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Improving development efficiency through decision analysis: Reservoir protection in Burkina Faso

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ABSTRACT

In the arid areas of Sub-Saharan Africa, perennial challenges of water scarcity and food insecurity are exacerbated by climate change and variability. The development of robust strategies to cope with the region's climatic challenges requires thorough consideration of uncertainty and risk in decision making. We demonstrate the use of probabilistic decision analysis to compare intervention options to prevent reservoir sedimentation in Burkina Faso. To illustrate this approach, we developed a causal impact pathway model based on the local knowledge of expert stakeholders. Input parameters were described by probability distributions derived from estimated confidence intervals. The model was run in a Monte Carlo simulation to generate the range of plausible decision outcomes, quantified as the net present value and the annual cash flow. We used Partial Least Squares regression analysis to identify the parameters that most affected projected intervention outcomes and we computed the Expected Value of Perfect Information (EVPI) to highlight critical uncertainties. Numerical results show that the preferred intervention to secure agricultural production is a combination of dredging, rock dams and a buffer scheme around the reservoir. The EVPI calculation reveals an information value for the profit per ton of vegetables, indicating that more information on this variable would be useful for supporting the decision. However, without the need for follow-up analysis, the results show high probability of benefits given the combined interventions, which, given the current state of information, should be preferred over inaction.

1. Introduction

Harsh climatic conditions and population growth are major challenges to food security in sub-Saharan Africa (SSA) (Omisore, 2017). In arid and semi-arid regions across SSA, farmers face highly fluctuating water supply, a situation that will likely be exacerbated by climate change (Wood et al., 2014). At the same time, water demand for food production is expected to rise as populations grow (Amisigo et al., 2015; World Bank, 2017). These issues are of particular concern to the Upper Volta river basin. The region is considered highly sensitive to environmental changes and rainfall variability (Amisigo et al., 2015), and agriculture is dominated by small-scale, rainfed production, with very few farmers having access to irrigation (less than 1% of agricultural land is irrigated; Bharati et al., 2008). As a consequence, agricultural productivity is very low.

In Burkina Faso, these conditions are the root cause of widespread rural poverty (Sanfo and Gérard, 2012). To cope with the local challenges, many communities, governments, and NGOs have constructed small-scale reservoirs for irrigation in rural areas. More than 2000 of these structures have been built in the Upper Volta basin (Cecchi et al., 2008). They provide seasonal water storage for small-scale irrigation during the cropping season (Bharati et al., 2008), water for livestock and an opportunity for fish farming (Venot and Cecchi, 2011). They act as a buffer against extreme weather events (Boelee et al., 2013) and are considered instrumental for local food security and livelihoods (Palmieri et al., 2001; Wisser et al., 2010; Poussin et al., 2015).

However, the performance of many of these reservoirs has fallen short of expectations (Barbier et al., 2011), and many are subject to degradation and poor maintenance (Venot and Hirvonen, 2013). One of the major problems is sedimentation caused by soil erosion within the reservoir catchment, which can damage the irrigation system in the short term (Kondolf et al., 2014) and eventually fill in the reservoir completely, rendering the infrastructure useless (Schmengler, 2011;

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Chitata et al., 2014; Kondolf et al., 2014). Rehabilitation of a reservoir damaged by sedimentation is costly at best, and sometimes not possible at all (Kondolf et al., 2014). Possible intervention points for managing sedimentation are the initial design of the reservoir, management of the agricultural activities and the establishment of structures in the riparian areas (Kondolf et al., 2014).

Sedimentation is a major investment risk, since it limits the time horizon, over which communities can benefit from a reservoir. This highlights the importance of appropriate management strategies, through which the productive lifetime of these structures can be greatly extended (Palmieri et al., 2001). However, the best way to manage sedimentation is often not directly apparent to communities and governments, due to uncertainty regarding the costs and benefits and the poor understanding of sediment generating processes and their response to management actions (Schleiss et al., 2016). To choose appropriate strategies, many policy-makers, development practitioners and NGOs need scientific support.

Predicting sediment yield and accumulation through time is very difficult (Morris and Fan, 1998). The Universal Soil Loss Equation (USLE) (Wischmeier and Smith, 1978), later modified to the Revised Universal Soil Loss Equation (RUSLE) (Renard et al., 1997) has been widely applied for this purpose at the watershed scale (Griffin et al., 1988; Jain et al., 2001), but it suffers from high uncertainty in factors influencing reservoir sedimentation (Salas and Shin, 1999). Limitations in data availability, among other factors, can lead to high uncertainty in model results.

Bayesian frameworks have been used to link model calibration and uncertainty assessment. The most common approaches include the Bayesian Monte Carlo method (Qian et al., 2003), Markov chain Monte Carlo (Kattwinkel and Reichert, 2017) and the generalized Likelihood Uncertainty Estimation (GLUE) pseudo-Bayesian method (Zheng and Keller, 2007), which are used, among other applications, to establish uncertainty bounds for simulated flows (Fonseca et al., 2014). Chaudhary and Hantush (2017) presented a novel approach that combines a Bayesian Monte Carlo simulation with a maximum likelihood estimation. Yet such advanced treatments of uncertainty have largely been restricted to uncertainties about classic hydrological parameters, whereas the success of watershed interventions often depends on a host of additional factors, e.g. in the social and economic domains, which can have a major impact on success or failure of innovations. Comprehensive consideration of all relevant factors is required.

Here we present the use of decision-centered models to address risks and uncertainties in sedimentation management decisions. The approach embraces complexity, makes recommendations that account for the imperfect state of available knowledge and identifies critical uncertainties that decision-supporting research should address (Luedeling and Shepherd, 2016).

Decision-centered models can be collaboratively developed between analysts, stakeholders and decision-makers through participatory processes, where all important factors involved in a decision are gathered and synthesized into an ex-ante impact projection model (Luedeling et al., 2015). Tools that determine the value of information can be used to identify the most critical knowledge gaps, from the perspective of a decision-maker aiming to optimize overall desired outcomes (Luedeling and Goehring, 2017). Such modeling techniques can prioritize the knowledge gaps that should most urgently be narrowed in order to reduce uncertainty about the decision or inform the design and prioritization of future research (Hubbard, 2014; Rosenstock et al., 2014; Strong et al., 2014; Luedeling et al., 2015). Collecting additional information on such high-value variables and using this information to update the decision model allows decision-makers to iteratively improve their ability to anticipate decision outcomes and identify the preferred option. When sufficient data is available, the coupling with a watershed hydrological transport model might be considered.

Research into sedimentation control in small reservoirs has largely been based on disciplinary analyses, but it has not yet been able to capture many important uncertainties related to the social and natural systems on which reservoirs depend. We use the specific example of a small reservoir that serves the communities of Lagdwenda in the Northern Volta basin, Tenkodogo district, Bougou province, Burkina Faso, to demonstrate the application of Decision Analysis tools for sustainable management of small reservoirs. Sedimentation is the main operational concern affecting the reservoir. It impacts the reliability of irrigation systems and is a major threat for the resilience of the local communities to all types of climatic shocks. Sedimentation in the reservoir results from a number of known factors, such as, among others, poorly planned grazing of river banks or conversion of natural vegetation. We demonstrate tools that can support the difficult task of deciding which interventions to choose, if any, to mitigate the problems of sedimentation due to the absence of riparian vegetation. We make use of a causal impact pathway model, constructed and parameterized based on the knowledge of local expert stakeholders. We use Monte Carlo simulations to compare the ranges of plausible outcomes for several locally recognized interventions (buffer strips, rock dams, dredging and combinations of these). Such an exercise typically involves synergies and trade-offs between interventions, which have been shown to affect the achievement of environmental targets at large scales (Gao and Bryan, 2017). By evaluating model outputs, we seek to identify the parameters that most affect projected intervention outcomes and to highlight critical uncertainties.

2. Materials and methods

2.1. The reservoir of Lagdwenda

The reservoir of Lagdwenda is located in the Northern Volta basin, in Tenkodogo district, Bougou province, Burkina Faso. The site is semi-arid, with a dry season from October to mid-May and a rainy season from mid-May to October. Average annual rainfall varies between 800 and 900 mm. The warmest period is from March to May and a relatively cooler period from June to February, with an annual average temperature of 29 °C. The reservoir of Lagdwenda (Fig. 1) had a capacity of 63,000 cubic meters in 2002 (year of construction) and benefited more than 7,000 people in 2005.

The main use of the reservoir is irrigation for rice and vegetable production. Downstream from the reservoir, a formal irrigation scheme has been developed (Fig. 1a). In addition, farmers have established an informal cropping area upstream of the reservoir (Fig. 1a), which violates key recommendations on reservoir protection (Schleiss et al., 2016) and contributes to sedimentation. An important secondary use of the reservoir is water provision for livestock and animals in the riparian area, which also contributes to sedimentation.

Reservoir size, as well as the types of crops that are cultivated, vary markedly between the wet and the dry season (Fig. 1b), with the reservoir reaching its maximum extent of 55 ha at the end of the wet season, when farmers practice paddy rice cultivation. During the dry season, farmers grow mixed vegetables and some cereals. Sedimentation control interventions are urgently needed and local decision-makers are looking for cost-effective ways to restore reservoir functions and ensure their provision over the long term.

2.2. Overview of the approach

The method proposed in this paper provides a new approach to support practical decisions on agricultural systems in the face of risk and imperfect information. It is inspired by the Applied Information Economics (AIE) approach developed by Hubbard Decision Research (Hubbard, 2014). This decision analysis approach, which has been widely used in business decision support and a number of other contexts (e.g. Luedeling et al., 2015; Wafula et al., 2018), employs participatory processes to explore in detail the consequences of a particular decision. Rather than aiming to precisely predict results for all available

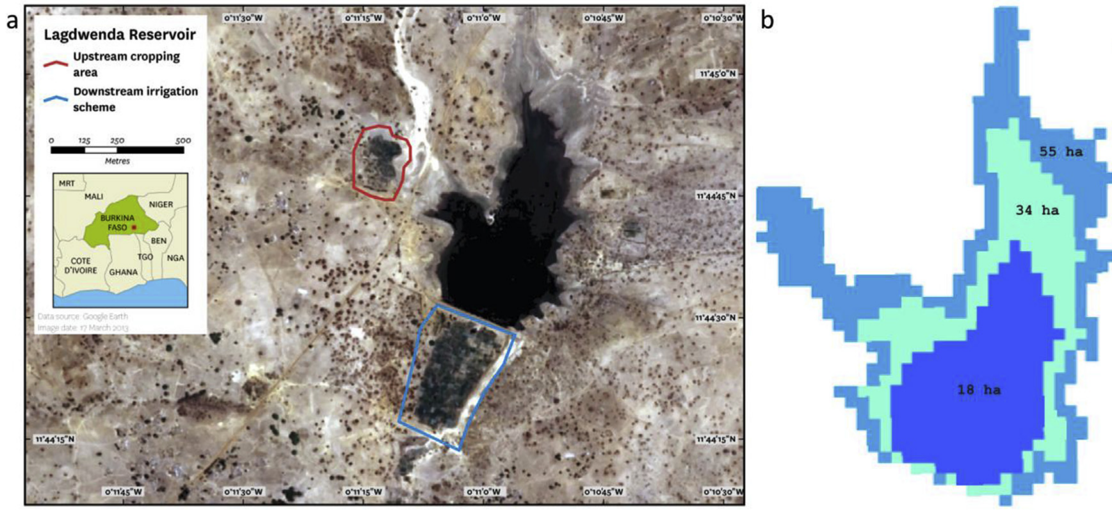

Fig. 1. Lagdwenda reservoir in the Northern Volta basin of Burkina Faso. **a.** Map of the reservoir. The blue polygon at the bottom center represents the downstream irrigation scheme, while the top red polygon represents the upstream cropping area. **b.** Variation in reservoir surface area. Dark blue indicates year-round water (April 2016, 18 ha), light blue indicates low-wet season water (January 2016, 34 ha), and the outer blue layer indicates high wet-season water (October 2015, 55 ha). Data from Landsat 8 (MNDWI). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

decision options, which is usually impossible for even moderately complex systems, AIE attempts to capture the state of knowledge on all processes and input variables, e.g. in the form of probability distributions, and translate these into probabilistic simulations that predict the full range of plausible outcomes. From these outputs, critical knowledge gaps can be derived, measurements can be undertaken to narrow these gaps, and the model can successively be updated until confident decision support is possible.

Building on the AIE approach, we conducted quantitative ex-ante impact analyses for several decision options, using Monte Carlo simulations to account for risks and uncertainties. The methodology combines participatory approaches and modeling techniques. As a first step, a decision-centered model is collaboratively developed between analysts, main stakeholders and decision-makers during a workshop. Model development seeks to capture all important factors for the decision, regardless of whether they can easily be measured or modeled. After synthesizing these variables into a model, the state of knowledge on all variables is quantified through the use of probability distributions. When no information is available on particular variables, values are elicited from participants. Before providing these estimates, participants are subjected to calibration training (Hubbard, 2014) to improve their ability to estimate their state of uncertainty. Such training has been shown to increase people's capacity to provide accurate estimates by reducing errors of judgment (Lichtenstein et al., 1982). All estimates are consolidated into one single probability distribution for each model parameter (Luedeling et al., 2015). In this way, uncertainty is explicitly represented as probabilities of different possible states of the world (Pannell and Glenn, 2000). A description of the process can be found in Hubbard and Millar (2014). Basically, the principle is to combine methods from decision theory, economics and actuarial science in order to improve on human expert judgments.

In a second step, once numbers are available, the model is run in order to convert probabilistic inputs into probabilistic outputs, which express the range of plausible decision results that can be expected. We then use the expected value of perfect information (EVPI) to determine the most critical knowledge gaps (Oakley et al., 2010). The variables with the highest information value can be interpreted as priorities for measurements to be undertaken to reduce uncertainty around the decision (Rosenstock et al., 2014). The EVPI can thus be used to inform the design and prioritization of future research (Strong et al., 2014) and may help reduce the range of plausible outcomes.

2.3. *Analysis protocol*

2.3.1. *Step 1: selecting experts*

The design of an efficient sedimentation management intervention for the reservoir of Lagdwenda requires assessment of multiple uncertain quantities and risks. Beyond the lack of well-established knowledge on the natural and anthropogenic origins of sedimentation, the issue is very often context-specific. To gather appropriate information, we relied on experts' knowledge about various ways to manage sedimentation and for identifying parameters of interest (such as benefits, costs and risks).

Therefore, the first stage of the protocol focuses on the delicate process of selecting the most relevant experts. The selection process started five months before the decision workshop, with a field visit of the area, in which we met the local communities and their representatives. We also participated in a stakeholder workshop organized in the province by the local office of SNV (Netherlands Development Organization). We used the event as an opportunity to establish direct contacts with officers from the ministries of agriculture and environment, as well as local NGOs, and to get a better overview of local experts and relevant stakeholders. We collected names and details of potential participants and worked closely with SNV and the agricultural officer of Tenkodogo Province to maintain connections with the local community representatives.

The list of potential invitees to a decision analysis workshop was then reduced using selection criteria, e.g. those who have relevant expertise for the specific context of the Lagdwenda reservoir. From these, we selected a group of eight national-level and local experts, who were agricultural specialists, donors, policy-makers and the local communities.

2.3.2. *Step 2: eliciting model structure*

The process to elicit model structures through experts has several steps. First, experts are invited to participate in a decision workshop. The information collected in the participatory analysis of the decision problem is assembled into a conceptual, graphical model. This is constructed as a decision's impact pathway, with causal relationships based on experts' expectations, gathered during brainstorming sessions. The conceptual model development aims to capture the 'big picture' of the decision by gathering all system dynamics and relevant issues, without taking constraints of measurement into account.

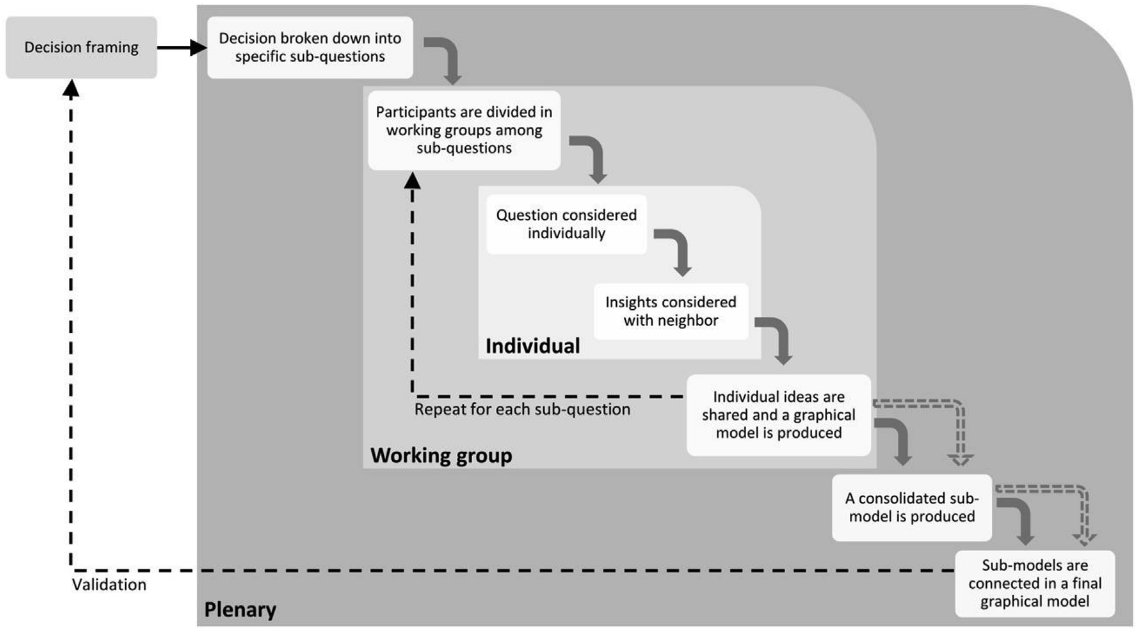

Fig. 2. Diagram of a four-stage protocol for eliciting expert knowledge when designing a decision model of different interventions to reduce sedimentation in the Lagdwenda reservoir in Burkina Faso.

To elicit more details, we followed the four-stage procedure (Fig. 2) outlined by Whitney et al. (2018). In the first stage of the procedure the decision about sedimentation control was broken down by the entire group into specific sub-questions. In the second stage, participants were split into working groups to address the different questions both individually and within their groups. We used participatory techniques to avoid problems of variation among experts (Bolger and Wright, 2017). For example, individual outputs were peer-reviewed by the other members of the group, after which the outputs were revised until a consensus was reached. In the third stage the models produced in working groups were unified into consolidated models, one for each of the initial sub-questions. In the fourth stage the consolidated sub-models were combined into one single conceptual model. The final conceptual model represented the impact pathway of the management decision that could be formally modeled and simulated.

2.3.3. Step 3: calibrating experts

Parameters of the model are catalogued and grouped into two categories (cf. Fig. 3). The first category gathers parameters that can be documented by existing academic or technical sources (e.g. databases, reports, literature). The second category consists of all parameters for which no such sources exist and that should be estimated. These data are simply too costly (and could take too much time) to obtain through survey or field studies. To account for this in the Lagdwenda case, we relied on experts' knowledge to assess the value of these parameters, but also the uncertainty around these values. It should be noted here that this methodology can be applied regardless of whether these uncertainties result from lack of theoretically attainable knowledge or parameter uncertainties, such as future rainfall amounts, that cannot currently be known precisely.

Elicitation techniques are a well-recognized form of knowledge generation in situations where sampling efforts would be impractical or too expensive (Samantha et al., 2009), and formal procedures for

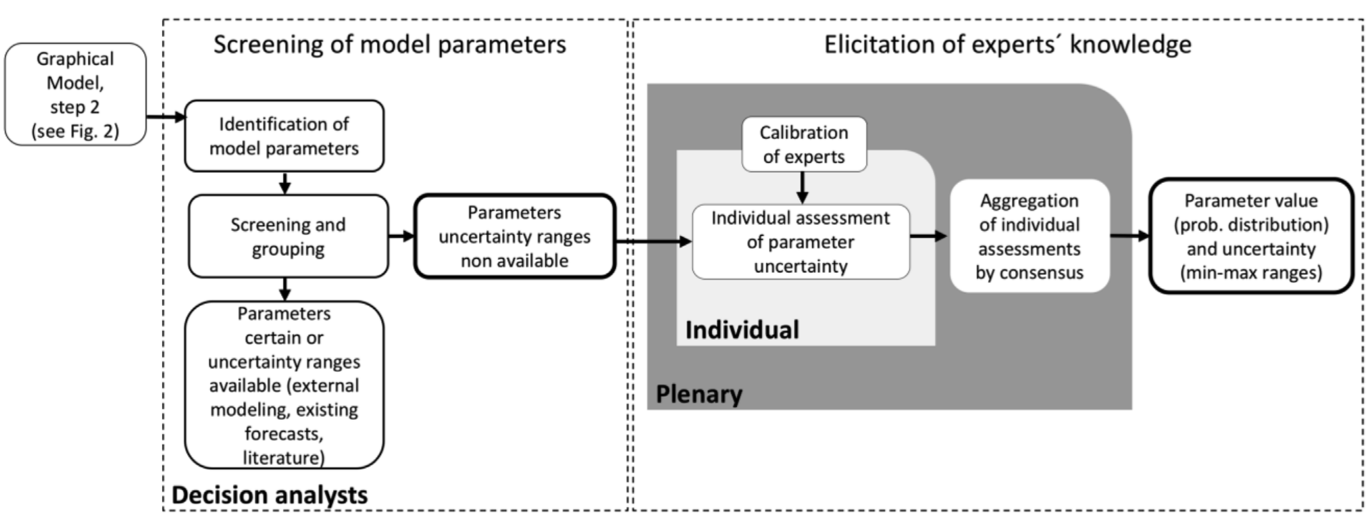

Fig. 3. Diagram of the process of expert calibration training for model parameter estimation when parameterizing a decision model of different interventions to reduce sedimentation in the Lagdwenda reservoir in Burkina Faso.

eliciting and encoding have been adopted and tested for application in conservation science (Martin et al., 2012). Expert knowledge can be valuable for decision support, provided it is combined with explicit consideration of uncertainty (Fred et al., 2017). If uncertainty is ignored, however, expert knowledge can manifest as spurious opinions, which can undermine any well-intentioned decision analysis process (Morgan, 2014). It is therefore crucial to elicit this information rigorously in order to get valid estimates. This requires recognition and correction for several biases that can affect people's judgement (Lichtenstein et al., 1982; Soll and Klayman, 2004). In order to avoid such biases, we train experts in techniques that have been shown to improve people's ability to estimate their own uncertainty and thereby reduce errors of judgement. This is a crucial step in the elicitation process (Fig. 3).

All experts are required to undergo ‘calibration training’, which teaches them how to make estimates as reliably as possible. The training consists of a series of procedures, grounded on research findings in cognitive psychology. Through these procedures participants learn how to assess their state of uncertainty and reduce errors of judgement through exercises that reveal to them their personal biases (overconfidence or underconfidence). To this end, they compare their performance in responding to trivia questions to the correct answers to these questions. Rather than providing ‘best guesses’, participants are requested to provide two numbers, for which they are 90% sure that the correct answer is between these numbers. Perfectly ‘calibrated’ estimators should get 90% of their range estimates correct. Once exposed to their biases (most people are initially overconfident), experts are instructed in a set of mental techniques that has been shown to improve people's ability to provide accurate estimates. More information on these procedures can be found in Hubbard (2014).

2.3.4. Step 4: estimation and simulation

Calibrated experts were trained to use conscious estimation procedures to provide subjective probability distributions for uncertain variables in the decision model. This is usually done by eliciting confidence intervals (defined by their upper and lower bounds) that have a 90% chance of containing the value of interest. Selecting a distribution is not always easy for experts, who often default to a normal, uniform or triangular distribution. To help with this, common distribution shapes were displayed during the estimation process.

When multiple experts estimate the same quantities, a subsequent process to reconcile different estimates is needed. A general conclusion from the literature on how to combine the diverse elicited values is that averaging is often a preferred strategy (Aidan et al., 2015). Since we had a small expert group, we were able to aggregate individual assessments by consensus.

The resulting conceptual model was then reformulated as a set of equations that reflected as much as possible the experts' and analysts' understanding of the decision. This mathematical model was coded as a function in R programming language (R Core Team, 2017). All formulas and scripts are available in the supplementary materials as well as in a separate data repository (Luedeling et al., 2018). The model was then parameterized (either with hard data or “calibrated” estimates) and run 10,000 times as a probabilistic Monte Carlo simulation. This number of runs was sufficient for generating smooth outcome distributions for all cases, which was verified by visual inspection. Each run provided one possible outcome. The totality of all model runs generated a probability distribution that illustrates the plausible outcomes given the experts' current state of uncertainty.

2.3.5. Step 5: sensitivity analysis and refinement of the model

The output of a Monte Carlo simulation often directly reveals a clearly preferable option (e.g. a specific intervention in a group of possible interventions). However, the value of expected outcomes can remain unclear, when uncertainty about input values is high. Sensitivity analysis can identify variables that outcome projections respond to. We used Partial Least Squares (PLS) regression analysis, in particular its Variable Importance in the Projection (VIP) metric, for identifying the variables that most affected the decision outcomes projected by the simulation (Wold, 1995; Luedeling and Gassner, 2012). We preferred this method over more systematic sensitivity analysis methods such as the eFAST (Gao et al., 2016) or Morris (Gao and Bryan, 2016) methods, because it determines sensitivity to input variables based on the outputs of the Monte Carlo analysis, rather than requiring computationally expensive additional simulation runs. For Monte Carlo simulation and sensitivity analysis, we used the ‘decisionSupport’ package (Luedeling and Goehring, 2017) in R.

In cases where the outputs of the Monte Carlo simulation clearly identify one decision option as preferable over the alternatives, the current state of knowledge is sufficient for issuing a recommendation on how the decision should be taken. When no option emerges as clearly preferable, decision-critical uncertainties can be identified using the Expected Value of Perfect Information (EVPI). The EVPI is the difference between the value of a decision made with perfect information and the value of a decision made with information that is currently available. It can be interpreted as a rational willingness-to-pay to gain access to perfect information. Rather than referring to the absolute value of the decision outcome, the EVPI is concerned only with whether this value is positive or negative. This is the only criterion that matters to a rational decision-maker, and additional information only needs to be collected on variables that could potentially lead to a change in the sign of the decision outcome. EVPI analysis identifies such variables and assigns a value to the possible information gains that could arise from additional research on them.

As a first step in the EVPI computation procedure, we used Spearman's rank correlation test to check whether each of the input variables was correlated with projected outcomes. If this was not the case, the EVPI for such variables was set to zero. For all other variables, the relationship between input and output variables was identified by first sorting the array of output values produced by the Monte Carlo simulation according to values of the respective input variable. The resulting set of values was then smoothed using a second-order low-pass Butterworth filter (Proakis and Manolakis, 1992), with a critical frequency of one divided by one tenth of the number of values in the Monte Carlo output. Smoothing is necessary at this stage to separate the signal emerging from the variable under scrutiny from the substantial noise caused by variation in all other variables, which vary randomly within the Monte Carlo simulation. The EVPI was then calculated as the sum of all outputs with a sign that did not correspond to the sign of the expected value, multiplied by the probability assigned to this outcome (Wafula et al., 2018).

Measurements of input variables with the highest EVPI, which can be used to update the decision model, help to narrow uncertainty about how the decision should be taken. The process is repeated until the best option is determined.

3. Chapter 3 results

3.1. The decision model

3.1.1. Scoping and design

In July 2016, eight experts (see acknowledgments) were consulted in a four-day workshop, where they collaborated to produce graphical models of expected decision impact pathways.

The workshop began with framing the decision to be modeled. The overall context was defined in plenary discussions, after which the group of participants was split into working groups. Participants were asked to consider the whole impact pathway and break it down into several stages. As a second step, the team identified the most relevant interventions for sedimentation management. In order to support the process, ten interventions based on recommendations from international experts and lessons learned from other studies (Kondolf and al.

2014), were proposed and debated by the experts (see Supplementary Information). These were intended to stimulate the discussion; experts of the modeling team were free to define other sediment control interventions. Ultimately, they identified three possible interventions:

- Dredging along the main stream inlet, allowing water to flow to agricultural fields west of the reservoir and reduce sediment build-up. The intervention consists of dredging 3 m deep for 2 km along the main stream inlet.
- Building permeable rock dams, also known as 'check dams', along the reservoir's tributaries, reducing flow velocities and the erosive potential of water. These are low dams of loose stone retained by mesh wire that prevent large quantities of sediment from being deposited in the reservoir. These would be constructed every 5 km along the stream network upstream of the reservoir, a spacing that has frequently been used for similar interventions in this region.
- A buffer protection scheme around the reservoir and stream inlets, preventing sedimentation from agriculture around the reservoir and reducing deposits of sediments coming from the surrounding catchment. The protection is composed of 3 buffer strips of 75–100 m each. The first strip is made of stone barriers/contour bounding with stabilizing plants (grasses). The second strip consists of vegetables mixed with shrubs for firewood. The third zone is a mix of crops with fruit trees.

Graphic representations of all interventions are shown in Fig. 4.

We carried out comprehensive investigations of costs, benefits and risks associated with each intervention. Causal relationships between variables were taken into account.

3.1.2. Benefits, costs and trade-offs

Formally, we defined a benefit as an economic surplus (e.g. net revenue from agricultural production) generated by an intervention (or a combination of intervention options) in comparison to the baseline case (current situation). Broadly speaking, water for irrigation and viability of the irrigation water supply system were regarded as the main benefits of sedimentation control.

Water for irrigation **–** Because sediments accumulate in the reservoir, the dam gradually loses its capacity to store water. We modeled the avoided decline in irrigable area (area in both upstream and downstream irrigation schemes that can be irrigated given the water stock in the reservoir) as a benefit for the different scenarios.

Viability of the irrigation water supply system **–** The main irrigation scheme of Lagdwenda is located downstream from the dam. Water supply is achieved through a system of pipes underneath the dam's barrier. Sediments regularly disrupt the functioning of this system, blocking the pipes and preventing water from flowing into the agricultural area. Interventions that reduce sedimentation prevent the obstruction of irrigation pipes that supply this downstream irrigation scheme.

Changes in land use **–** Trade-offs were expected among land uses when implementing the buffer intervention. In the current situation (baseline case), communities of Lagdwenda grow rice and vegetables in an informal irrigation scheme, located upstream close to the shore of the reservoir, near the main inlet. The buffer protection scheme intervention consists of three buffer strips of 75–100 m each. This would result in taking this area out of cultivation. On the other hand, two buffers of the scheme are expected to be partially cultivated (vegetables, fruits and cereals).

3.1.3. Risks and uncertainties

The model seeks to take into account all risks (either natural or anthropogenic) that may impact the project, along its different stages. To this end, two categories of risks were considered: ex-ante risks and ex-post risks.

Ex-ante risks impact the probability that an intervention is completed, which affects intervention costs. When the project is implemented, the full cost of the intervention applies, while a reduced, sunk cost applies otherwise. We considered three ex-ante risks: the lack of community involvement, the lack of institutional involvement and the lack of donor involvement.

Ex-post risks impact the effectiveness of the intervention, which affects the benefits. Ex-post risks can be natural, social or technical. We considered three ex-post risks: natural hazards, poor maintenance and poor design.

Additional risk factors, especially risks arising from knowledge limitations, are implicitly captured by the model's probabilistic inputs. For instance, the risk of changes to the future sediment load of the inlet streams due to climate change was not explicitly expressed but covered by experts' providing wide confidence intervals for future sedimentation rates.

Consideration of risks and uncertainties enables a risk-adjusted cost-benefit analysis to inform decision-making. The decision model that emerged integrates all benefits, costs and risks into estimates of the Net Present Value of each option (Fig. 5).

3.1.4. Decision model code

We translated information on costs, benefits and risks obtained from

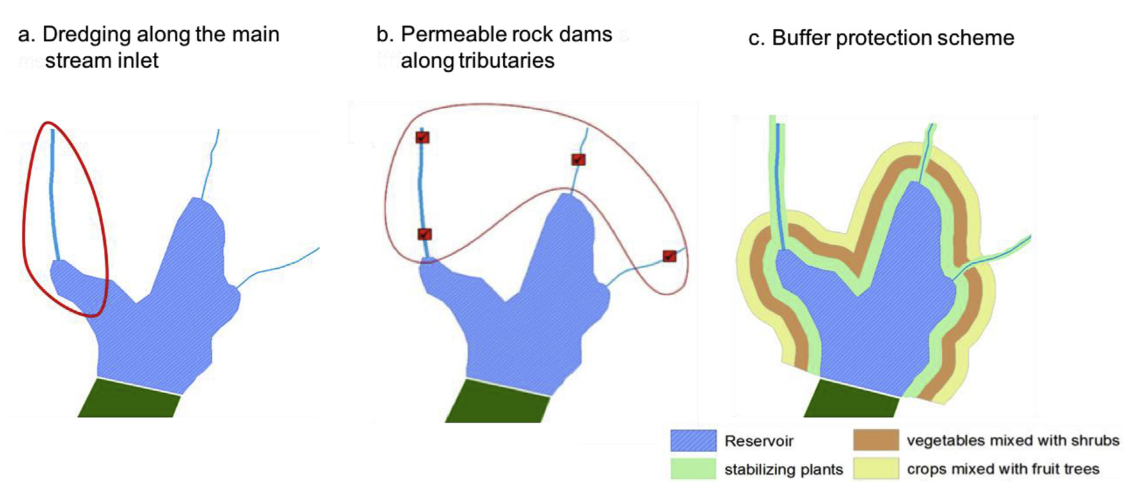

Fig. 4. Intervention options to reduce sedimentation in the Lagdwenda reservoir in Burkina Faso, co-designed by workshop participants: **a.** dredging for 2 km along the main stream inlet to a depth of 3 m; **b.** low dams of loose stone retained by mesh wire every 5 km along the stream network upstream of the reservoir; **c.** three buffer strips of 75–100 m each.

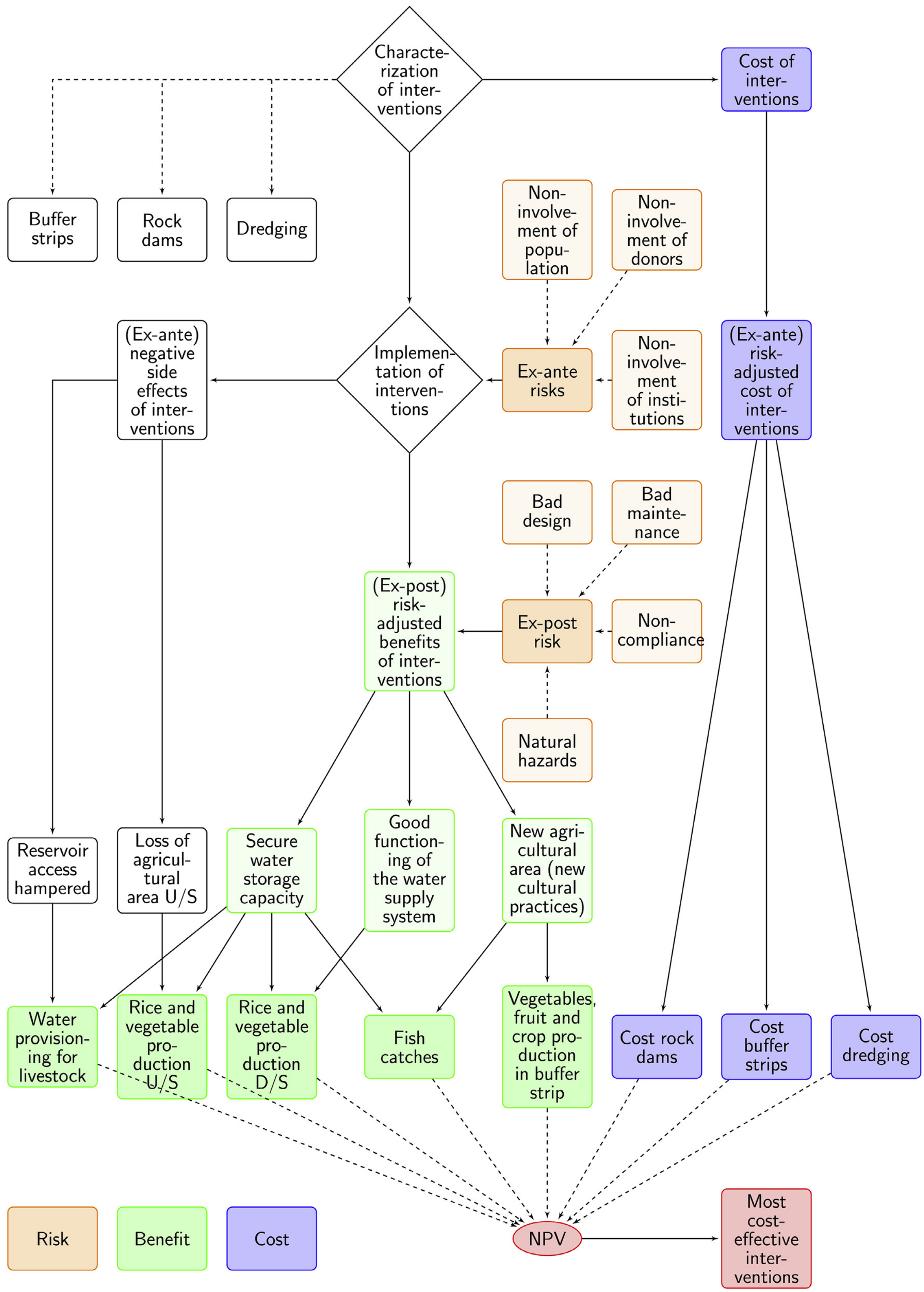

Fig. 5. Diagram of the overall model structure of interventions to reduce sedimentation in the Lagdwenda reservoir in Burkina Faso. NPV is the Net Present Value for all interventions. D/S = downstream; U/S = upstream.

the expert workshop into mathematical equations. Code was developed by an expert panel of three decision analysts (D. Lanzanova, C. Whitney and E. Luedeling). Assumptions, model inputs, and the process definitions were formulated beforehand. Formally, this phase included four steps.

- **Step 1: Specification of input variables.** Based on the conceptual model (Fig. 5), we stated the appropriate input information to run the model, either estimated by the experts or computer-generated, as well as the output results (Fig. 6). All input variables were estimated by experts except some general, rather specific parameters

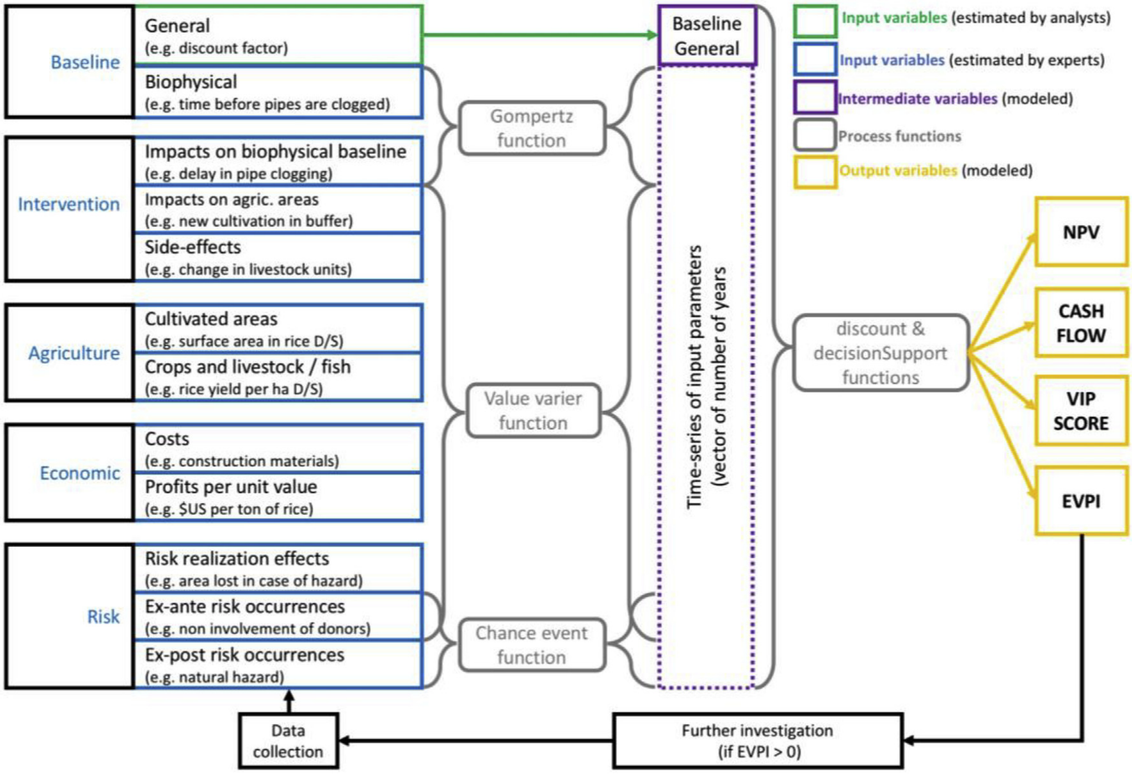

Fig. 6. Input-Output diagram of the simulation model of decisions to implement dredging, rock dams and buffer scheme interventions, as well as all their combinations, to reduce sedimentation in the Lagdwenda reservoir in Burkina Faso. Process functions are detailed in Step 3.

such as the project time horizon, the coefficient of variation or the discount factor (supplementary material, section 1.4). Time-series of intermediate variables were generated from these input parameters in order to introduce variability in estimates and randomness in risk realization. Final outputs of Monte Carlo simulation were obtained using the decisonSupport package for R (see step 3 for details on process functions).

- **Step 2: Definition of assumptions.**

  We made several assumptions regarding costs, land management, representation of the sedimentation processes and intervention effectiveness.

  - Total costs for an intervention depend on the realization of ex-ante risks, as well as the type of intervention itself. Generally, if an ex-ante risk occurs, the project is not implemented and only study costs apply. Specifically, some ex-ante risks could be irrelevant (e.g. risk of non-involvement of donors for dredging) and are not considered in that case (supplementary material, section 2.1.1).
  - Crop land allocation in the irrigation scheme downstream is assumed to remain unchanged following an intervention. Potential behavioral adjustments by farmers (e.g. new cropping choice in reaction to a change in the water resource available) are not considered.
  - The effect of sedimentation on water storage capacity is modeled as a decline in irrigable area over time. The total irrigable area (area that can be irrigated given the water stock in the reservoir) follows a sigmoid function. It is likely to be the largest in the first two years, before it gradually decreases until half of the area is able to receive irrigation water (supplementary material, section 2.3.5).
  - The effect of sedimentation on the functioning of the irrigation system is modeled as a reduction in the irrigated area due to an obstruction of pipes by sediments that prevent the scheme from being watered. As for the water storage, the decline in the irrigated area follows a sigmoid function: blockages are likely to be rare for a few years but gradually become more frequent until the irrigation pipes are no longer operational (supplementary material, section 2.3.6).
  - Interventions mitigate the sedimentation effects both regarding the water storage capacity and the functioning of the irrigation system. Formally, the impact of an intervention is modeled as delays in the decrease of the reservoir capacity to store water or in the decline of the irrigated area because of clogged pipes, as well as in the chance of the pipes being cleared (supplementary material, section 2.3.5 and 2.3.6).

- **Step 3: Selection of functional specifications.**

  As introduced in Fig. 6, we used several functions from the R decisionSupport package (Luedeling and Goehring, 2017).

  - The *chance_event()* function was used for random simulation of ex-ante risks as impacts on the implementation of interventions and of ex-post risks as impacts on the benefits (supplementary material, section 2.1)
  - The *value varier vv()* function was used to introduce variation in time-series of variables that are assumed to vary over time. The function was applied to ex-ante risks and for simulation of common random draws for all intervention model runs (supplementary material, section 2.2)
  - The *Gompertz_yield()* function was used to simulate the loss in water storage capacity (“irrigable area”), the loss of irrigated area (because of the obstruction of pipes), as well as the delays in these two sedimentation outcomes as a result of the implementation of an intervention. It was also applied for other minor benefits such as mitigation of the decline in fish in the reservoir (supplementary material, sections 2.3.5 and 2.3.6).
  - The *discount()* function was used to calculate the net present value, which is the sum of the discounted values of the time series of net benefits (supplementary material, sections 2.3.6.1).
  - The *decisionSupport()* function was used to perform the welfare decision analysis via a Monte Carlo simulation from input

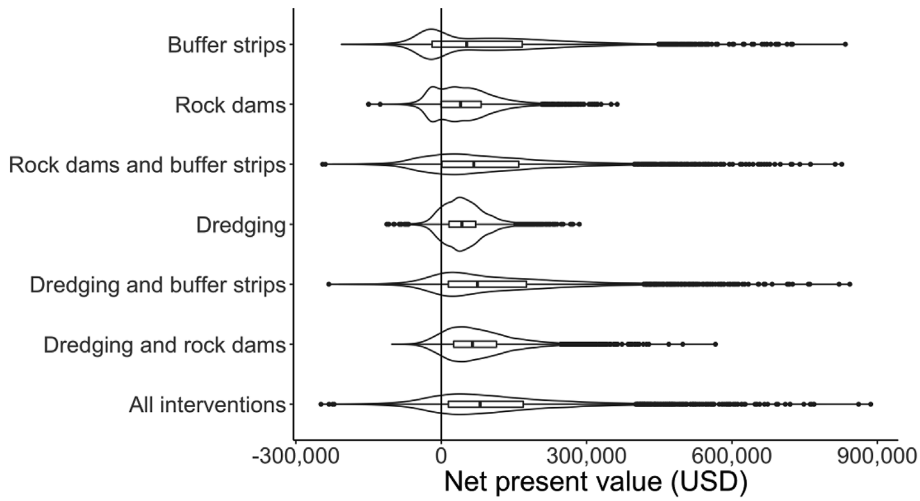

Fig. 7. Distributions of projected outcomes of decisions to implement dredging, rock dams and buffer scheme interventions, as well as all their combinations, to reduce sedimentation in the Lagdwenda reservoir in Burkina Faso.

variables and to analyze the value of information from these variables (supplementary material, sections 3.1).

Step 4: Validation of the model. Acceptance of the model assumptions, process flow, choice of specifications and input parameters implies a validation of the decision analysts' model. To the extent possible, feedback on the emerging code was elicited from the experts involved in building the conceptual model.

The complete model code, as well as a detailed explanation of its components can be found in the supplementary materials.

3.2. Simulation results

3.2.1. Projected intervention outcomes and synergies

Net Present Values projected for the various options varied widely (Fig. 7), reflecting high uncertainty about many input variables. However, some indications about overall risks and expected benefit levels could be obtained. All intervention options, and all their combinations, had positive expected values, indicating that all options promised greater benefits than inaction, though all options also incurred a risk of negative net outcomes.

Among single interventions, dredging appeared to have the lowest potential for benefits, but also the lowest risk of negative outcomes, followed by rock dams (Fig. 7). Due to relatively high up-front costs, buffer strips had the greatest potential for net losses, but they also promised the highest returns among the three options. An intervention that combines all three options looks most promising, in terms of expected value, risk of losses and potential returns.

A careful examination of the simulation values (Table 1) provides more detailed insights. Even though dredging alone was found to be a viable low risk/low return option, it was inferior in all respects (all NPV quantiles, as well as the risk of losses) to an intervention that combined dredging with rock dams. A similar picture emerged for rock dams implemented in isolation, which promised lower returns and greater risks than a combination of rock dams and dredging. Both rock dams and dredging implemented alone can thus be excluded as candidates for the optimal sediment management strategy, regardless of the decision-maker's perception of risk. However, combining interventions, rather than implementing only single ones, may generate synergies and thus promise greater benefits and lower risks than single interventions (Table 1).

A decision maker's perception of an investment depends both on its risk/return characteristics and on the investor's degree of risk aversion. The selection of an optimal intervention is therefore related to the preferences of the decision-maker. The exception to this rule is when an option is strongly dominant in all aspects, but this does not apply here. Among all intervention options, the combination of dredging and buffer strips and the combination of all three options appear to be most efficient. Associating dredging and buffer strips looks slightly less risky, but the combination of the three options promises a higher median return, and a greater expected value. The group of experts also preferred this option. Therefore, we will only present results for this option below.

3.2.2. Projected intervention outcomes and value of information

Our decision analysis approach produces two outputs related to the return on investment – the probability distribution for the net present value (NPV) and the annual cash flow (Fig. 8a and b). We also provide information on the most influential uncertainties regarding the overall magnitude of the NPV – the VIP statistic of Partial Least Squares (PLS) regression – and regarding the emerging decision recommendation – the EVPI. These outputs are presented for the combined intervention consisting of dredging, rock dams and buffer strips (Fig. 8).

Monte Carlo simulation revealed a wide range of plausible outcomes for the intervention's NPV. Positive outcomes are likely (80.0%), but

Table 1
Lower and upper bounds of 90% confidence intervals (i.e. 5% and 95% quantiles), median and mean (in USD) or the NPV distribution for different combinations of reservoir protection interventions and probability of loss (in USD) for the different interventions to reduce sedimentation in the Lagdwenda reservoir in Burkina Faso.

Intervention options	5% quantile	95% quantile	Median	mean	Probability of loss
Dredging	−112373	284780	42458	46165	0.1306
Rock dams	−150328	362929	39748	46576	0.2545
Buffer strips	−205929	833868	52285	84972	0.3611
Dredging and rock dams	−102018	565771	64233	76142	0.1070
Dredging and buffer strips	−232082	842954	74432	104937	0.1819
Rock dams and buffer strips	−244915	826407	67109	90969	0.2449
Dredging, rock dams and buffer strips	−248294	886126	80124	101924	0.2004

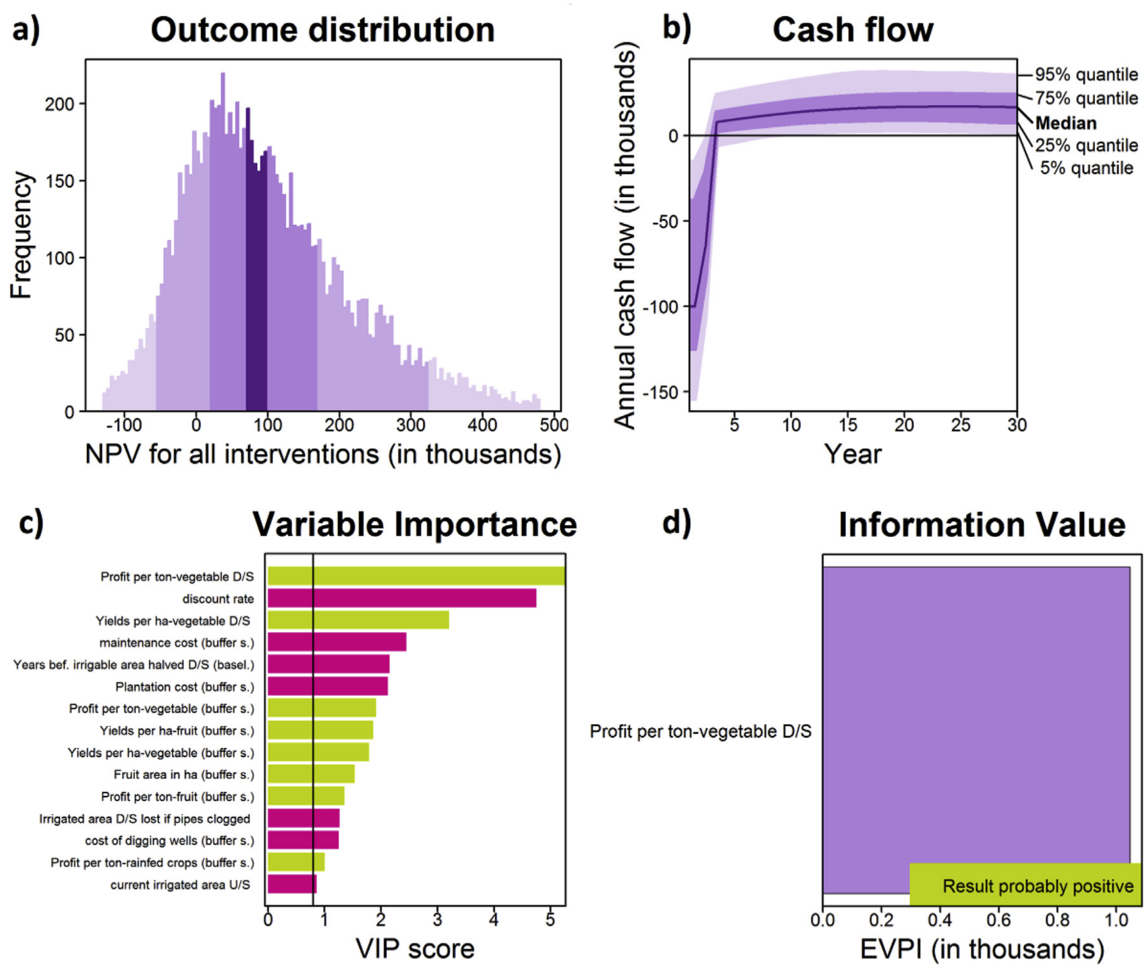

Fig. 8. Outputs of a Monte Carlo simulation (with 10,000 model runs) for ex-ante analysis of the decision to implement an intervention consisting of dredging, rock dams and a buffer scheme to reduce sedimentation in the Lagdwenda reservoir in Burkina Faso. **a)** projected distribution of net present value (NPV) for the intervention (with 100%, 90%, 50% and 10% confidence intervals shown by shades of purple); **b)** probability distribution of annual cash flow; **c)** sensitivity of projected outcomes to uncertain input variables, quantified by the VIP statistic of PLS regression (colors indicate positive (green) and negative (red) input/output relationships); **d)** Expected Value of Perfect Information (EVPI) for all variables with non-zero EVPI (only one variable in this case). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

results also showed a significant chance of loss (20.0%). The total net present value (over 30 years) is likely to be between −64 thousand and 338 thousand USD (the 5th and 95th percentiles of the distribution), with a mean value of 102 thousand USD (Fig. 8a).

The cash flow analysis illustrated that substantial initial investments are needed (Fig. 8b) for implementing the intervention. Accordingly, the expected cash flow in year 1 was negative, with a 90% confidence interval between −300 and −53 thousand USD. From year three, cash flow analysis shows predominantly positive annual net revenue prospects, ranging between −5 and 24 thousand USD. The cash flow stabilized around its highest level (median of 17 thousand USD) towards the end of the time series, emphasizing the viability of this intervention as an effective long-term strategy. Annual benefits appeared quite predictable, with a fairly narrow distribution and little variation over time.

3.2.3. *Important uncertainties*

The sensitivity analysis (implemented by PLS regression) indicated that a number of input variables had important effects on the NPV (Fig. 8c). A total of 15 variables had VIP scores exceeding 0.8 – a threshold that is often interpreted as signifying importance (Eriksson et al., 2001). The most influential variable was the profit on a ton of vegetables in the downstream irrigation scheme, followed by the discount rate (Fig. 8c).

The expected value of perfect information (EVPI) can be expressed in monetary terms as the decision-maker's willingness to pay to gain access to perfect information (Hubbard, 2014). Decision analysis typically reveals that the decision recommendation can only be influenced by a very small number of uncertain variables, with many others affecting the projected NPV, but not its sign (e.g. Wafula et al., 2018). This, however, is the only important criterion to a decision-maker choosing the optimal option. In the present case, only a single variable – the profitability of vegetable production in the downstream irrigation scheme – had a non-zero EVPI (Fig. 8d). Even for this variable, the EVPI was only around 1,100 USD, which is low compared to the overall value of the intervention. This implies that even with the initial state of knowledge, a relatively confident recommendation can be made, but that a small investment in obtaining more information on the economics of vegetable production downstream from the reservoir would be justified by increasing certainty about the decision.

4. Discussion

Here we have demonstrated the application of Decision Analysis techniques to support practical decisions in the face of risk and uncertainty. The approach provides customized analysis for a particular decision context (Howard and Abbas, 2016). Although the approach is widely applicable to other decision contexts, a different set of variables would likely emerge as important for decison models of other reservoirs. In the case of Lagdwenda, the profit per ton of vegetable and the yields of the different crops offered the most critical information to inform decision making. This information, especially concerning yields, is highly context specific.

In comparison with the physical empirical models that are commonly used to evaluate intervention impacts on sedimentation, which are usually deterministic and restricted to consideration of physical system dimensions (Uusitalo et al., 2015), our modeling approach has two major advantages: First, it allows doing justice to the considerable importance of political and social factors that are often major determinants of intervention impacts (Holzkämper et al., 2012). Second, it recognizes that uncertainty is present at every step of an environmental management analysis (Refsgaard et al., 2007), allowing incorporation of such uncertainties into probabilistic models.

The extent to which a strategy is preferred over another depends on many factors, including both its costs (investments, implementation) and its benefits, which in the case of Lagdwenda are mainly the value of the agricultural output over a period of time (in our case 30 years). Costs are generally based on technical information (such that can be provided by engineers), whereas benefits depend on a number of uncertain agricultural and economic factors (e.g. profit per ha, discount rate). The use of the holistic modeling techniques described here can help decision-makers consider the uncertainties instead of making decisions based only on the available technical information.

Despite being considered the most effective technical solution to prevent sedimentation (Kondolf et al., 2014; Palmieri et al., 2001; Schmengler, 2011), buffer strips were not the dominant option, mainly because of the high initial costs of implementation. This illustrates the discrepancy between the technical optimum and the best economic option for solving a problem. All intervention options, and all their combinations had positive expected values, indicating that all options promised greater benefits than inaction, though all options also incurred a risk of negative net outcomes. In the context of Lagdwenda, sedimentation can be controlled most effectively when several interventions are implemented simultaneously. Synergies are generated through the interactions of the different interventions, and the extra costs are more than offset by the benefits of the reduction in sedimentation. This is explained by the non-linear impacts of siltation on farmers' irrigation system. Sediments that originate from erosion of the reservoir shores and from the main inlets interact with each other and result in amplified effects (e.g. threshold effects in the clogging of irrigation pipes, which makes them inoperable after a certain amount of sedimentation.

Assessment of the Value of Information was useful in identifying and addressing critical uncertainties in the model. The EVPI helps to focus research and decrease overall uncertainty about which decision option to choose. This capability makes the EVPI a useful addition to a wide range of decision processes. In the case of Lagdwenda, uncertainties arise predominantly regarding the value of benefits (Fig. 8). The two most important uncertainties are the profit per ton of vegetables (with a positive information value) and the discount rate. Many of the important parameters, such as yield and profit, depend mainly on exogenous factors, e.g. price, macroeconomic policy and evolution of inflation. Consequently, it could be challenging (or impossible) to gather reliable information on them, especially for a longer time horizon such as the one used in this model. The uncertainties exposed by the VIP analysis may offer insights into where decision makers may want to conduct further technical research, but such a decision should take external constraints into account.

Through the use of the EVPI analysis, we were able to determine decision-critical uncertainties, the reduction of which could help to narrow uncertainty about how the decision should be taken. EVPI (Fig. 8d) values are low, and only the profit per ton of vegetables has a non-zero value. This means that uncertainty could be reduced by taking measurements on the profits from crop production. However, this may not even be necessary, since the low EVPI and the low chance of loss (20%) indicate that the combined intervention should be preferred over inaction. This demonstrates how decision-supporting research does not have to eliminate all uncertainty, but can focus on a few key pieces of information.

5. Conclusion

Sedimentation in Lagdwenda's reservoir impacts the reliability of irrigation and thereby the livelihoods of local people, a problem that is common for small-scale reservoirs in the Upper Volta. This problem requires a sediment management strategy that is appropriate to the local context. Development of such a strategy is hindered by data scarcity for many important variables. Decision analysis approaches allow comprehensive ex-ante assessment of the effectiveness of intervention options through collaborative development of impact pathway models. Data limitations are addressed through probabilistic simulation, for which all variables are expressed as probability distributions, and decision-critical knowledge gaps are highlighted by sensitivity analysis and Value of Information analysis.

A combination of all three candidate interventions – dredging, rock dams and buffer strips – emerged as the most effective management strategy, with a relatively low chance of losses and long-lasting net benefits for local communities. The magnitude of net benefits depended on several uncertain variables, but only a single variable – the profitability of vegetable production in the downstream irrigation scheme – had positive information value. In consequence, a relatively confident recommendation can be provided to decision-makers, even in the face of multiple uncertainties. In addition to this, the analysis revealed that most of the residual uncertainty about whether the intervention is worth doing can be addressed through limited measurements on just one variable, which is probably quite easy to measure.

Coupling local knowledge systems with rigorous simulation techniques, our methodology provides actionable information for robust decision-making. The model is grounded on the knowledge of local experts and stakeholders who provided a unique understanding of the socio-ecological system that could not have been obtained with traditional disciplinary approaches.

Declaration of interest

None.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envsoft.2019.01.016.

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