example

The application to the long-term planning case study is now presented following the workflow given in Figure 5-7. In the case study example, we consider a decision about whether or not to build a new irrigation scheme along the Nile River downstream of Lake Kyoga. As a baseline, we assume that three hydropower facilities are in operation on the Nile River, and no major irrigation schemes. Therefore the case study consists of comparing two alternatives:

1. Baseline (existing hydropower only)
2. New irrigation (existing hydropower plus one new irrigation)

Although three hydropower schemes are present in the baseline, we limit economic analysis to the most downstream of the three (Bujagali) in order to simplify the analysis.

Develop ensembles of future conditions

Scenarios of future conditions are developed using the basin planning tool. The uncertain factors that were varied to develop the scenarios are presented in Table 5-8. The table also presents the total number of scenarios used to evaluate each alternative.

Table 5-8 Uncertain factors varied in basin planning tool, along with total number of scenarios for each alternative

Uncertain factor	Number of scenarios	Comments

Climate	10	One gas concentration scenario (rcp85), with ten ensemble members for each scenario. Only end-of-century simulations used.
Irrigation demand*	3	One irrigation location, with three demand estimates
Irrigation annual return*	3	One irrigation location, with three annual return estimates
Hydropower annual return	3	One hydropower location with three annual return estimates
Total combinations (Baseline alternative)	30	10 climate * 3 hydropower annual return
Total combinations (New irrigation alternative)	270	10 climate * 3 hydropower annual return * 3 irrigation demand * 3 irrigation annual return

*Only relevant for new irrigation alternative

Agree on failure thresholds for each performance indicator

Two indicators are used to evaluate the performance of both alternatives, while an additional indicator is used to evaluate the performance of the irrigation alternative.

Indicators used to evaluate both alternatives include:

- NPV of Bujagali hydropower facility
- Average flows downstream of Lake Kyoga

The second indicator is chosen because it is located just downstream of the proposed irrigation location and therefore provides an indicator of the impact of irrigation on river flows.

The indicator used to evaluate the new irrigation alternative is:

- NPV of new irrigation project

The following minimum values are used to define failure thresholds for each of the indicators:

Indicator	**Threshold value (units)**
NPV (hydropower)	0 (USD)
NPV (irrigation)	0 (USD)
Average flow, Nile downstream of Kyoga	1630 (m^3/s)

Simulate performance of each alternative for each scenario

Each alternative was simulated once for each scenario. The baseline alternative was simulated 30 times and new irrigation alternative was simulated 270 times. Results are presented in the next section.

Select alternative that exceeds failure threshold in the largest number of scenarios

Values of the robustness metric for the hydropower NPV indicator are presented in Table 5-9. Average values for all ensemble members are also presented. The table suggests that there is no difference between the alternatives in terms of impacts on hydropower.

Table 5-9 Comparison of hydropower NPV indicator

Alternative	Expected value (USD)	Robustness metric
Baseline	1,732,000,000	1
New irrigation	1,732,000,000	1

Values are presented for the Nile River flow below Lake Kyoga in Table 5-10. The table suggests that there are also limited differences between the alternatives in terms of impacts on river flows.

Table 5-10 Comparison of average flows, Nile River below Lake Kyoga

Alternative	Expected value (m^3/s)	Robustness metric
Baseline	1629.7	0.4
New irrigation	1630.6	0.4

Based on the above tables, it appears that impacts of the proposed irrigation scheme on the two common indicators will not be significant, and that the irrigation scheme should be developed if the projected value of the irrigation indicator is acceptable. Values of the indicator are presented in Table 5-11.

Table 5-11 Irrigation NPV indicator values

Indicator	Expected value	Robustness metric
Irrigation NPV	85,000,000 USD	0.667

Although the average value of the irrigation scheme NPV is positive, the robustness indicator shows that the irrigation scheme has a negative NPV in 33% of scenarios. Conditions under which the irrigation scheme fails are presented in the next section.

Identify subset of uncertain factors that cause unacceptable performance

The irrigation NPV indicator is plotted as a function of two uncertain factors, the irrigation annual return and the climate scenario, in Figure 5-8. Acceptable values (>0) are displayed with open circles, while unacceptable values are displayed with blue circles. The chart suggests that water supply is not the limiting factor for the irrigation scheme, as the indicator is not sensitive to climate conditions. On the other hand, the indicator is sensitive to low annual return values. If the irrigation scheme is to be developed, then development should be accompanied by efforts to reduce the likelihood of low annual returns, such as measures to improve crop yields.

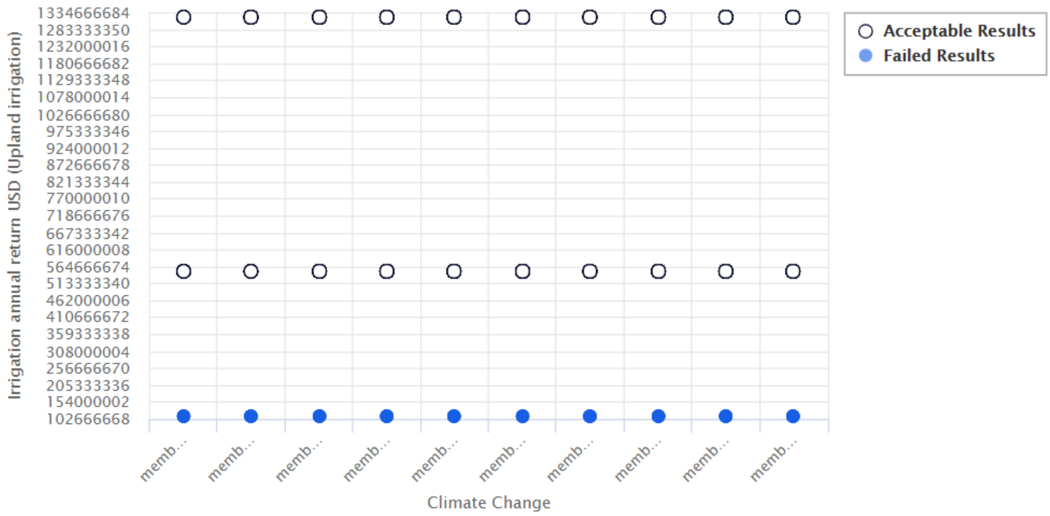

Figure 5-8 Irrigation NPV as a function of irrigation annual return and climate

6 Conclusions

These guidelines have demonstrated two methods to support decision making under uncertainty, using two different case studies. A seasonal case study was used to demonstrate an “agree on assumptions” approach, probabilistic decision analysis, while a long-term planning case study was used to demonstrate an “agree on decisions” approach, robust decision making.

Probabilistic decision analysis is reasonable approach that allows for uncertainty to be incorporated into a decision rule that reflects the risk preferences of decision makers. However, robust decision making facilitates exploration of conditions that may cause a decision alternative to fail, and therefore is useful for identifying strategies to increase robustness. Such exploration is not facilitated by “agree on assumptions” approaches, which may neglect important opportunities to improve alternatives that emerge during the decision making process.

7 References

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