Feature

Decision-Focused Agricultural Research

by Eike Luedeling and Keith Shepherd

Trees for the Future

Farmers learn how to prune branches in Kenya.

In Brief

Agriculture provides most of our food and many other products. It also affects ecosystem services, such as water regulation, soil protection, and biodiversity conservation. Decision-makers on agricultural systems, from farmers to agricultural ministers, should consider all these functions and their trade-offs, but this rarely happens. Many of agriculture's products and services are regularly ignored in decision-making, mainly because they are difficult to appraise. This easily leads to decisions with adverse side effects, such as land degradation, pollution, or loss of cultural heritage. 'Holistic' decision-making needs decision support approaches that consider factors that are difficult to quantify.

Decision Analysis can potentially solve this problem. It recognizes that rational decisions do not normally require precise information on all factors of interest. Decision Analysis harnesses the knowledge of system experts to produce a high-level model of a decision, which reflects the best available information on plausible decision impacts. The model should include all factors experts consider relevant and all important decision impacts, regardless of data availability. Since most variables cannot be precisely quantified, experts estimate their state of uncertainty as confidence intervals or probability distributions. These allow an initial model run, in which these inputs are translated into decision impact forecasts. These are imprecise, but they allow estimating a plausible range of decision outcomes. Often, this is sufficient for selecting one of the decision alternatives. When no clear recommendation emerges, Value of Information analysis can identify key uncertainties that decision-supporting research should address.

Decision Analysis solves the problem of data gaps, which has often prevented research from comprehensively and holistically forecasting decision impacts. It also allows explicit consideration of risks and variability. We present several applications of Decision Analysis in agricultural development, demonstrating its ability to convey a holistic understanding of likely decision impacts, in the face of risk and imperfect information.

Agriculture serves a wide range of purposes, and new requirements and objectives continue to be added. Besides food and fiber production, we expect modern agricultural systems to conserve soils and biodiversity, regulate water and carbon cycles, provide fuel, generate employment, and offer many other ecosystem services.[1] Whether agriculture succeeds in delivering all these services depends on a complex array of cultural, technological, educational, political, legal, demographic, sociological, climatic, and economic drivers. The goals and values of people working on farms also influence agricultural outcomes.[2]

Predicting how farms respond to changes—such as new farming practices, price shocks, or climatic events—is very difficult. There is normally no way of knowing with precision how such changes will play out. This dilemma has often left people making decisions on agricultural systems with little certainty that these decisions are right.

But it is not only decision-makers that struggle with the complexity of agricultural systems. Researchers are also challenged by how to study them effectively. Many common research methods are not well equipped to deal with complexity. They are designed for investigating systems that can easily be controlled and manipulated and for testing hypotheses about their behavior, aiming to identify generally applicable rules that help us understand how these systems work. While there continues to be great need for research that follows these principles, such work rarely allows comprehensive assessment of system dynamics. When it comes to supporting practical decisions on complex agricultural systems affected by many uncertain, related, and dynamically changing variables, classical hypothesis testing based on controlled experiments is of little relevance.

Key Concepts

- **Agricultural systems are influenced by a host of environmental, economic, and socio-cultural factors, and they are expected to provide many products and services to humanity. The complexity that arises from this requires decision-supporting research to consider a wide range of issues, spanning many disciplines. Classic research approaches struggle with this challenge.**

- **There is rarely sufficient high-quality data to form a robust foundation for precise data-driven decision support. Since many research approaches cannot deal with missing and uncertain information, policymakers and other development professionals find themselves making decisions without meaningful scientific guidance.**

- **Research for agricultural development should embrace methods that are designed for supporting decisions on complex systems in the face of uncertainty. Decision Analysis methods have been used for similar purposes in numerous fields, including computer science, public health, business decision-making, and natural resource management, but they are new to agricultural research.**

- **Decision Analysis is based on the following principles: 1) focus research on a particular decision, 2) use the current state of knowledge to forecast decision impacts, 3) include experts, stakeholders, and decision-makers in the analysis, 4) explicitly express uncertainty, 5) consider everything that matters to the decision, and 6) use the concept of Value of Information to identify information needs.**

- **The World Agroforestry Centre has completed several case studies that have used Decision Analysis procedures in research for agricultural development. It aims to strengthen the capacity of development-oriented researchers to apply these methods, to increase the share of development decisions that receive robust and context-specific scientific support.**

The Unsurmountable Complexity Challenge

Many studies have tried to precisely predict agricultural outcomes, often using complex models fed with large datasets.[3,4] It is striking that virtually all successful simulations dealt with relatively simple settings, mostly working on highly mechanized single-crop systems, with homogeneous soils and advanced management of nutrients, water, pests, diseases, and weeds.[5] Simulations also generally assume well-functioning input and output markets and predictable social and economic environments.

We suspect that successful simulations for fairly simple systems are the main reason many agricultural scientists have confidence in their models. While many models convincingly describe photosynthesis, nutrient uptake, or light competition,[6,7] the impacts of pests and diseases, labor constraints, and weather extremes are often either excluded or not captured sufficiently. Many researchers have seen opportunities for precise modeling, even when some components of systems get a little more complex.[8,9] For instance, we could possibly make models that describe tree-crop interactions,[10] other intercropping situations,[11] or biotic stresses.[12] However, such models will probably never be able to become sufficiently complex for simulating many real-life agricultural systems.

We work on agroforestry systems, which are agricultural systems that integrate trees (or shrubs) with crops and/or livestock.[13] Such systems are widespread throughout the tropics and subtropics, especially among smallholder farmers. In addition to their biophysical settings, smallholder farms are normally shaped by a host of economic, social, and cultural factors that influence farm performance. They are also highly variable,[14] so that generalizations about them become very problematic (Figure 1). There is little hope for making precise predictions

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Figure 1. Complex agroforestry systems in Africa—difficult to study with purely data-driven research approaches.

for such systems. Fortunately, we probably don't need such predictions for good decision making.

A possible answer to the challenge of modelling complex systems could be a massive increase in data collection. Unfortunately, this strategy is often not promising for complex systems, because it would devour far more resources—time and money—than are available in most contexts. Complex models can also be quite error-prone because they often involve the simulation of many processes, each of which may introduce inaccuracies.[15] System analysts should therefore aspire to initially build lean but balanced models (Figure 2), in which all major processes are adequately represented, rather than models that cover some parts of the system in detail but largely ignore others.

Towards Meeting the Complexity Challenge: Accept Inevitable Limitations

In the face of system complexity and data scarcity, which seem ubiquitous throughout much of the developing world (but not only there), it is hard to be optimistic about the ability of research to deliver meaningful decision support. This is not helped by reports indicating that most 'research for development' is never actually considered in decision-making processes.[16] In many cases, better communication by researchers could amend the situation, but we suspect that quite often decision-makers realize that studies do not address systems as comprehensively as they should. Where research fails to consider impacts on critical stakeholders, site-specific risk factors, or institutional constraints, people with intimate knowledge of the local context may easily dismiss the research findings.

This leaves researchers who aim to facilitate development with a problem: how can research meaningfully support decision processes? The first step towards a solution is accepting the inevitable limitations: no matter how hard we try, we cannot eliminate uncertainty on complex agricultural systems! Accepting that complexity and uncertainty are part of the systems that we are attempting to manage is the first step towards a solution. In fact, research approaches that can accommodate complexity and uncertainty do exist in other disciplines but are not yet commonly used in Agricultural Sciences.

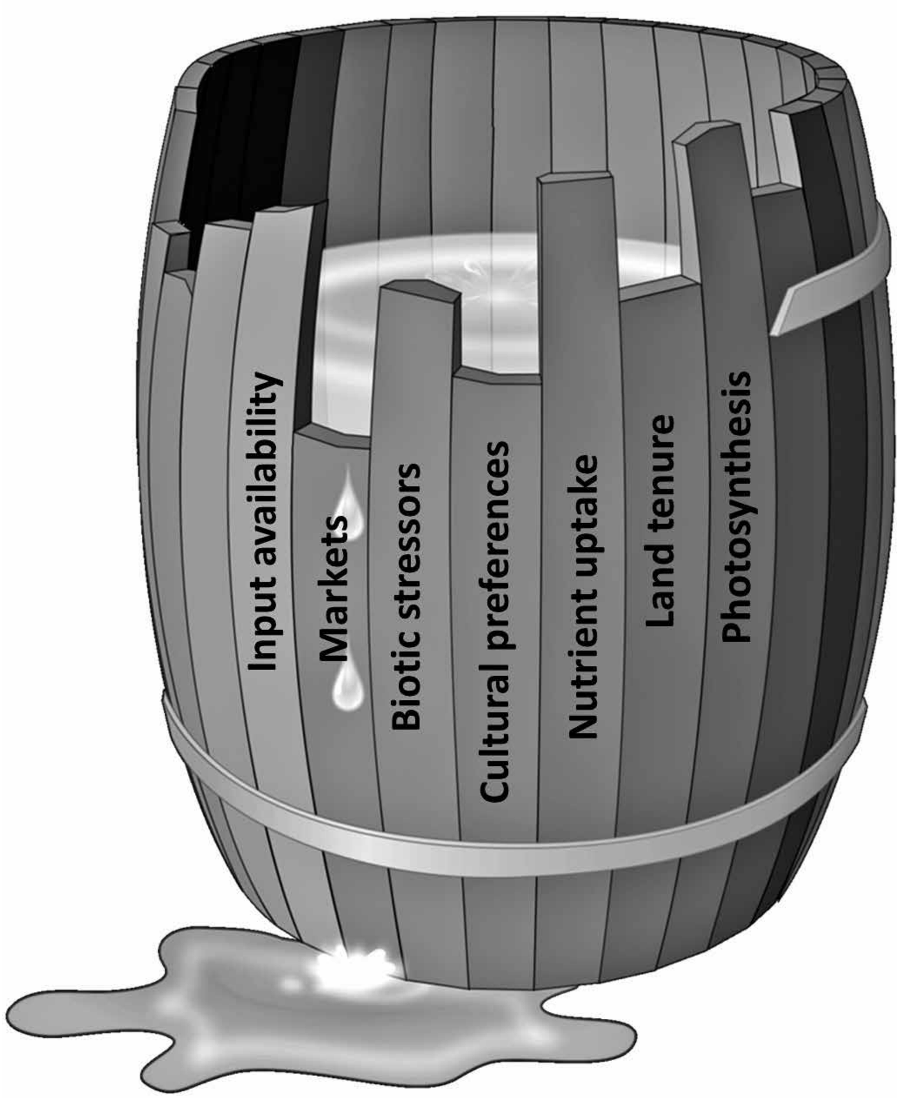

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Figure 2. 'Liebig's barrel' of model precision (borrowing from an illustration commonly used to illustrate the concept of essential plant nutrients). The precision we can expect from our model is limited by the process we understand least (where the barrel loses water). More detailed information on aspects we already understand well will not make our models much more precise.

Decision Analysis: A Promising Solution for the Complexity Challenge

Having to understand complex systems sufficiently well to make decisions on them, even without perfect information, is a very common challenge. Similar situations are regularly faced by entrepreneurs deciding on whether to launch new products, by judges having to decide on court cases, by governments contemplating new policies, and in a large number of other contexts. In fact, we meet similar decision challenges in our everyday lives all the time.

Such decision dilemmas are the object of interest of Decision Theory. This discipline has a long history of working on exactly the kind of problem agricultural decision-makers face: how to make risky decisions on complex systems with limited information. This problem has attracted the attention of researchers working in many scientific fields, including economics, psychology, sociology, mathematics, computer science, and statistics. Thanks to the combined efforts of this community and the abundance of potential applications, pragmatic approaches, known as Decision Analysis, have been developed to support real-life decisions. Decision Analysis is widely applied in many contexts, including business decision support,[17,18] public health intervention planning,[19,20] legal reasoning,[21] policy process support,[22] and natural resource management.[23]

So far, research for agricultural development has not seen broad application of Decision Analysis methods. We posit that embracing this discipline and its principles could constitute a solution for the difficulty agricultural research has been having with supporting decisions. We are working to introduce pragmatic Decision Analysis approaches into research for development in order to overcome the disconnect between research and practice that has been standing in the way of evidence-based decision-making.

The Principles of Decision Analysis

Focus on a Decision

'Decision Analysis' is concerned with making rational recommendations on how decisions should be taken. Decisions are situations where a decision-maker or decision-making body can choose between at least two alternative options, with some uncertainty as to which option is preferable. Decision Analysis aims to identify the rational choice, based on the current state of knowledge and preferences of decision-makers. This motivation draws our attention away from the classic scientific pursuit of trying to understand how the system works towards the more focused context determined by a particular decision question. The analysis then no longer needs to describe all parts of a system but can instead focus on the parts that stand to be affected.

Use the Current State of Knowledge

Much modern research, including research for development, is very much focused on empirical data, as opposed to other sources of information. We often assume that we know next to nothing about a particular issue until we have collected data on it. On the other hand, we place great—and probably often unwarranted—trust in results from surveys or experiments. This so-called 'frequentist' mindset originates from the common belief that science should be objective and that scientists' beliefs and values should not be allowed to interfere with analyses. The problem with this mindset is that studying complex systems is very difficult if our starting point is a blank slate. Even given that most frequentist researchers naturally consider earlier work in designing their studies, it is difficult to comprehensively describe systems with this approach. An alternative mindset is the so-called 'Bayesian' approach to research, which allows analysts to insert their initial state of knowledge—their prior beliefs—into their studies. These prior beliefs, which can be updated through additional information, can serve as a starting point for systems analysis.

The difference between these views on the scientific process has substantial implications for our ability to study complex systems. While the frequentist approach requires us to first invest significant effort in data collection, before we can say anything at all about a system, the Bayesian approach allows us to progress towards a coarse understanding of system dynamics relatively quickly and much more cheaply. This cost and time effectiveness is a prerequisite for research that supports decisions in real time.

Include Experts, Stakeholders, and Decision-Makers

If researchers without much knowledge on a particular system make a model of that system, the results are often not very useful. This is why decision analysts engage subject matter experts and stakeholders—often the best available source of information—in participatory processes to harvest their knowledge and construct models that reflect their beliefs and priorities. Besides improving the models, this participation allows for considering different perspectives on the decision and—especially if decision-makers themselves participate—it also raises the chance that research outputs will be considered when the decision is finally made.

Explicitly Express Uncertainty

In working with expert knowledge, it is crucial to adopt robust procedures to acknowledge that the information we use is uncertain. We can express uncertainty about variable values by using probability distributions that describe our beliefs about the true values. If we adopt simulation techniques that can work with such distributions, we can then also express our expectations of decision outcomes in a similar manner. We cannot offer certainty about what the outcome of the decision will be, but we can produce a plausible range for its impacts. Given that uncertainty about decision outcomes is inevitable in practice, this may be the most honest answer science can provide. Common methodologies used to implement such analyses are Monte Carlo simulation or Bayesian Networks, which allow representing uncertainty in variable values and to some extent even in the processes involved in translating decisions into outcomes.

An important obstacle to including uncertainty in simulations is the observation that most people, including experts, are not very good at accurately expressing their state of knowledge in quantitative terms.[17,24] Experts are commonly overconfident, meaning they think they know more than they actually know. For instance, an expert who says she is 90 percent confident that a value is within a specified range, is likely to be right less than 90 percent of the time. Overconfidence is only one of a large number of cognitive biases that have been described.[25] Decision analysts often attempt to counteract such biases by subjecting experts to so-called calibration training, where they are made aware of their biases and instructed in techniques that help to overcome them.[17,21]

Consider Everything that Matters

The capacity to work with uncertain information opens new opportunities for taking holistic perspectives on systems that consider everything the experts, stakeholders, and decision-makers that we work with think should be included. This may often include factors for which there are no hard data or that are difficult to measure in principle. However, if they are expected to affect system dynamics, it is possible to express these expected effects in quantitative terms. Decision analysts have referred to such factors as 'intangibles,' and many instances of their successful inclusion into decision models have been reported.[17]

Not having to be absolutely precise also opens opportunities for expanding the range of outcome dimensions we consider. If, for instance, we want to predict the impacts of a decision to adopt agroforestry practices, we now no longer have to restrict our assessment to outcomes that can be precisely measured, such as the yields of annual crops. Instead, we can now estimate other outcome dimensions, such as the benefits of soil conservation, sequestered carbon, fuelwood, etc., even though in the absence of data these estimates may initially remain quite uncertain. For reliable decision support, inclusion of such factors is critical.

Use the Value of Information to Prioritize Decision-Specific Research

A key concept in Decision Analysis is the Value of Information. It expresses that not all uncertainties associated with a decision need to be reduced to reach a good decision. There are normally many knowledge gaps whose closure would contribute very little additional clarity to the decision

Trees for the Future

Farmers in Senegal discuss a young, income-generating papaya tree.

challenge. Conversely, some variables typically stand out with substantial information values, meaning that investments in their measurement could significantly facilitate decision-making. Value of Information analysis aims to identify such decision-specific research priorities. It has often been shown that the most pertinent knowledge gaps only become apparent after reaching an initial understanding of the overall decision context and analyzing the uncertainties. One might therefore look at Decision Analysis as a transdisciplinary umbrella for systems analysis, which serves to first appreciate the way the entire system works, before evaluating its performance based on the current state of knowledge and then pointing out where measurements would be most useful. In this way, Decision Analysis can integrate expert knowledge with available data, providing a much better basis for supporting decisions than either source of information on its own.

Decision Analysis in Development Practice

For the past four years, we have been applying Decision Analysis methods in research for agricultural development. We started by using the well-established procedures of Applied Information Economics in partnership with the developer of this approach.[17] The process starts with participatory analysis of the decision problem. Decision analysts convene decision-makers, stakeholders, and potentially additional experts to jointly develop a decision model (Figure 3). Participants are encouraged to bring up any factors they deem important for the decision, in particular the various costs, benefits, and risks, as well as the objectives and concerns of decision-makers and stakeholders. This information is arranged into a conceptual model, which aims for a balanced representation of the entire decision context. It should not include excessive detail on some parts of the model while disregarding other important parts (Figure 2).

The analyst converts the conceptual model into a mathematical model, translating stakeholder inputs into equations as accurately as possible. The members of the model-building team, and possibly additional experts, are critical informants in parameterizing the model, especially where no reliable data are available. Even when there are data, they often need to be filtered or adapted to the given context. All experts are subjected to

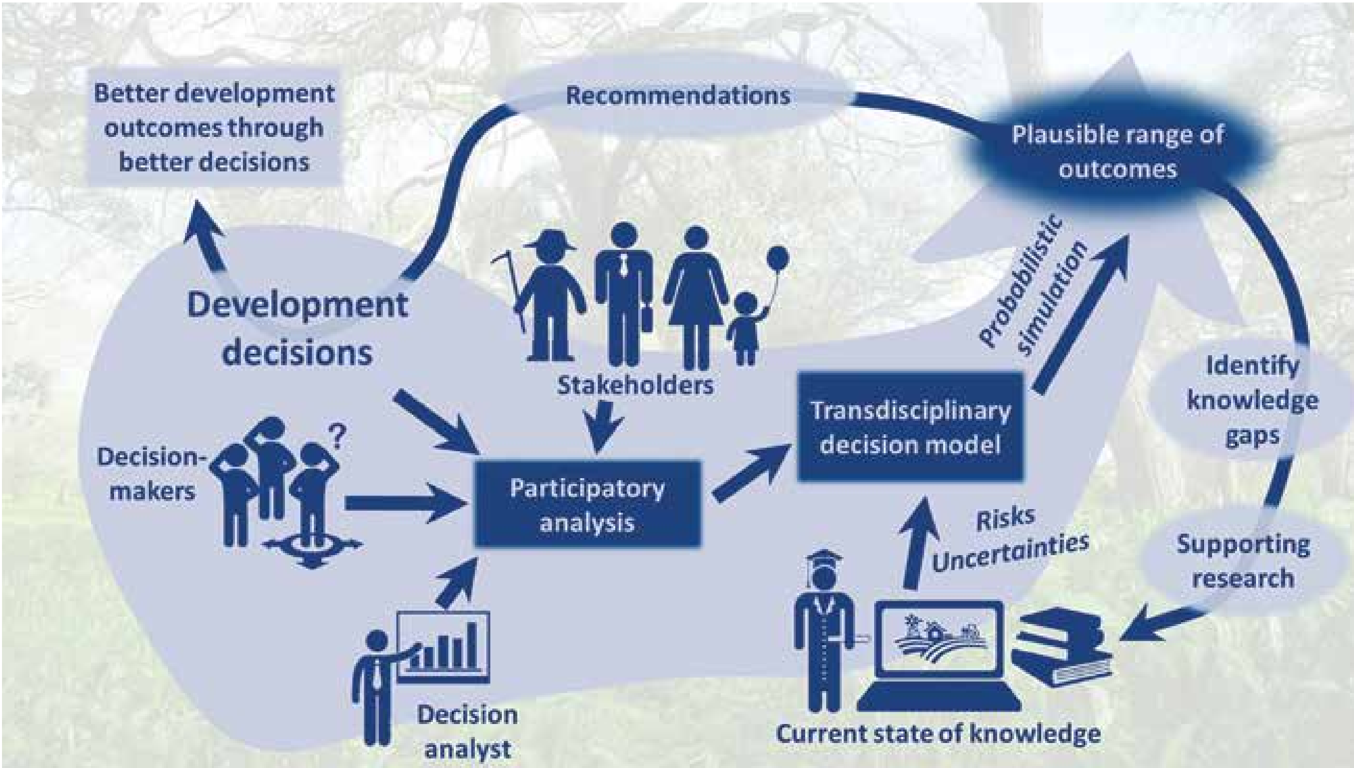

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Figure 3. Illustration of the Decision Analysis process used at the World Agroforestry Centre. Decision-makers, stakeholders, and analysts join hands in a participatory analysis of the decision in question. This joint understanding is translated into a transdisciplinary decision model. After parameterizing the model based on the current state of knowledge, using various sources of information, probabilistic simulation can indicate plausible ranges of outcomes for decision alternatives. Models can be refined based on supporting research on key knowledge gaps identified by Value of Information analysis.

calibration training to make their estimates as reliable as possible. The major techniques we apply are based on a substantial body of research in cognitive psychology and have been described in detail by Douglas Hubbard and others.[17,24,26] Experts are then requested to estimate their state of knowledge for all uncertain variables. With this information, simulations can be run, producing plausible outcome ranges for alternative decision options. In many cases, these simulations reveal a preferred course of action. Where no clearly preferable option emerges, Value of Information analysis can identify the most important knowledge gaps, which can then be narrowed by targeted research. With the new information, the model can be run again. The process is repeated until decision-makers feel confident that they can make a well-informed decision.[27]

Applications in Development

Over the past four years, we have used this process in a number of decision contexts. In one of the first applications, we built a simple decision model for estimating the yield benefits that African smallholder farmers can expect from introducing Conservation Agriculture principles. Unlike most other studies, our decision model considered not only biophysical factors that can easily be measured but also less tangible aspects, such as land tenure or access to markets and information. Including these influences, which were considered in the form of calibrated expert estimates, we found that, in many types of socio-economic settings, farmers stand to gain little from introducing Conservation Agriculture, even though their biophysical setting appears favorable.[28]

Working with teams of scientists involved in water, land, and ecosystem research, we evaluated several potential development decisions, ranging from establishment of a large dam in Laos to the use of payments for ecosystem services to manage urban water supply in Kenya. Addressing a controversial decision in northern Kenya, we modeled plans to ensure the water supply to a dryland city by tapping an aquifer and transporting water through a 100-km pipeline. We convened stakeholder workshops and worked with local experts to model outcomes of this intervention for several stakeholder groups. Our main finding was that implementing this project carried high risks for all stakeholders. Key uncertainties included the feasibility of a commercial water supply business, the extent and valuation of a reduction in infant mortality, and the risk of political interference (Figure 4).[27]

We have also evaluated the potential of several agricultural interventions in East Africa, the applicability of a Decision Analysis framework for monitoring and evaluating development projects, and the prospects of strengthening resilience through large-scale irrigation, watering boreholes for livestock, or improving roads with innovative technology. Current projects include a cost–benefit analysis for small reservoirs in West Africa and the nutrition impacts of tree-based agriculture in East Africa. We have also reflected on the benefits of using Decision Analysis methods for monitoring the Sustainable Development Goals (SDGs), which could provide a low-cost alternative to large-scale data collection, while actually supporting decision-makers aiming to further the cause of the SDGs.[29] We have published some of our tools in an open-access analysis package and started exploring the use of Bayesian Networks as an additional Decision Analysis strategy, including for project management.[30,31]

The Way Forward

We feel confident that the tools and methods of Decision Analysis can lead to major progress in the analysis of complex systems, especially where concrete decisions are contemplated. The ability to make projections even in the absence of precise information opens opportunities to support a much wider range of decisions than would be feasible with a purely data-driven approach. Working directly with decision-makers on the concrete decisions they face can bridge the gap between science and practice, fostering a solution-oriented dialogue that allows science to truly inform decision-processes.

This dialogue requires decision-makers and experts to make explicit their expectations of how the impacts of the decision will unfold, with particular focus on trade-offs and risks. This allows for identifying potential weaknesses in the intervention that is decided on and strengthening it by modifying the intervention design. Decision models can also explicitly capture decision-makers' preferences by eliciting directly from these decision-makers value estimates or utility weights to be assigned to various costs and benefits. This can be critically important for capturing real constraints to the adoption of new technologies.

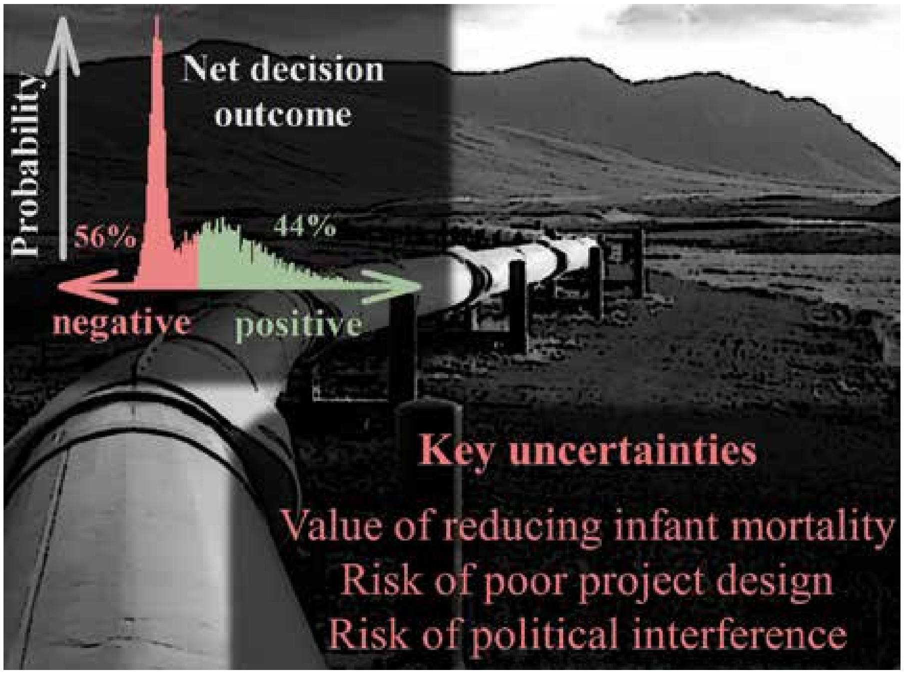
Decision models can be of value even after a decision has been made. As an intervention is implemented, measurements can be taken on many variables that are uncertain in the beginning, allowing continuous updating of impact projections. Expected impacts can be adjusted for the effects of variable factors, such as the weather or political stability, which may strongly impact intervention outcomes. Decision models are useful tools for intervention impact evaluation, because they allow comparison of actual project outcomes with targets that are realistic given the occurrence of influential events beyond the project's control. Such 'random' factors are difficult to account for when impact evaluation relies on before–after comparisons that do not consider causal relationships in the intervention's impact pathway.

Decision Analysis principles have potential as an entry point to transdisciplinary systems analysis. They allow analyses to start with a coarse understanding of the system of interest before zooming in to the detailed system components on which research is needed. This forms a contrast to traditional multidisciplinary approaches that start with robust research on particular system elements but often struggle to put the various pieces together to generate system understanding.

There have been challenges in applying Decision Analysis in development. Most researchers and many stakeholders in development have been trained in data-driven research approaches, making many uncomfortable with making estimates and with using information that is not thoroughly supported by data. Moreover, when given the freedom to insert into models everything they think worthy of inclusion, stakeholders may come up with models that are far from accurate. They can fail to consider important processes, dedicate attention to unimportant ones, and—intentionally or inadvertently—introduce their personal biases and opinions. Good facilitation can safeguard against this to some extent, but a residual risk remains. Where initial models are wrong and analysts fail to recognize this, the Decision Analysis approach to knowledge generation may not produce useful results. Finally, analysts may introduce their own biases and interpretations into the decision model because they normally have to make at least some choices when translating participatory models into computer code.

In light of these challenges, however, it is important to recognize that the primary motivation of Decision Analysis is to improve the way people make decisions. Hence, its use has to lead to better decisions than unaided intuition, which is often the only alternative. Decision models should not be compared to hypothetical resource-intensive research projects serving the same purpose, because such projects are very rarely a realistic possibility.

Our experience so far has shown that decision analysts should be skilled in facilitation, mathematical modeling, and ideally in the subject matter of the model—skills that rarely coincide in one person. Teams of analysts with complementary skills can be an effective solution. In the longer term, the necessary skill base for wider deployment of Decision Analysis in research for development could be produced through a shift in



Graphic by Eike Luedeling

Figure 4. Distribution of projected overall net impacts of constructing a groundwater-fed water supply pipeline for Wajir, a town in northern Kenya, and key uncertainties determined through Decision Analysis procedures.

the educational focus of development-related study courses, away from an exclusive reliance on data-driven research methods and towards more systems-oriented approaches. This could produce a generation of decision analysts, which could make full use of pragmatic Decision Analysis methods to further the cause of sustainable development.

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