Working Paper

A decision analysis framework for development planning and performance measurement

Application to land restoration investments

Keith D Shepherd, Cory W Whitney, Eike Luedeling

World Agroforestry

A decision analysis framework for development planning and performance measurement

Application to land restoration investments

Keith D Shepherd, Cory W Whitney, Eike Luedeling

LIMITED CIRCULATION

Correct citation: Shepherd K D, Whitney C W, Luedeling E. 2021. A decision analysis framework for development planning and performance measurement: application to land restoration investments. ICRAF Working Paper no 324. World Agroforestry, Nairobi, Kenya. DOI https://dx.doi.org/10.5716/WP21042.PDF

Titles in the Working Paper series aim to disseminate interim results on agroforestry research and practices, and stimulate feedback from the scientific community. Other publication series from World Agroforestry include Technical Manuals, Occasional Papers and the Trees for Change Series.

Published by World Agroforestry
United Nations Avenue
PO Box 30677, GPO 00100
Nairobi, Kenya
Tel: +254 20 7224000, via USA +1 650 833 6645
Email: worldagroforestry@cgiar.org
Website: https://www.worldagroforestry.org/

Working Paper No. 324

Table of contents

About the authors

Keith Shepherd is a Senior Research Fellow at World Agroforestry and Chief Scientist at Innovative Solutions for Decision Agriculture (iSDA). He previously led ICRAF's science domain on land health decisions and the Centre's Soil-Plant Spectral Diagnostics Laboratory. His research leverages diagnostics and decision analytics to provide improved decision support to policy makers and farmers. He holds a PhD in agricultural botany from the University of Reading, UK.

Eike Luedeling is a professor of Horticultural Sciences within the Institute of Crop Sciences and Resource Conservation (INRES) at the University of Bonn, Germany. Before starting this position in 2018, he worked at the World Agroforestry for 8 years. His research interests include fruit tree dormancy, agroforestry, climate change impacts on agricultural and horticultural systems, and the application of decision analysis methods in agricultural research.

Cory Whitney is a scientist at the University of Bonn. He uses collaborative research and holistic analysis approaches to describe systems and model decision impact pathways. Cory works with diverse groups including researchers, food activists, small-scale farmers and indigenous communities to address issues of direct relevance and offer new lenses through which to view the development process. He holds a PhD in agricultural sciences from the University of Kassel in Germany.

Acknowledgements

We thank Todd S. Rosenstock and Ermias Aynekulu from the World Agroforestry Centre (ICRAF) and Lulseged Tamene from the International Center for Tropical Agriculture (CIAT) for helpful comments on the manuscript. We acknowledge the inputs of Douglas W Hubbard and Jan de Leeuw in the design of Figure 2 and helpful suggestions in relation to comparison and evaluation of methods. This research is carried out under the CGIAR Research Program on Water, Land and Ecosystems with support from CGIAR Fund Donors (http://www.cgiar.org/about-us/our-funders/).

Abstract

While the principles of sustainable development are widely accepted, considering these principles effectively during implementation planning and performance measurement remains a challenge. We argue that predominantly-used results-based approaches, which monitor performance against pre-defined targets and indicators, are ill-suited to performance management of complex systems, such as sustainable land management. These approaches tend to cause distortions and may even constrain performance. As an alternative, we propose a decision analysis framework, Stochastic Impact Evaluation (SIE), that considers multiple goals and trade-offs. This framework produces decision recommendations that are based on the current state of knowledge and designs measurements to reduce decision uncertainty. We describe how SIE can be used to prioritise measurements through value of information analysis and to evaluate impact and improve adaptive management.

Using synthetic case studies, we illustrate how SIE could be applied to guide countries and organizations towards meeting their commitments to restore millions of hectares of degraded land. Adoption of SIE would help countries evaluate intervention alternatives against multiple outcomes, minimize implementation risks, and measure performance in terms of overall return on investment. We evaluate the widely promoted United Nations Land Degradation Neutrality framework and its Target Setting Programme, which has been adopted for monitoring Sustainable Development Goal Target 15.3, and indicate how SIE could overcome many of its shortcomings. We recommend that performance evaluation of land restoration initiatives should focus on *decision quality* and adaptive learning rather than only on final *results* against targets. Finally, we suggest actions to increase adoption of decision analysis for development.

Keywords: Land restoration, performance measurement, decision analysis, uncertainty, value of information

1 Introduction

In response to a growing environmental crisis and social inequalities in global development, the international community has endorsed a sustainable development agenda, starting with Our Common Future (WCED, 1987) and more recently re-enforced by the 2012 Rio Summit (Rio+20) and the new global Sustainable Development Goals (SDGs) (UN, 2015). The multi-dimensional nature of sustainable development and the high level of uncertainty, both on the current state and direction of the human-environment system and on its responses to interventions, present challenges for planning and performance assessment, especially in data limited environments.

Governments, development organizations and donors widely promote a results-based approach to measuring performance in development (e.g. Global Affairs Canada, 2016; SDSN, 2015; UNDG, 2011). This often involves setting targets and pre-defining common indicators with which to track progress. However, target-setting approaches, which place the focus on meeting narrowly-defined targets, are not well suited to managing the performance of complex systems. They tend to cause distortions and constrain performance, as opposed to learning how to better adaptively manage a system towards a set of desired outcomes (Shepherd et al., 2015a). For instance, Seddon (2008) gives examples of perverse effects of target setting approaches in the public sector, while Unterhalter (2014) reported perverse outcomes due to the narrow framing of the education targets and indicators in the Millennium Development Goals. Leeuwis et al. (2018) have critiqued the way that agricultural researchers are forced to make unrealistic quantitative promises about the eventual impacts they will achieve, and instead recommended strengthening ex-ante assessment and monitoring of research in terms of the plausibility of proposed 'theories of change' and investment decisions. The SDG targets (SDSN, 2015) have also been criticized as vague, weak, or meaningless (Holden et al., 2017). There is a danger that costly measurement of standard indicators could be imposed on developing countries to serve poorly defined higher-level needs.

Various authors have pointed to the limitations of results-based approaches in natural resources management and conservation and proposed alternative approaches. These include adaptive management (Herrick et al., 2012; Holling, 1978; Walters & Holling, 1990; Williams, 2011; Williams & Brown, 2014), structured decision making (Convertino et al., 2013; Gregory et al., 2012; Lyons et al., 2008) and decision analysis (Shepherd, 2015; Shepherd et al., 2015a). Such approaches focus on iterative learning from monitoring management outcomes, with the aim of reducing uncertainty over time, as opposed to gauging progress against pre-defined targets.

Many countries and organizations have made commitments to restore millions of hectares of degraded land (Table 1). These commitments amount to billions of dollars of planned investments. In addition, stakeholders are increasingly demanding accountability for investments in terms of performance (UNCTAD, 2014). Yet there is little guidance on how to evaluate and monitor performance in terms of impacts on multiple outcomes and value for money (Hajkowicz, 2009; Reed et al., 2016). In the Land Degradation Neutrality (LDN) framework of the United Nations Convention to Combat Desertification (UNCCD), goals are determined through a specific Target Setting

Programme (LDN-TSP) (Cowie et al., 2018; Minelli et al., 2017; Orr et al., 2017; UNCCD/GM, 2016a). The LDN-TSP is currently the most widely adopted framework for tracking national and global progress on combatting land degradation, in which 120 countries are participating (UNCCD, 2019). LDN-TSP recommends defining national baselines, targets and associated measures to achieve LDN by 2030. The LDN framework has also been endorsed by the United Nations Economic and Social Council (ECOSOC, 2017ab) for monitoring and reporting on SDG Target 15.3: "By 2030, combat desertification, restore degraded land and soil, including land affected by desertification, drought and floods, and strive to achieve a land degradation-neutral world" (UNCCD/GM, 2016a).

Table 1. Land restoration initiatives and commitments

Initiative	Target
The Aichi Biodiversity Target 15 (CBD, 2017)	By 2020, ecosystem resilience and the contribution of biodiversity to carbon stocks have been enhanced, through conservation and restoration, including restoration of at least 15 per cent of degraded ecosystems, thereby contributing to climate change mitigation and adaptation and to combating desertification.
The Bonn Challenge (Bonn Challenge, 2017)	Restore 150 million ha of deforested and degraded lands by 2020 and 350 million hectares by 2030. It is estimated that achieving the 350 million hectare goal will generate about USD170 billion per year in net benefits from watershed protection, improved crop yields and forest products, and could sequester up to 1.7 gigatonnes of carbon dioxide equivalent annually
The Initiative 20x20 (Initiative 20x20, 2017)	Restore 20 million ha degraded land in Latin America and the Caribbean by 2020
The African Forest Landscape Restoration Initiative (AFR100, 2017)	Restore 100 million ha by 2030.
The 4 per 1000 initiative (4 per 1000, 2017).	A 4‰ annual growth rate of the global soil carbon stock
Land restoration commitments under Intended Nationally Determined Contributions (INDCs) under the United Nations Framework Convention on Climate Change (UNFCCC, 2015)	China, Brazil, Bolivia and Democratic Republic of Congo included INDC commitments to curb deforestation, which together will reduce global emissions by 2.5 percent
The Land Degradation Neutrality framework (LDN) (UNCCD/GM, 2016a)	Target of the United Nations Convention to Combat Desertification (UNCCD) to achieve a land degradation neutral world by 2030
The United Nations Sustainable Development Goals (SDGs) (UN, 2017)	More than 150 countries have pledged to mobilize efforts to achieve the SDGs, and which includes Goal 15 to protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss.

We extend a previously proposed decision analysis framework for improving planning and performance measurement in development (Luedeling & Shepherd, 2016; Shepherd et al., 2015a), which we refer to as Stochastic Impact Evaluation (SIE), and apply it to land restoration. After a brief overview of SIE, we use synthetic cases to illustrate how SIE could be applied to improve land restoration planning and performance management at (i) national or project level, and (ii) at the level of a global investor. We then evaluate the LDN-TSP framework against decision analysis principles and suggest how SIE could be used to improve planning and performance management. Finally, we lay out needs for capacity and tools development for the wider adoption and application of decision analysis principles as an intervention in its own right to improve development performance.

2 Stochastic Impact Evaluation

2.1 Decision quality and analysis

SIE focuses on improving the coherence of decision making considering multiple goals and uncertainties when designing and implementing development interventions. The approach is based on the principles of decision quality and decision analysis (Clemen, 1996; Howard & Abbas, 2016; Raiffa, 1968) and can be applied at any scale. As the world is uncertain, a decision cannot be judged on the basis of eventual outcomes, but only on the coherence of the thinking used in the decision making. We argue that performance management should be focused on improving *decision quality*.

Decision quality can broadly be equated with coherent thinking (Baron, 2007), which can be defined in terms of a search-inference framework, with the following elements:

- Goals – the set of outcomes desired, which also form the criteria for evaluating options.
- Options or possibilities – which make up the choices being evaluated and may be designed using both internal and external sources of information.
- Evidence – any belief or potential belief that helps you determine the degree to which an option achieves some goal.
- Inference – the process of selecting an option based on the goals and evidence.

Decision quality is hampered by many types of human biases (Baron, 2007; Tversky and Kahneman, 1997). For example, we tend to be too narrow when searching for goals, options, and evidence, and to favour our own ideas when making inferences (Baron, 2007). Decision makers often think they are making good decisions based on experience and intuition, but there is overwhelming evidence that human decision making is "predictably irrational" (Ariely, 2009). Even simple quantitative decision models have been shown to consistently outperform intuitive decision making (Hubbard, 2014; Meehl, 1986). The goal of decision analysis is to move stakeholder decision-making further towards norms for coherent decision making. More specifically, the objective of SIE is to help make better decisions by gaining insights into what actions could most increase multiple benefits given stakeholder preferences, while minimizing costs and risks, and to do that on a continuous basis through the intervention planning and implementation process.

2.2 SIE steps

The basic steps (Figure 1) in SIE are inspired by Applied Information Economics (Hubbard, 2014). They have been outlined in Shepherd et al. (2015a) and Luedeling & Shepherd (2016) and are augmented here with further description in relation to performance monitoring. Key features of SIE associated with each step are given in Table 2. We have applied the framework to several decisions in agriculture and natural resources management (Favretto et al., 2017; Lanzanova et al., 2019; Luedeling et al., 2015; Rosenstock et al., 2014; Wafula et al., 2018; Whitney et al., 2018; Yet et al., 2016).

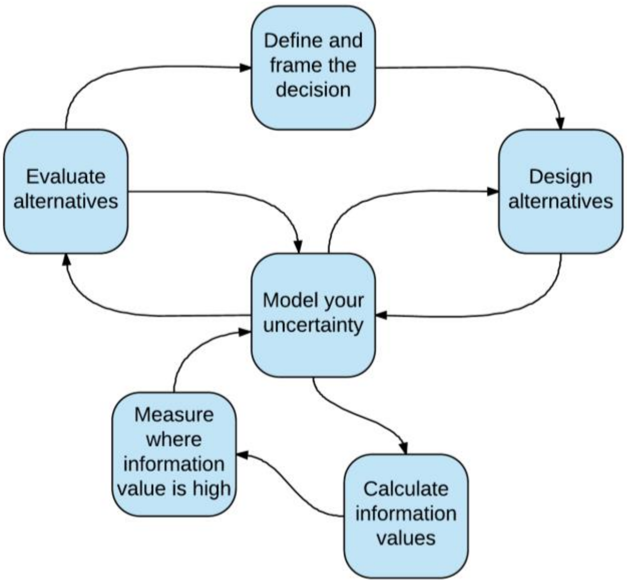


Figure 1. Technical diagram of the decision analysis process, which is implemented with participation of key stakeholders and experts to improve the design of policy or landscape management interventions and monitor their impact. The main loop in the top half of the diagram evaluates alternatives in relation to the decision goals (starting with the step 'Define and frame the decision'), whereas the lower loop uses value of information analysis to determine what should be measured to clarify the decision. There are iterative feedback loops throughout the process.

The value of information is a central concept in our framework. It is the amount that a rational decision-maker would be willing to pay for knowledge on a particular variable before making a decision — the value of clairvoyance (Howard and Abbas, 2016), expressed as the expected value of perfect information (Raiffa & Schlaifer, 1961). We use the value of information to guide decisions on the level of complexity to be considered in a decision model and the need for further measurement to clarify decision alternatives. From applying probabilistic decision modelling to over 80 diverse problems, Hubbard (2014) observed that only a few variables typically had high information value in any given decision, and interestingly they were rarely variables receiving current measurement effort. Value of information analysis guards against the danger that monitoring programs, enabled by technological advances, aim to collect more data across many indicators with ever higher frequency and spatial resolution on the assumption that more data will improve decision making (SDSN, 2015).

We propose that SIE can help strengthen monitoring and impact evaluation. A decision model of intervention alternatives is essentially a model of the impact pathway of the intervention with uncertainties quantified. This provides a Bayesian learning framework that can be used to compare actual performance with modelled performance, and which can be updated with new information as the implementation proceeds. The variables that have high information value, and are therefore important to monitor, will vary according to the specific decision problem, the current state of uncertainty, and the local conditions. They may change with time as the intervention is implemented, and new uncertainties and decisions emerge, providing a basis for adaptive monitoring and management (Williams & Brown, 2014), with each model update providing the next set of measurement priorities. If a variable is found to be off-course early in the implementation, then there is time for corrective action to be taken.

We further propose that SIE could provide an alternative or supplement to the use of study designs where these are too difficult, too expensive or unethical to implement, typically the more so the larger the scale of the intervention. If actual outcomes along the model's impact pathway match with the model predictions, then this provides cumulative evidence for the intervention impact. On the other hand, indications of drift can provide opportunity for re-evaluation and pivoting. SIE shifts the emphasis away from monitoring against perverse targets and long-term outcome indicators. Instead, the emphasis is on learning how to improve decision making based on continuous comparison of actual versus modelled behaviour.

Table 2. Key steps and features of Stochastic Impact Evaluation

Step	Features
Define and frame the decision	• Defines decision makers and stakeholders • Participatory, iterative definition of the decision • Considers multiple goals of stakeholders • Quantifies stakeholder preferences (e.g. time value of money, risk aversion)
Design alternatives	• Wide search for alternatives • Alternatives specified in detail (costs, benefits, risks)
Model your uncertainty	• Modelling starts by constructing an influence diagram that captures all the important components and their relationships, but not in considerable detail • All important factors represented regardless of measurement difficulty - if a variable is important a way is found to quantify it • All variables represented as probability distributions • Expert knowledge and local knowledge used in model specification and as sources of data • Experts trained and calibrated in probability estimation • All outcome variables are usually monetized • Models are implemented using Monte Carlo simulation (e.g. Luedeling et al., 2015) or Bayesian Networks (e.g. Fenton & Neil, 2018).
Calculate information values	• Value of information analysis used iteratively to determine: • Level of model complexity (model decomposition) • Need for additional information or measurements • Justifiable cost of further measurement • High value variables for monitoring during implementation
Measure where information value is high	• Lowest cost information sources used first to narrow uncertainty (in order of: literature, local or expert knowledge, survey, experiment) • Measurement sample sizes only sufficient to narrow uncertainty to clarify the decision
Evaluate alternatives	• Distribution of net present values used to evaluate alternatives • Trade-offs among goals are quantified • The differential costs, benefits and risks among different stakeholders are quantified • Knowledge of main factors driving negative outcomes is used to improve design of alternatives • Continuous learning achieved through comparison of actual performance versus predicted performance and model updating • Impact evaluation possible through degree of alignment of actual performance versus projected impact pathway

3 How to apply SIE to land restoration decisions

In this section, we provide two idealised examples of how decision analysis principles and SIE could be applied to guide land restoration initiatives. In the Supporting Material, we also provide examples of the application of SIE and decision analysis more broadly in natural resources management.

3.1 Project and national level planning

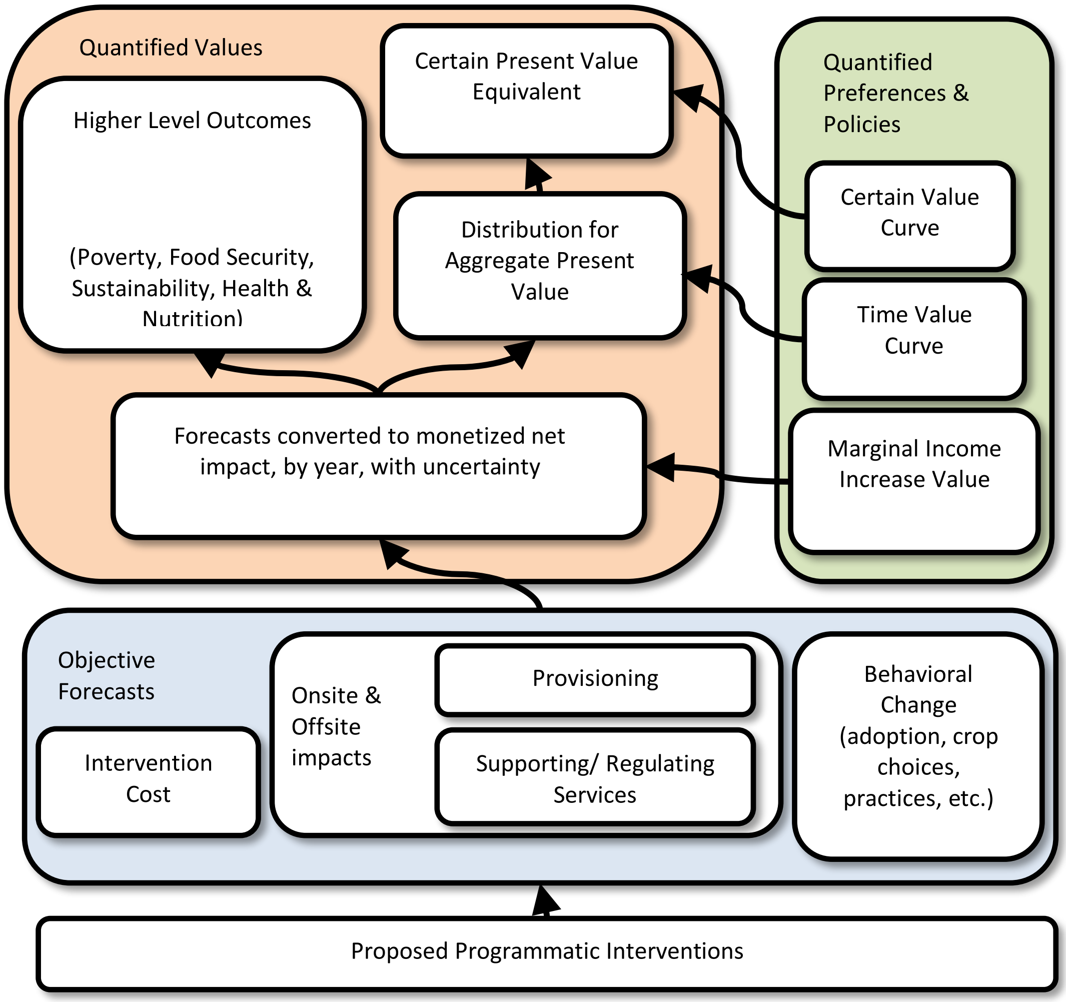
Local government authorities may be designing an integrated watershed management project (Table 3). They may choose to adapt a generic conceptual model for evaluating land management interventions (Figure 2) to the specific purposes of their planned intervention. This risk return model can be run over a chosen time period to quantify the distribution of net present values associated with various outcomes, adjusted for stakeholder preferences, such as the time value of money and risk preferences (Figure 2). The model makes transparent the stakeholder preferences and the trade-offs. For example, there will typically be trade-offs between risk and return, near and long-term benefits, production and ecosystem service benefits, and benefits among different stakeholder groups. As a result, the decision stakeholders gain clear insights into the implications of potential interventions, enabling coherent, informed and transparent decision making.

The uncertainty of on-site and off-site impacts of the intervention are specified, as well as behavioural factors like the adoption rate of a new practice or how incentives change behaviour. Utility curves are used to make preferences explicit. They specify what risks are acceptable, how to value long-term effects, the value of equitable improvements in income, and the relative value of a near-term certain impact versus a long-term uncertain impact. This allows various interventions to be evaluated against the same standards of risk aversion and other preferences. Ultimately, the effects of an intervention and the quantified preferences are combined into a single monetized value so that interventions of different types and sizes can be compared. Each intervention creates a set of estimated impacts over a period of time. The timing and uncertainty of these impacts are adjusted so that they can be rolled into a single number. The model can also be used to assess likely impacts on individual higher-level outcomes such as poverty, food security and sustainability.

This analysis approach has the advantage of including variables that are not often considered when planning land management projects. Some examples include factors affecting the risk of project implementation failure or dis-adoption of the proposed interventions (e.g., Figure 3). The process of identifying and quantifying such risks can lead to pre-emptive modifications at the project design stage. If certain variables have residual information value, they should be closely monitored during implementation.

Table 3. Outline of a decision analysis of whether or not to proceed with a land restoration initiative

Decision	• **Whether or not to proceed with an investment in an integrated watershed management project – is it a wise investment?**
Decision maker	• An actor from the government or aid community whose preferences on outcomes are those of a benevolent stakeholder.
Decision context	• A government is designing an integrated watershed management project in one of its key river basins. The proposed project considers a variety of interventions including changes in soil management, water resource management, integration of trees, mixed livestock, and grazing systems.
Decision alternatives	• Implementing the project versus business as usual
Stratification	• The River basin is split into three zones - humid, semi-arid, and arid. These zones have different characteristics and capacities in terms of agricultural yields and livestock density. The differential costs and benefits of upstream versus downstream stakeholders is also of interest. Estimates for the costs and benefits associated with each zone are different, and these differences are reflected throughout the model.
Time frame	• 20 years with annual time step
Costs	• Initial per area input costs of the interventions and period of allocation • Ongoing input costs of interventions per unit area and over time
On-site benefits	• Production-related benefits of each intervention per unit area • Reduced risks of crop failure due to improved soil quality
Off-site benefits	• Increase in freshwater availability due to interventions • Reduced damage from stream run-off and floods • Reduced costs of water body eutrophication • Reduced greenhouse gas emissions due to interventions • Reduced loss of electricity generation due to reduced silting of dams • Other ecosystem service benefits • Reduced rural to urban migration
Risks	• Likelihood of project cancellation • Likelihood of abandonment or individual cancellation
Behaviours	• Adoption rates: occurrence and rate of innovation and imitation, time to peak adoption • Variables likely to affect rates of adoption
Preferences	• Environmental discount rate to capture both long-term concerns and large short-term discount rates. • Income distribution utility curve, which allows the stakeholder to specify preference for benefits accruing to recipients at different income levels.
Analysis	• Distribution of the net present value • Disaggregated costs and benefits for populations of each zone and socioeconomic sub-populations where relevant. • Insights from trade-offs among production and environmental benefits, stakeholder groups, near and long-term returns • Identification of improvements to project design to maximise benefits and reduce costs and risks • Value of information analysis to identify further measurements needed to clarify choices and to prioritise monitoring efforts
Action	• Implement the preferred alternative • Measure high value variables • Update or adjust the decision model with new evidence • Identify and analyse new critical decisions



• Certain Value Curve	A utility function that expresses a stakeholder's risk attitude. A risk averse stakeholder will assign greater value to receiving a given income at a low level of risk than a higher benefit with a higher level of risk.
• Time Value Curve	A utility function that expresses preference in terms of the value of money over time (discounting). A stakeholder with a high time preference places more value on a given sum of money in the present and the immediate future than in the long-term.
• Marginal Income Increase	A utility function that assigns more weight to a given increase in income for people that are below the poverty line than if they are above the poverty line.
• Distribution for Aggregate Present Value	Income adjusted using the Time Value Curve
• Certain Present Value Equivalent	Income further adjusted using the Certain Value Curve

Figure 2. Conceptual decision model for evaluating land management interventions. Objective forecasts are made of the impacts of proposed interventions (blue box), which are converted into monetized outcomes and aggregated (orange box), modified by quantified stakeholder preferences (green box).

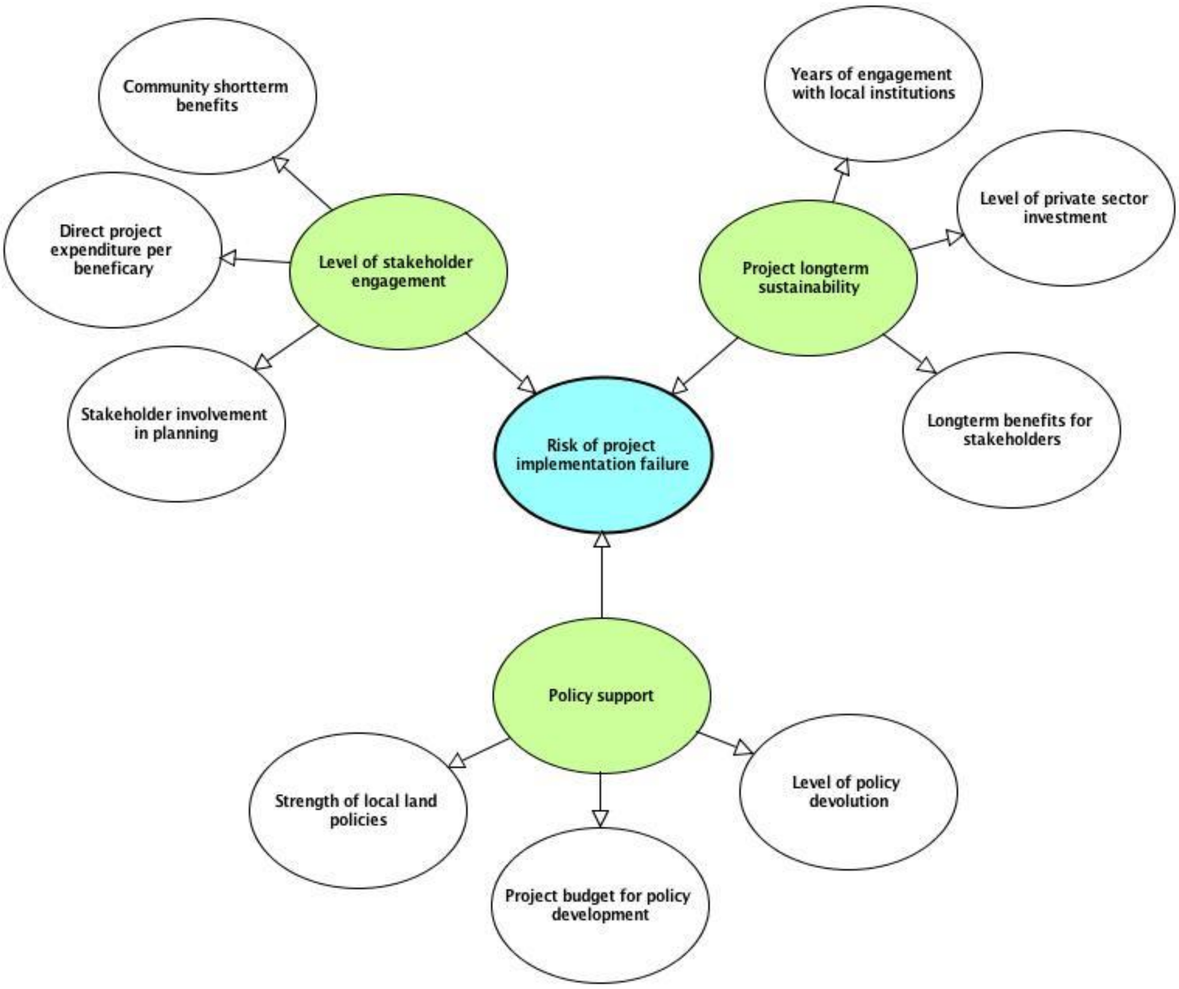


Figure 3. Example of three causal factors affecting risk of project implementation failure (extracted and modified from Sayer et al. (2015)) and possible indicator variables (unshaded), represented as a Bayesian Network. The risk factors are not directly measurable and are inferred from the indicator nodes. The relative weighting of the indicator nodes is determined by the level of uncertainty ascribed in their relationship with the associated risk factor (Fenton & Neil, 2018).

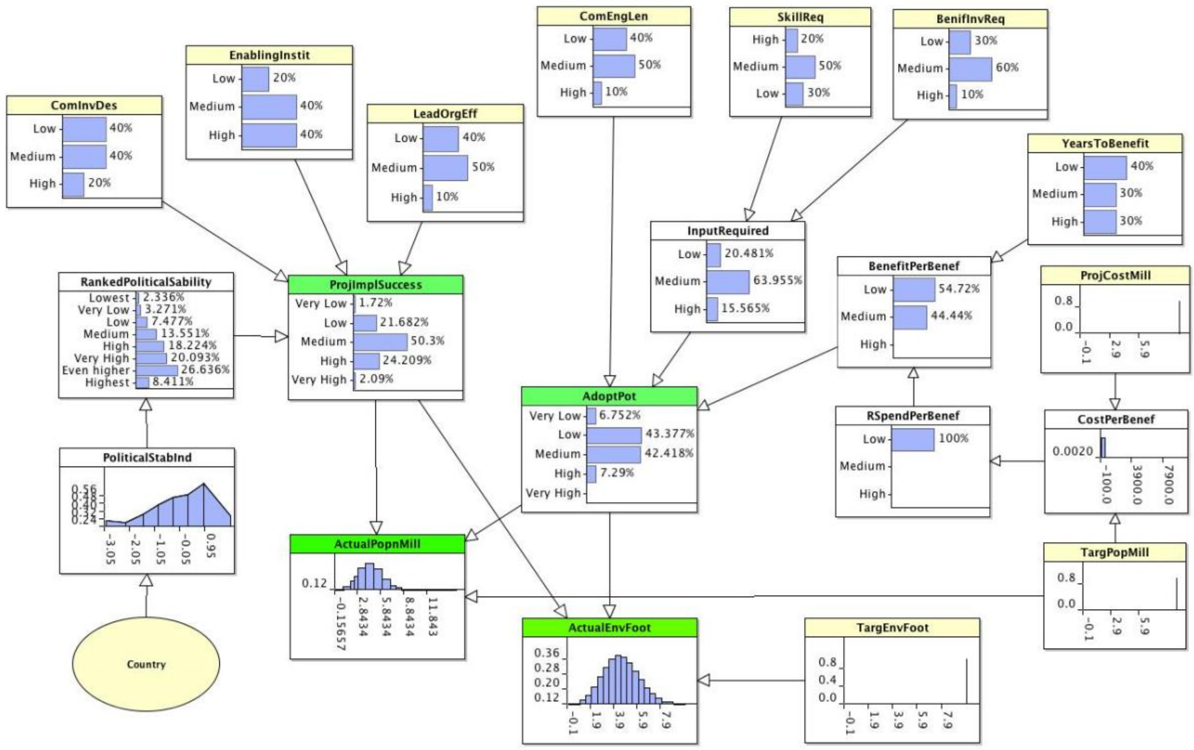
The project level framework described above could easily be extended to planning of national land restoration strategies. A typical decision is how to allocate resources among land restoration interventions to generate the greatest return on investment considering multiple development and environment outcomes. There will often be a number of possible preventive and restorative strategies with trade-offs and synergies among them. A strategy table may be helpful to examine whether different intervention options could be combined and to reduce complexity in terms of the number of options considered (Howard & Abbas, 2016)). A portfolio approach could also be used to bundle interventions or projects (Keisler, 2011).

3.2 A global investment decision

An example of another category of decision is global level investment prioritisation. For example, the UNCCD Global Mechanism, which hosts the LDN Fund, supports projects that not only deliver land restoration, but also provide environmental, social and financial returns (Global Mechanism, 2016). This resource allocation challenge could be framed as a concrete decision and candidate investments could be evaluated with a decision model (Figure 4).

Figure 3 shows a Bayesian Network model for prioritising project proposals for approval. This model is parameterised based on information that is commonly available in a project proposal document (Shepherd, 2019). For this decision problem, the modelling of benefits is quite coarse, and greater attention is given to factors affecting risks of project implementation failure and adoption potential. For example, published values of a political stability index of countries are used as one indicator of project implementation failure (Figure 4). Bayesian Networks allow the relative weight of different indicators and the uncertainty in those relationships to be easily modelled (Fenton & Neil, 2018). One advantage of Bayesian Networks is that partial evidence can be entered if some data is missing, and posterior probabilities can still be obtained. A more detailed example of a Bayesian Network for project cost, benefit and risk analysis in an agricultural development context is given by Yet et al. (2016). In this case, the investor may want to fund a balanced portfolio of projects that combines a few projects with a high potential for benefits but higher risk of implementation failure or higher environmental risk, with a large number of low-risk projects with more modest projected benefits.

Simple causal, probabilistic models can go a long way to identifying, quantifying and managing Black Swan (highly unpredictable) events (Taleb, 2007), for example by representing the connected processes that prevent, control or mitigate the rare catastrophic event. Bayesian Networks can also be used to establish whether one system design is more resilient than others when faced with multiple threats (Fenton & Neil, 2018).



ProjImplSuccess	Project implementation success	**BenefitPerBenef**	Benefit per beneficiary
CommInvDes	Degree of community involvement in design	**YearsToBenefit**	Number of years until first benefits
EnablingInstit	Involvement of an enabling institution	**RSpendPerBenef**	Project cost per beneficiary ranked
LeadOrgEff	Efficacy of the lead organization	**CostPerBenf**	Project cost per beneficiary
RankedPolitical Stability	Political stability index as ranked node	**BenefInvReq**	Beneficiary investment required
Political StabilityInd	Political stability index	**ProjCost$Mill**	Project investment per beneficiary
Country	Country	**TargPopMill**	Target population (millions)
AdopPot	Adoption potential	**TargEnvFoot**	Target environmental footprint (1000 sq km)
CommEngLen	Length of community engagement	**ActualEnvFoot**	Actual environmental footprint
InputRequired	Level of inputs required from beneficiary	**ActualPopnMill**	Actual population
SkillReq	Skill levels required for intervention		

Figure 4. A Bayesian Network decision model for prioritising land intervention projects based on potential livelihood and environmental impacts and probability of success. Each node or variable is represented as a probability distribution. Yellow nodes are input variables. Green nodes are output nodes of interest for project evaluation. Complete or partial evidence can be entered at any node and probabilities updated. Uncertainty in the relationships among variables (not shown) is also represented. Another summary module (not shown) calculates livelihood and environmental benefits and return on investment. Source: Shepherd (2015b).

4 Land Degradation Neutrality Framework

In this section we evaluate the UNCCD LDN-TSP approach against decision analysis principles (Table 4) and suggest how SIE could be used to improve decision quality.

Table 4. Summary of limitations of UNCCD's Land Degradation Neutrality Target Setting Programme in relation to steps in Stochastic Impact Evaluation

Principle	Limitation of LDN-TSP
Define and frame the decision	• LDN target and indicators are not connected to any specific decisions or learning objectives so that the value of information generated is questionable • Indicators represent a single goal set – achieving land degradation neutrality – ignoring a wider goal set related to SDGs
Design alternatives	• Range and type of land management options considered are constrained by the single goal of land degradation neutrality, rather than considering options for achieving multiple goals • Alternatives are not evaluated in terms of costs, benefits, risks and stakeholder preferences, leading to a lack of specificity and precluding iterative improvements to their design
Model your uncertainty	• There is no projection (impact model) of how the interventions will impact on the overall goals, or quantification of the current state of uncertainty in those projections • Only three biophysical indicators are considered, as opposed to holistic modelling of all the important factors, including risks, along an impact pathway that could affect outcomes • There is no framework for making use of expert knowledge and available data
Measure where information value is high	• Because measurements are not linked to decisions and uncertainty is ignored, there is no basis for knowing the value of information generated or how much spending is justified to collect it • Uncertainty in indicator measurements is ignored, which precludes assessment of their value in improving decisions • Separating real trends from noise in LDN indicators remains a significant challenge, given the multiple sources of errors, e.g. in measurement of soil organic carbon stocks • Detection of change in LDN indicators will be too late to guide action – there is need for measures that provide earlier indication of change • LDN indicators are insufficient in scope to capture important land degradation processes and can lead to anomalies.
Evaluate alternatives	• Evaluation of progress against LDN targets are likely to lead to gaming, block learning and result in perverse outcomes • Trade-offs are assessed only between areas of land that are degrading or improving, omitting analysis of trade-offs among a wider set of development goals and stakeholder preferences • LDN indicators are unable to inform on progress along an impact pathway and accumulate evidence for impact • Factors that are most likely to impede implementation success are ignored

4.1 Define and frame the decision

LDN is defined as "a state whereby the amount and quality of land resources necessary to support ecosystem functions and services and enhance food security remain stable or increase within specified temporal and spatial scales and ecosystems" (Orr et al., 2017). The monitoring of LDN is based on evaluating the significant changes (positive and negative) in three global sub-indicators (and associated metrics) which are intended to serve as proxies of most ecosystem services flowing from land-based natural capital: land cover (land cover change), land productivity (net primary productivity) and carbon stocks (soil organic carbon stocks) (Orr et al., 2017).

Decision quality is compromised by the focus of LDN on the single goal to measure the degree of achievement of the neutrality target, in terms of balancing degraded or improved land areas from the baseline (2015) to 2030. It is widely recognized that (i) conservation cannot be dissociated from socio-economic development (Frost et al., 2006; Milder et al., 2012, 2014) and (ii) sustainable agricultural intensification must integrate the dual and interdependent goals of meeting rising human needs while contributing to resilience and sustainability of landscapes and the biosphere (Rockström et al., 2017). The underlying LDN objectives actually elude to a much broader set of desired outcomes, including: sustainable delivery of ecosystem services; improved productivity; increased resilience; and synergies with other social, economic and environmental objectives, such as responsible and inclusive governance of land (Cowie et al., 2018; Orr et al., 2017; UNCCD/SPI, 2016). However, these goals are not explicitly carried through into the LDN measurement and evaluation framework. Recognizing this problem, Easdale (2016) proposed a concept of zero net livelihood degradation, to extend LDN to include livelihood outcomes rather than land practices or soil management alone. In such a scheme, improved land management could contribute to achieving a number of other SDGs (Akhtar-Schuster et al., 2017; Reed et al., 2016). Dallimer and Stinger (2019) also highlighted important risks of decision approaches that focus only on biophysical outcomes linked to the three global indicators and proposed use of triage principles, similar to those used under limited resourcing in biodiversity conservation decision making.

Even in the hypothetical case that perfect data were obtained on LDN or its sub-indicators for all countries, it is not clear who would use that data, or for which decisions it would be applied. It is not clear that the data would help the Global Mechanism in planning to decide on resource allocations to countries based on their performance against the LDN targets. If such decision-oriented purposes for data collection were specified, decision analysis can provide a realistic and relatively easy, more transparent and more cost-effective way of making them (e.g., Figure. 4).

Large monitoring initiatives, especially passive, mandated monitoring schemes, in which data are gathered as a stipulated requirement of government legislation or a political directive, have largely been ineffective in influencing agricultural policy and management (Lindenmayer & Likens, 2011; Shepherd et al., 2013). In the absence of well-articulated and scientifically tractable questions, measurement provides little understanding of causal factors underlying performance (Lindenmayer & Likens, 2011). For these reasons, Nichols and Williams (2006), working in ecological conservation, concluded that surveillance monitoring is inefficient, and that, instead, monitoring efforts should be targeted on information crucial to answering specific questions about conservation management.

Measuring trends against an arbitrarily set target offers little insight, instead we recommend that the LDN-TSP seek to help countries frame key questions and critical decisions related to improved land management.

4.2 Design alternatives

The LDN emphasis on the single goal of balancing land degradation versus improvement, or other singular targets, may restrict the range and type of land management options considered, compared with considering a broader range of goals. The framework may also drive the focus towards designing interventions to restore already badly degraded land, whereas in some cases the biggest gains may in fact rest with preventing further degradation on all land (Shepherd et al., 2015b) or in reversing degradation over small areas that have costly off-site impacts (e.g. siltation of dams). Adoption of SIE would also help countries be more specific in specifying alternatives in terms of costs, benefits, risks and stakeholder preferences, and encourage iterative improvements to intervention designs.

4.3 Model your uncertainty

The results-based target-setting approach of LDN-TSP fails to identify key uncertainties in the impact pathway of proposed interventions. As a result, factors that are likely to be critical to implementation will be missed. Risks to project implementation often determine the success or failure of interventions but are rarely identified for monitoring. For example, Sayer et al. (2017) concluded from a recent survey of over 1,500 published articles that there is a lack of evidence that landscape approaches are effective in delivering real benefits. The World Bank (2011) evaluated 86 agricultural projects and found that 41% had “non-positive outcomes”. LDN-TSP provides little specific guidance beyond that “interpretation of the monitoring result should consider quantitative and qualitative data from national and subnational indicators” (Orr et al., 2017, p. 109). SIE would help countries identify *ex ante* and *ex post* critical variables affecting success.

4.4 Measure where information value is high

There is a risk that UNCCD Country Parties could invest large resources in attempting to monitor the LDN sub-indicators but derive little value from them for informing the decisions they really need to take. There has been a history of measurement challenges with respect to land degradation (Caspari et al., 2015). Even when the problem is reduced to a few sub-indicators, there are enormous measurement challenges for monitoring changes or trends, including the propagation of errors from different sources, for example when measuring soil organic carbon stocks (e.g., Goidts et al., 2009; Lorenz et al., 2019; Schrumpf et al., 2011). Separating real trends and changes from the noise remains a significant challenge, given the multiple sources of errors, including in schemes for estimating soil organic carbon from proxies such as land cover and management (e.g., Eve et al., 2002).

Long time-series are required to untangle increases in land productivity variation due to management from rainfall variability (Le et al., 2017), and there is a risk of reacting to false trends. For example, changes in soil organic carbon are difficult to detect over intervals of less than 3 to 10 years. By the time trends will have been reliably detected, any decision opportunity to influence them would most likely have already been missed. Lessons could be learned from the public health sector where much of the surveillance on chronic health problems is centred on behavioural risk factors, providing a much earlier indication of the likely direction of outcomes (Shepherd et al., 2015a). Land cover change may provide some indication of early changes in soil organic carbon, but it is often the *management* of land that determines levels of organic inputs to soils. Others (Sayer et al., 2017) have emphasized the need for short-term metrics in addition to long-term impact metrics of outcomes and their highly situation-specific nature that must be derived from a credible theory of change. There is a risk that monitoring of land degradation can become a form of inadvertent displacement behavior, whereby the emphasis is placed on a perceived need for obtaining baselines, as opposed to focusing on reducing decision uncertainty (Nichols & Williams, 2006).

While there have been advances in the use of remote sensing to provide globally consistent measures of land productivity (Le et al., 2017), which are recommended for Tier 1 baselines in UNCCD/GM (2016a), there are significant challenges in translating observed trends into reality on the ground. For example, a review of LDN baselines by Aynekulu et al. (2017), found that while bush encroachment is considered the most severe form of land degradation in Namibia, it would be assessed as land improvement on all three LDN indicators. This is because bush encroached lands usually show positive trends in both net primary productivity and soil organic carbon, and also constitute a land cover change from grassland/shrubland to bushland/forest, which is considered a positive change from the LDN perspective. The review considered that there is a need for additional indicators and higher resolution (primary) data in order to develop baselines at sub-national level, requiring additional field data collection depending on the characteristics of degradation occurring locally. SIE would help countries integrate existing data and local expert knowledge on important land degradation processes, controls, triggers and mitigants, and identify any further information needs required to clarify which actions to take forward.

4.5 Evaluate alternatives

Land management outcomes inevitably involve trade-offs: among goals of different stakeholder groups; between short term and long term costs and benefits; and between risks and returns. Failure to recognize trade-offs has been identified as one of the prime reasons for failure of integrated landscape management projects (e.g. Reed et al., 2016).

In its current form, the LDN-TSP measurement framework would only assess trade-offs between areas of land that are degrading or improving. This also makes it acceptable to trade off land degradation in one area with land restoration in another (on an area or magnitude basis), without regard to the impacts that land degradation might have on livelihoods or other environmental variables. Under LDN-TSP sub-national targets do not necessarily seek to achieve neutrality but can help to avoid, reduce and reverse degradation in particular systems but are reduced to singular (sub)national targets suggested by LDN-TSP include “LDN is achieved in the Western province of country X by 2030, compared to the 2015 baseline (no net loss)” and “Rehabilitate X million hectares of degraded and abandoned land for crop production by 2030" (UNCCD/GM, 2016b). This target-focused approach provides no basis for gauging how a given level of investment in one area would compare with the same investment in another area. Use of SIE would help quantify the various trade-offs in monetary terms – the same units that investments are to be made in.

4.6 Summary of limitations of LDN

LDN-TSP's target setting approach runs the risk that countries invest in demonstrating their progress against arbitrary targets as opposed to coherent decision making and learning on which interventions best serve multiple development and environmental goals. The rationale for having globally uniform indicators for LDN is weak given the lack of clarity on how these will be used in decision-making. Furthermore, many indicators will be difficult to measure and interpret consistently, and do not adequately represent important dimensions of land degradation. We maintain that a decision analysis approach would better serve countries' needs in planning and evaluating land restoration initiatives. Countries' reporting on progress on implementation of the UNCCD could be based on documenting steps taken to improve decision quality in land management planning and performance measurement, as opposed to documenting progress against LDN targets or measured changes in the LDN indicators.

5 Developing capacity and tools for decision analysis

Decision analysis, although increasingly used in many fields, has only marginally penetrated the development sector, and very few stakeholders in land use planning and management are familiar with the approach and methods. Research by Matheson and Matheson (2007) concluded that cultural and organizational elements are the key determinants of adoption success or failure of decision analysis. In the authors' experience, common barriers to adoption of decision analysis methods are: (i) a lack of knowledge about biases in decision making, the norms of coherent decision making and how decision analysis can help; (ii) lack of knowledge about the importance of considering uncertainty and the purpose of measurement; (iii) discomfort with quantitative methods; (iv) suspicion over the value of expert knowledge in data limited situations; and (v) the time demands on experts.

We propose a combination of actions to help overcome barriers to decision analysis. First, there is a need for sensitizing development decision makers and organizations on decision quality and decision analysis. Such sensitisation can fundamentally change an organisation's approach to decision-making. For example, GM Motors and Chevron have institutionalised decision quality throughout their organizations (Neal & Spetzler, 2015; Spetzler, 2011). At Chevron, over a 20-year period, critical decision makers down to the level of project and functional managers, approximately 6,000 people (or 10% of Chevron's workforce), have been trained and certified in decision quality, and every large capital project requires decision analysis for approval. Since the effort that goes into making important decisions is usually relatively small when compared to the effort and expense of executing the decisions, Chevron regularly shows thousand-fold returns on the dollars invested in decision quality (Spetzler, 2011).

Second, development organizations need to recruit and embed decision analysts in their planning departments. Analysts can help steer the decision analysis process, interact with experts and stakeholders, train stakeholders in probability estimation, and conduct the mechanics of decision modelling.

Third, there is a need for education and training of land and environmental management experts as decision analysts. Development of university curricula, training materials and examples will help this process.

Fourth, the development of user-friendly on-line tools to help conduct participatory decision modelling will accelerate uptake. This includes the development of probability management systems (Savage, 2012), which are databases of probability distributions for commonly re-occurring variables that can be re-used or modified in decision modelling. An example of such common distributions is information on the costs of alternative land restoration interventions.

Fifth, early adoption may be facilitated by the development of guidelines, simple rules and examples on decision quality that can be applied with limited time resources. These could include, for example, to: "turn objectives into specific decisions", "clarify the goals of all principal stakeholders", "scope widely for alternatives", "identify causal associations among outcomes, preventive actions and mitigation actions", and "focus on reducing uncertainties that are likely to have a large impact on outcomes". Getting organizations to start thinking about decision quality could reduce barriers to the use of quantitative methods.

Lastly, adoption would be aided by evidence from comparative studies that test the value of decision analysis approaches on populations of decisions, based on their final outcomes. Ideally, a critical measure is whether a set of project approval decisions informed by SIE measurably outperformed a set of project approval decisions made without SIE. This requires that the decisions made without the benefit of SIE must have measured outcomes, even if intermediate ones. Unfortunately, projects that do not use decision analysis methods are less likely to quantify objectives at the proposal stage and measure success. Less rigorous, but still useful, would be (i) retrospective application of SIE to past projects that quantified outcomes, and (ii) documentation of changes in behaviour or decisions where SIE is used in new projects, and valuation of their likely impacts. For example, it is useful to document potential measurements and improvements to projects that would be unlikely to have been made without SIE.

Implementation of the above recommendations may be easier in developing than developed countries, as development needs are pressing, resources for development are limited, and there is more flexibility for trying new approaches, supported by a large, increasingly highly educated, young population.

6 Conclusions

We advocate for the use of a decision analysis framework for planning and performance management of complex development interventions, such as land restoration, as an alternative to results-focused approaches. The process shifts the focus from attempting to demonstrate results against targets, to improving the quality of decision making and adaptive learning towards desired outcomes.

Encouraging countries to set targets for achieving the LDN's narrow goal of balancing geographical areas of land degradation and improvement, assessed using a restricted set of indicators, is likely to result in perverse outcomes. LDN is also difficult to implement in practice due to a number of definitional and measurement problems. Locally important variables that will determine the success or failure of land management interventions may be missed, leaving little reliable learning on determining factors. Even if the selected LDN indicators are measured, there is no indication that they will have any information value, since the decisions they will inform have not been clearly identified. We recommend that the UNCCD and its country parties encourage uptake of decision analysis frameworks, such as SIE, to help improve decision quality on land restoration and achievement of the SDGs. Performance assessment should be focused on improvements in decision quality, not satisfying targets. Decision analysis cannot overcome distortions due to disparities in power or entrenched interests, but it can make decision making processes more participatory and more transparent.

We have suggested actions to increase the adoption of decision analysis in development. Dissemination of qualitative guides to improving decision quality, could reap large early benefits, as has been demonstrated in other sectors, and could facilitate a transition to quantitative methods. Developing capacity in decision analysis could be the single most effective development investment toward achieving land restoration and the SDGs.

References

4 per 1000 (2017). Understand the “4 per 1000” initiative. http://4p1000.org/understand

AFR100 (2017). *African Forest Landscape Restoration Initiative*. http://www.wri.org/our-work/project/AFR100/about-afr100.

Akhtar-Schuster M., Stringer L. C., Erlewein A., Metternicht G., Minelli S., Safriel U., & Sommer S. (2017). Unpacking the concept of Land Degradation Neutrality and addressing its operation through the Rio Conventions. *Journal of Environmental Management, 195*, 4-15. https://doi.org/10.1016/j.jenvman.2016.09.044

Ariely, D. (2009). *Predictably irrational: The Hidden forces that shape our decisions*. Harper: New York.

Aynekulu E., Lohbeck M., Nijbroek R., Ordóñez J. C., Turner K. G., Vågen T., & Winowiecki L. (2017). *Review of methodologies for Land Degradation Neutrality baselines: sub-national case studies from Costa Rica and Namibia.* CIAT Publication No. 441. International Center for Tropical Agriculture (CIAT) and World Agroforestry Centre (ICRAF): Nairobi, Kenya. 58 p. Retrieved from: http://hdl.handle.net/10568/80563

Baron, J. (2007). *Thinking and deciding* (4th ed.). Cambridge University Press: New York.

Bonn Challenge (2017). *The Bonn Challenge*. http://www.bonnchallenge.org

Caspari T., van Lynden G., & Bai Z. (2015). *Land Degradation Neutrality: An evaluation of methods*. ISRIC-World Soil Information: Wageningen, Netherlands. On behalf of the Federal Environment Agency, Germany), pp. 1e57. Report No. (UBA-FB) 002163/E. https://www.umweltbundesamt.de/sites/default/files/medien/378/publikationen/texte_62_2015_land_degradation_neutrality__0.pdf

CBD (2017). *Aichi biodiversity targets*. Convention on Biological Diversity. https://www.cbd.int/sp/targets/

Clemen, R. T. (1996). *Making hard decisions: An introduction to decision analysis.* Second edition. Duxbury Press, Wadsworth: Belmont, California, USA.

Convertino M., Foran C. M., Keisler J. M., Scarlett L., LoSchiavo A., Kiker G. A., & Linkov I. (2013). Enhanced adaptive management: integrating decision analysis, scenario analysis and environmental modeling for the Everglades. *Scientific Reports, 3*, 2922. https://doi.org/10.1038/srep02922

Cowie A. L., Orr B. J., Castillo Sanchez V. M., Chasek P., Crossman N. D. Erlewein A., Louwagie G., Maron M., Metternicht G. I., Minelli S., Tengberg A. E., Walter S., & Welton S. (2018). Land in balance: The scientific conceptual framework for Land Degradation Neutrality. *Environmental Science & Policy, 79*, 25-35. https://doi.org/10.1016/j.envsci.2017.10.011

Dallimer M., & Stringer L.C. (2019). Informing investments in land degradation neutrality efforts: A triage approach to decision making. *Environmental Science and Policy, 89,* 198-205. https://doi.org/10.1016/j.envsci.2018.08.004

ECOSOC (2017a). *Report of the Inter-agency and Expert Group on Sustainable Development Goal Indicators*. Statistical Commission of the United Nations Economic and Social Council. E/CN.3/2017/2.

ECOSOC (2017b). *Progress towards the Sustainable Development Goals: Report of the Secretary-General.* E/2017/66. https://unstats.un.org/sdgs/files/report/2017/secretary-general-sdg-report-2017--EN.pdf

Easdale M. H. (2016). Zero net livelihood degradation – the quest for a multidimensional protocol to combat desertification. *SOIL, 2*, 129–134. https://doi.org/10.5194/soil-2-129-2016

Eve M. D., Sperow M., Paustian K., & Follett R. F. (2002). National-scale estimation of changes in soil carbon stocks on agricultural lands. *Environmental Pollution, 116*, 431-438. https://doi.org/10.1016/s0269-7491(01)00220-2

Favretto N., Luedeling E., Stringer L. C., & Dougill A. J. (2017). Valuing ecosystem services in semi-arid rangelands through stochastic simulation. *Land Degradation and Development, 28*, 65–73. https://doi.org/10.1002/ldr.2590

Fenton N., & Neil M. (2018). *Risk assessment and decision analysis with Bayesian networks*. 2nd edition. CRC Press: Boca Raton. https://doi.org/10.1201/b21982

Frost P., Campbell B., Medina G., & Usongo L. (2006). Landscape-scale approaches for integrated natural resource management in tropical forest landscapes. *Ecology and Society, 11*, 30. https://doi.org/10.5751/es-01932-110230

Global Affairs Canada (2016). *Results-based management for international assistance programming at global affairs Canada: A how-to guide*. Global Affairs Canada. http://www.international.gc.ca/development-developpement/assets/pdfs/partners-partenaires/bt-oa/rbm-gar-guide-e.pdf

Global Mechanism (2016). *Scaling up Land Degradation Neutrality target setting. from lessons to actions: 14 pilot countries' experiences*. Global Mechanism (GM) of the United Nations Convention to combat Desertification (UNCCD). http://www.unccd.int/Lists/SiteDocumentLibrary/Publications/10_2016_ll_brochure_rgb_final.pdf

Goidts E., Van Wesemael B., & Crucifix M. (2009). Magnitude and sources of uncertainties in soil organic carbon (SOC) stock assessments at various scales. *European Journal of Soil Science, 60*, 723–739. https://doi.org/10.1111/j.1365-2389.2009.01157.x

Gregory R., Failing L., Harstone M., Long G., McDaniels T., & Ohlson D. (2012). *Structured decision making: A practical guide to environmental management choices*. Wiley-Blackwell. https://doi.org/10.1002/9781444398557

Hajkowicz S. (2009). The evolution of Australia's natural resource management programs: Towards improved targeting and evaluation of investments. *Land Use Policy, 26*, 471–478. https://doi.org/10.1016/j.landusepol.2008.06.004

Herrick J. E., Duniway M. C., Pyke D. A., Bestelmeyer B. T., Wills S. A., Brown J. R., Karl J. W., & Havstad K. M. (2012). A holistic strategy for adaptive land management. *Journal of Soil and Water Conservation, 67*, 105A-113A. https://doi.org/10.2489/jswc.67.4.105a

Holden E., Linnerud K., & Banister D. (2017). The Imperatives of sustainable development. *Sustainable Development*, *25*, 213–226. https://doi.org/10.1002/sd.1647

Holling C. S. (1978). *Adaptive environmental assessment and management.* John Wiley & Sons.

Howard R. A., & Abbas A. E. (2016). *Foundations of Decision Analysis*. Pearson.

Hubbard D. W. (2014). *How to measure anything. Finding the value of "intangibles" in business*. John Wiley. https://onlinelibrary.wiley.com/doi/book/10.1002/9781118983836

Initiative 20x20 (2017). *Initiative 20x20*. http://www.wri.org/our-work/project/initiative-20x20/restoration-commitments

Keisler J. (2011). Portfolio decision quality. In A., Salo, J. Keisler, & A. Morton (Eds), *Portfolio decision analysis: Improved methods for resource allocation* (pp 29-51). International Series in Operations Research & Management Science 162. Springer Science and Business Media. DOI 10.1007/978-1-4419-9943-6 2. https://doi.org/10.1007/978-1-4419-9943-6

Lanzanova D., Whitney C., Shepherd K., & Luedeling E. (2019). Improving development efficiency through decision analysis: reservoir protection in Burkina Faso. Environmental Modelling & Software 115:164-175. https://doi.org/10.1016/j.envsoft.2019.01.016

Le Q. B., Mirzabaev A., Nkonya E., & van Lynden G. W. J. (2017). The extent and cost of land degradation. In P.L.G. Vlek, A. Khamzina, and L. Tamene (Eds), *Land degradation and the sustainable development goals: Threats and potential remedies*. CIAT Publication No. 440. International Center for Tropical Agriculture (CIAT): Nairobi, Kenya. 67 p. http://hdl.handle.net/10568/81313.

Leeuwis, C., Klerkx, L., & Schut, M. (2018). Reforming the research policy and impact culture in the CGIAR: Integrating science and systemic capacity development. *Global Food Security, 16,* 17-21. https://doi.org/10.1016/j.gfs.2017.06.002

Lindenmayer D. B., & Likens G. E. (2011). Effective monitoring of agriculture. *Journal of Environmental Monitoring, 13,* 1559-1563. https://doi.org/10.1039/c0em00691b

Lorenz K., Lal R., & Ehlers K. (2019). Soil organic carbon stock as an indicator for monitoring land and soil degradation in relation to United Nations' Sustainable Development Goals. *Land Degradation & Development 2019*: 1-19. https://doi.org/10.1002/ldr.3270

Luedeling E., & Shepherd K.D. (2016). Decision-focused agricultural research. *The Solutions Journal, 7*, 46-54. https://www.thesolutionsjournal.com/article/decision-focused-agricultural-research/

Luedeling E., Oord A. L. Kiteme B., Ogalleh S, Malesu M., Shepherd K. D., & De Leeuw J. (2015). Fresh groundwater for Wajir – ex-ante assessment of uncertain benefits for multiple stakeholders in a water supply project in Northern Kenya. *Frontiers in Environmental Science, 3*, Article 16. https://doi.org/10.3389/fenvs.2015.00016

Lyons J. E., Runge M. C., Laskowski H. P., & Kendall W. L. (2008). Monitoring in the context of structured decision-making and adaptive management. *Journal of Wildlife Management, 72,* 1683–1692. https://doi.org/10.2193/2008-141

Matheson D., & Matheson J. E. (2007). From decision analysis to the decision organization. In W. Edwards, R. F. Miles Jr., and D. von Winterfeldt (Eds), *Advances in decision analysis: From foundations to applications.* Cambridge University Press, Cambridge, New York. https://doi.org/10.1017/cbo9780511611308

Meehl P. E. (1986). Causes and effects of my disturbing little book. *Journal of Personality Assessment, 50*, 370-375. https://doi.org/10.1207/s15327752jpa5003_6

Milder J. C., Buck L. E., Declerck F., & Scherr S. J. (2012). *Landscape approaches to achieving food production, natural resource conservation, and the Millennium Development Goals. Integrating ecology and poverty reduction*. Springer: New York, USA. https://doi.org/10.1007/978-1-4419-0633-5_5

Milder J. C., Hart A. K., Dobie P., Minai J., & Zaleski C. (2014). Integrated landscape initiatives for African agriculture, development, and conservation: A region-wide assessment. *World Development, 54*, 68–80. https://doi.org/10.1016/j.worlddev.2013.07.006

Minelli S., Erlewein A., & Castillo V. (2017). Land Degradation Neutrality and the UNCCD: From political vision to measurable targets. *International Yearbook of Soil Law and Policy 2016*, 85-104. Springer International Publishing. https://doi.org/10.1007/978-3-319-42508-5_9

Neal L., & Spetzler C. (2015). An organization-wide approach to good decision making. *Harvard Business Review, May 27*, 2015. https://hbr.org/2015/05/an-organization-wide-approach-to-good-decision-making.

Nichols J. D., & Williams B. K. (2006). Monitoring for conservation. *TRENDS in Ecology and Evolution, 21*, 668-673. https://doi.org/10.1016/j.tree.2006.08.007

Orr B. J., Cowie A. L., Castillo Sanchez V. M., Chasek P., Crossman N. D. Erlewein A., Louwagie G., Maron M., Metternicht G. I., Minelli S., Tengberg, A. E., Walter S., & Welton S. (2017). *Scientific conceptual framework for Land Degradation Neutrality. A report of the Science-Policy Interface*. UNCCD. Bonn: Germany. http://www2.unccd.int/sites/default/files/documents/LDN%20Scientific%20Conceptual%20Framework_FINAL.pdf.

Raiffa H. (1968). *Decision analysis: Introductory lectures on choices under uncertainty.* Addison-Wesley: Reading, Massachusetts, USA.

Raiffa H., & Schlaifer R. O. (1961). *Applied statistical decision theory*. Graduate School of Business Administration. Harvard University: Cambridge, MA, USA.

Reed R., Van Vianen J., Deakin E. L., Barlow J., & Sunderland T. (2016). Integrated landscape approaches to managing social and environmental issues in the tropics: Learning from the past to guide the future. *Global Change Biology,* 22, 2540–2554. https://doi.org/10.1111/gcb.13284

Rockström J., Williams J., Daily G., Noble A., Matthews N., Gordon L., Wetterstrand H., DeClerck F., Shah M., Steduto P., de Fraiture C., Hatibu N., Unver O., Bird J., Sibanda L., & Smith J. (2017). Sustainable intensification of agriculture for human prosperity and global sustainability. *Ambio, 46*, 4–17. https://doi.org/10.1007/s13280-016-0793-6

Rosenstock T. S., Mpanda M., Rioux J., Aynekulu E., Kimaro A. A., Neufeldt H., Shepherd K. D., & Luedeling, E. (2014). Targeting conservation agriculture in the context of livelihoods and landscapes. *Agriculture, Ecosystems and Environment, 187*, 47–51. https://doi.org/10.1016/j.agee.2013.11.011

Savage S. (2012). *The flaw of averages: Why we underestimate risk in the face of uncertainty*. Wiley.

Sayer F., Margules C., Boedhihartono A. K., Dale A., Sunderland T., Supriatna J., & Saryanthi R. (2015). Landscape approaches: What are the pre-conditions for success? *Sustainability Science, 10*, 345–355. DOI 10.1007/s11625-014-0281-5. https://doi.org/10.1007/s11625-014-0281-5

Sayer J. A., Margules C., Boedhihartono A. K., Sunderland T., Langston J. D., Reed J., Riggs R., Buck L. E., Campbell B. M., Kusters K., Elliott C., Minang P. A., Dale A., Purnomo H., Stevenson J. R., Gunarso P., & Purnomo A. (2017). Measuring the effectiveness of landscape approaches to conservation and development. *Sustainability Science, 12*, 465–476. https://doi.org/10.1007/s11625-016-0415-z

Schrumpf M., Schulze E. D., Kaiser K., & Schumacher, J. (2013). How accurately can soil organic carbon stocks and stock changes be quantified by soil inventories? *Biogeosciences, 8*, 1193–1212. https://doi.org/10.5194/bg-8-1193-2011

SDSN (2015). *Indicators and a monitoring framework for the sustainable development goals. A report to the Secretary-General of the United Nations by the Leadership Council of the Sustainable Development Solutions Network*. Sustainable Development Solutions Network. http://unsdsn.org/wp-content/uploads/2015/05/150612-FINAL-SDSN-Indicator-Report1.pdf.

Seddon J. (2008). *Systems thinking in the public sector*. Triachy Press.

Shepherd K. D. (2015). How much development data is enough? *Project Syndicate, 29 December 2015*. https://www.project-syndicate.org/commentary/decision-science-role-in-policymaking-by-keith-d--shepherd-2015-12.

Shepherd K. D. (2019). *Intervention decision screening model*. A Bayesian Network Model in AgenaRisk©.World Agroforestry Centre (ICRAF), Nairobi. https://cgiar.sharepoint.com/:u:/s/WLE/EamoVQlBK5tHu0vVHO3FYSgBU_hs44T4hzACjyMIz27O6A?e=suoWaN

Shepherd K. D., Farrow A., Ringler C., Gassner A., & Jarvis A. (2013). *Review of the Evidence on Indicators, Metrics and Monitoring Systems*. Commissioned by the UK Department for International Development (DFID). World Agroforestry Centre, Nairobi. http://r4d.dfid.gov.uk/output/192446/default.aspx.

Shepherd K., Hubbard D., Fenton N., Claxton K. Luedeling E., & De Leeuw J. (2015a). Development goals should enable decision-making. *Nature, 523*, 152-154. https://doi.org/10.1038/523152a

Shepherd K. D., Shepherd G., & Walsh M. G. (2015b). Land health surveillance and response: a framework for evidence-informed land management. *Agricultural Systems, 132*, 93–106. https://doi.org/10.1016/j.agsy.2014.09.002

Spetzler C. S. (2011). *Chevron overcomes the biggest bias of all*. Strategic Decisions Group. https://www.sdg.com/wp-content/uploads/2015/06/SDG_-_Chevron_Overcomes_Biggest_Bias_of_All.pdf.

Taleb N. N. (2007). *The black swan: The impact of the highly improbable*. Random house, UK.

Tversky A., & Kahneman D. (1974). Judgment under uncertainty: Heuristics and biases. *Science, New Series, 185,* 1124–1131. https://doi.org/10.1126/science.185.4157.1124

UN (2015). *Transforming our world: the 2030 agenda for sustainable development.* Resolution adopted by the General Assembly on 25 September 2015, A/RES/70/1. UN General Assembly: New York.

UN (2017). *United Nations Sustainable Development Goal 15*. http://www.un.org/sustainabledevelopment/biodiversity/.
UNCCD (2019). The LDN Target Setting Programme. UNCCD: Bonn, Germany. https://www.unccd.int/actions/ldn-target-setting-programme
UNCCD/GM (2016a). *Land Degradation Neutrality: The target setting programme*. Global Mechanism (GM) of the United Nations Convention to combat Desertification (UNCCD). http://www.unccd.int/Lists/SiteDocumentLibrary/Publications/4_2016_LDN_TS%20_ENG.pdf
UNCCD/GM (2016b). *Achieving Land Degradation Neutrality at the country level – building blocks for LDN target setting.* Global Mechanism (GM) of the United Nations Convention to combat Desertification (UNCCD): Bonn, Germany. http://www2.unccd.int/sites/default/files/documents/160915_ldn_rgb_small%20%281%29.pdf
UNCCD/SPI (2016). Land in balance: The scientific conceptual framework for Land Degradation Neutrality. Science-Policy Brief 02. UNCCD: Bonn, Germany. http://www.unccd.int/Lists/SiteDocumentLibrary/Publications/10_2016_spi_pb_multipage_eng.pdf
UNCTAD (2014). *World Investment Report 2014. Investing in the SDGs: An action plan.* United Nations Conference on Trade and Development. United Nations: New York.
UNDG (2011). *Results-based management handbook*. United Nations Development Group: New York. https://undg.org/wp-content/uploads/2016/10/UNDG-RBM-Handbook-2012.pdf
UNFCCC (2015). Intended Nationally Determined Contributions (INDCs. United Nations Framework Convention on Climate Change (UNFCCC). https://unfccc.int/files/adaptation/application/pdf/all__parties_indc.pdf
Unterhalter E., J. (2014). Measuring education for the Millennium Development Goals: Reflections on targets, indicators, and a post-2015 framework. *Journal of Human Development and Capabilities: A Multi-Disciplinary Journal for People-Centered Development, 15,* 176–187. https://doi.org/10.1080/19452829.2014.880673
Wafula J., Karimjee Y., Tamba Y., Malava G., Muchiri C., Koech G., De Leeuw J., Nyongesa J., Shepherd K., & Luedeling E. (2018). Probabilistic Assessment of Investment Options in Honey Value Chains in Lamu County, Kenya. *Frontiers in Applied Mathematics and Statistics 4*, article 6, 1-11. https://doi.org/10.3389/fams.2018.00006
Walters C. J., & Holling C. S. (1990). Large-scale management experiments and learning by doing. *Ecology, 71,* 2060–2068. https://doi.org/10.2307/1938620
WCED (1987). *Our common future*, World Commission on Environment and Development: Oxford University Press: Oxford.
Whitney C. W., Lanzanova D., Muchiri C., Shepherd K., Rosenstock T. S., Krawinkel M., Tabuti J. R. S., & Luedeling E. (2018). Probabilistic decision tools for determining impacts of agricultural development policy on household nutrition. *Earth's Future*, 6, 359–372. https://doi.org/10.1002/2017EF000765
Williams B. K. (2011). Adaptive management of natural resources: framework and issues. *Journal of Environmental Management, 92*, 1346–1353. https://doi.org/10.1016/j.jenvman.2010.10.041
Williams B. K, & Brown E. D. (2014). Adaptive management: from more talk to real action. *Environmental Management, 53,* 465-479. https://doi.org/10.1007/s00267-013-0205-7
World Bank (2011). *Impact Evaluations in Agriculture an Assessment of the Evidence*. Washington DC: The World Bank. http://documents.worldbank.org/curated/en/2011/01/16755061/impact-evaluations-agriculture-assessment-evidence
Yet B., Constantinou A., Fenton N., Neil M., Luedeling E., & Shepherd K. (2016). A Bayesian network framework for project cost, benefit and risk analysis with an agricultural development case study. *Expert Systems with Applications, 60*, 141-155. https://doi.org/10.1016/j.eswa.2016.05.005

Supplementary Materials

A selection of case studies that apply decision analysis approaches to support decisions related to natural resources and environmental management.

Table S.1 Examples of application of Stochastic Impact Evaluation to natural resource management decisions (Luedeling et al., 2015; Tamba et al., 2017; and Favretto et al., 2017, respectively).

Decision	Stakeholders	Examples of variables included	Variables with high information value	Impacts
Whether to proceed with a water supply project in Wajir County, Kenya	Upstream users, Downstream users, Town users, Source communities, Water company Investor: Government of Kenya	• Infant mortality • Job creation • Revenue from payments for ecosystem services • Risk of salt water intrusion into the aquifer • Pipeline security • Risk of inadequate benefit sharing • Risk of political interference	• Value of surviving infant • Risk of poor project design • Risk of political interference	• Decision to implement the project was deferred in response to high risk of project failure • Stakeholders changed their opinions on the pipeline, requested more measurements, or proposed alternative water supply options
Whether to desilt and repair a check-dam in Hurri Hills, Marsabit County, Kenya	Local community Investor: International Union for Conservation of Nature (IUCN)	• Benefits from water sales and time saving • Land degradation • Wildlife losses • Human disease impacts • Effect of weak institutions • Amount of training	• Value of cattle • Probability that drought reduces the capacity of the dam • Probability of degradation due to the dam • Time saving	• Decision and options clarified with local community • Clearer understanding of trade-offs among environmental costs and social benefits
Which rangeland use type to promote in semi-arid areas of Kgalagadi District, Botswana	Land users Investor: Policy makers	• Production • Groundwater • Climate regulation • Recreation value • Cultural/spiritual benefits	• Profit of meat production • Value of plant/livestock diversity • Recreation and cultural/spiritual inspiration	• Policy decision making able to consider monetary and non-monetary values of ecosystem services

Table S.2. A selection of case studies that apply decision analysis approaches to support decisions related to natural resources and environmental management

Overview	Method*	Citation
Meta-modelling tool in integrated river basin management in Norway	BN	(Barton et al., 2008)
Assessment of ecosystem services from multifunctional trees in pastures in Nicaragua	BN	(Barton et al., 2016)
Project the outcomes of coral restoration in the Philippines	BN	(Benjamin et al., 2017)
Integration and participation in water resource planning in Italy	BN	(Castelletti & Soncini-Sessa, 2006)
Participatory river basin planning in Italy	BN	(Castelletti & Soncini-Sessa, 2007)
Management support for a multipurpose reservoir in Italy	BN	(Castelletti et al., 2006)
Valuation of ecosystem services in the rangelands of Botswana	MC	(Favretto et al., 2017)
Identify dryland ecosystem service trade-offs under different rangeland uses	MCDA	(Favretto et al., 2016)
Multi-criteria approach to the Great Barrier Reef catchment diffuse-source pollution problem	MCDA	(Greiner et al., 2005)
Habitat suitability modelling of rare species	BN	(Hamilton et al., 2015)
Assist the management, monitoring and evaluation of development-orientated research	BN	(Henderson & Burn, 2004)
Participatory management of groundwater contamination	BN	(Henriksen et al., 2007)
Decision support for the US Environmental Protection Agency on protecting water quality	AIE	(Hubbard, 2014)
A review of Bayesian belief networks in ecosystem service modelling	BN	(Landuyt et al., 2013)
Assess and visualize uncertainties in ecosystem service mapping	BN	(Landuyt et al., 2015)
Assessment of several options to reduce sedimentation in small irrigation dams in Burkina Faso	MC	(Lanzanova et al., 2019)
Evaluate complex multifactor problems using forward and backward reasoning for phosphorus loss in New Zealand	BN	(Lucci et al., 2014)
Ex-ante assessment of uncertain benefits for multiple stakeholders in a water supply project in Kenya	MC	(Luedeling et al., 2015)
Explore social representations of adapting to climate change	BN	(Lynam, 2016)
Management of riparian buffer strips	BN	(McVittie et al., 2015)
Stakeholder-driven spatial modeling for strategic landscape planning in urban-rural gradients in the USA	BN	(Meyer et al., 2014)

Overview	Method*	Citation
Incorporating multiple criteria into the design of conservation area networks	MCDA	(Moffett & Sarkar, 2006)
Decision support for sediment resource management in Canada	AM	(Owens, 2009)
Management of agriculture based greenhouse gas emissions in the UK	BN	(Pérez-Miñana et al., 2012)
Improve ecosystem services modelling	BN	(Pérez-Miñana, 2016)
A systematic review of applications of Bayesian belief networks in water resource management	BN	(Phan et al., 2016)
Mapping soil properties with uncertainty in Scotland	MC	(Poggio et al., 2016)
Ecological risk assessment for catchment management in Australia	BN	(Pollino et al., 2007)
Assessment of yield improvement potential of introducing conservation agriculture practices in East Africa	MC	(Rosenstock et al., 2014)
Support global out-scaling of water-efficient rice technologies from pilot project areas	BN	(Rubiano M et al., 2016)
Modelling cultural ecosystem services in the United States	BN	(Shaw et al., 2016)
Conservation planning through habitat suitability modelling of threatened species in Thailand	BN	(Tantipisanuh et al., 2014)
Assess the sustainability of coastal lakes in Australia	BN	(Ticehurst et al., 2007)
Informing regulatory requirements on soil protection for provision of ecosystem services in Sweden	MCDA	(Volchko et al., 2014)
Assess alternatives to invest in honey value chains in Kenya	MC	(Wafula et al., 2017)
Determining Impacts of Agricultural Development Policy on Household Nutrition	BN	(Whitney et al, 2018)
Project cost, benefit and risk analysis of agricultural investment project including environmental impacts	BN	(Yet et al., 2016)
Value of information analysis in environmental health risk management decisions	BN	(Yokota & Thompson, 2004)
Assess the spatial distribution of cattle dung using manageable factors	BN	(Yoshitoshi et al., 2016)

*AIE= Applied Information Economics, AM=Adaptive Management, BN=Bayesian Network, MC=Monte Carlo, MCDA=Multi-Criteria Decision Analysis, SDM= Structured Decision Making,

Supplementary references

Barton D. N., Benjamin, T., Cerdán C. R., DeClerck F., Madsen A. L., Rusch G. M., et al. (2016). Assessing ecosystem services from multifunctional trees in pastures using Bayesian belief networks. *Ecosystem Services, 18*, 165-174. https://doi.org/10.1016/j.ecoser.2016.03.002

Barton D. N., Saloranta T., Moe S. J., Eggestad H. O., & Kuikka S. (2008). Bayesian belief networks as a meta-modelling tool in integrated river basin management—Pros and cons in evaluating nutrient abatement decisions under uncertainty in a Norwegian river basin. *Ecological Economics, 66*, 91-104. https://doi.org/10.1016/j.ecolecon.2008.02.012

Benjamin C. S., Punongbayan A. T., dela Cruz D. W., Villanueva R. D., Baria M. V. B., & Yap H. T. (2017). Use of Bayesian analysis with individual-based modeling to project outcomes of coral restoration. *Restoration Ecology, 25*, 112-122. https://doi.org/10.1111/rec.12395

Castelletti A., & Soncini-sessa R. (2006). A procedural approach to strengthening integration and participation in water resource planning. *Environmental Modelling & Software, 21*, 1455-1470. https://doi.org/10.1016/j.envsoft.2005.07.013

Castelletti A., Cellina F., Soncini-Sessa R., & Weber E. (2006). Comprehensive testing and application of the PIP procedure: the Verbano project case study. *Topics on System Analysis and Integrated Water Resources Management, 223*. https://doi.org/10.1016/b978-008044967-8/50012-9

Castelletti A., & Soncini-Sessa R. (2007b). Coupling real-time control and socio-economic issues in participatory river basin planning. *Environmental Modelling & Software, 22*, 1114-1128. https://doi.org/10.1016/j.envsoft.2006.05.018

Favretto N., Stringer L. C., Dougill A. J., Dallimer M., Perkins J. S., Reed M. S., et al. (2016). Multi-Criteria Decision Analysis to identify dryland ecosystem service trade-offs under different rangeland land uses. *Ecosystem Services, 17*, 142-151. https://doi.org/10.1016/j.ecoser.2015.12.005

Favretto N., Luedeling E., Stringer L. C., & Dougill A. J. (2017). Valuing ecosystem services in semi-arid rangelands through stochastic simulation. *Land Degradation and Development, 28*, 65–73. https://doi.org/10.1002/ldr.2590

Greiner R., Herr A., Brodie J., & Haynes D. (2005). A multi-criteria approach to Great Barrier Reef catchment (Queensland, Australia) diffuse-source pollution problem. *Marine Pollution Bulletin, 51*, 128-137. https://doi.org/10.1016/j.marpolbul.2004.11.033

Hamilton S. H., Pollino C. A., & Jakeman A. J. (2015). Habitat suitability modelling of rare species using Bayesian networks: Model evaluation under limited data. *Ecological modelling, 299*, 64-78. https://doi.org/10.1016/j.ecolmodel.2014.12.004

Henderson J. S., & Burn R. W. (2004). Uptake pathways: the potential of Bayesian belief networks to assist the management, monitoring and evaluation of development-orientated research. *Agricultural Systems, 79*, 3-15. https://doi.org/10.1016/s0308-521x(03)00042-8

Henriksen H. J., Rasmussen P., Brandt G., Von Buelow D., & Jensen F. V. (2007). Public participation modelling using Bayesian networks in management of groundwater contamination. *Environmental Modelling & Software, 22*, 1101-1113. https://doi.org/10.1016/j.envsoft.2006.01.008

Hubbard D. W. (2014). *How to measure anything. Finding the value of "intangibles" in business*. John Wiley. https://onlinelibrary.wiley.com/doi/book/10.1002/9781118983836

Landuyt D., Broekx S., D'hondt R., Engelen G., Aertsens J., & Goethals P. (2013). A review of Bayesian belief networks in ecosystem service modelling. *Environmental Modelling & Software, 46*, 1-11. https://doi.org/10.1016/j.envsoft.2013.03.011

Landuyt D., Van der Biest K., Broekx S., Staes J., Meire P., & Goethals P. L. M. (2015). A GIS plug-in for Bayesian belief networks: towards a transparent software framework to assess and visualise uncertainties in ecosystem service mapping. *Environmental Modelling & Software, 71*, 30-38. https://doi.org/10.1016/j.envsoft.2015.05.002

Lanzanova D., Whitney C., Shepherd K., & Luedeling E. (2019). Improving development efficiency through decision analysis: reservoir protection in Burkina Faso. Environmental Modelling & Software (in press). https://doi.org/10.1016/j.envsoft.2019.01.016

Lucci G. M., Nash D., McDowell R. W., & Condron L. M. (2014). Bayesian network for point and diffuse source phosphorus transfer from dairy pastures in South Otago, New Zealand. *Journal of Environmental Quality, 43*, 1370-1380. https://doi.org/10.2134/jeq2013.11.0460

Luedeling E., Oord A. L., Kiteme B., Ogalleh S., Malesu M., Shepherd K. D., & de Leeuw, J. (2015). Fresh groundwater for Wajir - ex-ante assessment of uncertain benefits for multiple stakeholders in a water supply project in Northern Kenya. Frontiers in Environmental Science, 3, article 16, 1-18. https://doi.org/10.3389/fenvs.2015.00016

Lynam, T. (2016). Exploring social representations of adapting to climate change using topic modeling and Bayesian networks. *Ecology and Society, 21*, 1-16. https://doi.org/10.5751/es-08778-210416

McVittie A., Norton L., Martin-Ortega J., Siameti I., Glenk K., & Aalders I. (2015). Operationalizing an ecosystem services-based approach using Bayesian Belief Networks: an application to riparian buffer strips. *Ecological Economics, 110*, 15-27. https://doi.org/10.1016/j.ecolecon.2014.12.004

Meyer S. R., Johnson M. L., Lilieholm R. J., & Cronan C. S. (2014). Development of a stakeholder-driven spatial modeling framework for strategic landscape planning using Bayesian networks across two urban-rural gradients in Maine, USA. *Ecological Modelling, 291*, 42-57. https://doi.org/10.1016/j.ecolmodel.2014.06.023

Moffett A., & Sarkar S. (2006). Incorporating multiple criteria into the design of conservation area networks: a minireview with recommendations. *Diversity and Distributions, 12*, 125-137. https://doi.org/10.1111/j.1366-9516.2005.00202.x

Owens P. N. (2009). Adaptive management frameworks for natural resource management at the landscape scale: implications and applications for sediment resources. *Journal of Soils and Sediments, 9*, 578-593. https://doi.org/10.1007/s11368-009-0137-2

Pérez-Miñana E. (2016). Improving ecosystem services modelling: Insights from a Bayesian network tools review. *Environmental Modelling & Software, 85*, 184-201. https://doi.org/10.1016/j.envsoft.2016.07.007

Pérez-Miñana E., Krause P. J., & Thornton J. (2012). Bayesian Networks for the management of greenhouse gas emissions in the British agricultural sector. *Environmental Modelling & Software, 35*, 132-148. https://doi.org/10.1016/j.envsoft.2012.02.016

Phan T.D., Smart J.C.R., Capon S.J., Hadwen W.L., & Sahin O. (2016). Applications of Bayesian belief networks in water resource management: A systematic review. *Environmental Modelling & Software 85*, 98-111. http://dx.doi.org/10.1016/j.envsoft.2016.08.006

Poggio L., Gimona A., Spezia L., & Brewer M. J. (2016). Bayesian spatial modelling of soil properties and their uncertainty: The example of soil organic matter in Scotland using R-INLA. *Geoderma, 277*, 69-82. https://doi.org/10.1016/j.geoderma.2016.04.026

Pollino C. A., Woodberry O., Nicholson A., Korb K., & Hart B. T. (2007). Parameterisation and evaluation of a Bayesian network for use in an ecological risk assessment. *Environmental Modelling & Software, 22*, 1140-1152. https://doi.org/10.1016/j.envsoft.2006.03.006

Rosenstock T. S., Mpanda M., Rioux J., Aynekulu E., Kimaro A. A., Neufeldt H., Shepherd K. D., & Luedeling E. (2014). Targeting conservation agriculture in the context of livelihoods and landscapes. *Agriculture, Ecosystems and Environment, 187*, 47–51. https://doi.org/10.1016/j.agee.2013.11.011

Rubiano M, J. E., Cook S., Rajasekharan M., & Douthwaite B. (2016). A Bayesian method to support global out-scaling of water-efficient rice technologies from pilot project areas. *Water International, 41*, 290-307. https://doi.org/10.1080/02508060.2016.1138215

Shaw E., Kumar V., Lange E., & Lerner D. N. (2016). Exploring the utility of Bayesian Networks for modelling cultural ecosystem services: A canoeing case study. *Science of the Total Environment, 540*, 71-78. https://doi.org/10.1016/j.scitotenv.2015.08.027

Tamba Y., Muchiri C., Luedeling E., & Shepherd K. (2017). *Stakeholder Approach to Risk Informed and Evidence Based Decision Making (SHARED) for Resilience. Decision Analysis –Marsabit County Case Study Technical Report*. World Agroforestry Centre, Nairobi. http://www.worldagroforestry.org/publication/decision-analysis-–marsabit-county-case-study-technical-report

Tantipisanuh N., Gale G. A., & Pollino C. (2014). Bayesian networks for habitat suitability modeling: a potential tool for conservation planning with scarce resources. Ecological applications*, 24*, 1705-1718. https://doi.org/10.1890/13-1882.1

Ticehurst J. L., Newham L. T. H., Rissik D., Letcher R. A., & Jakeman A. J. (2007). A Bayesian network approach for assessing the sustainability of coastal lakes in New South Wales, Australia.

Environmental Modelling & Software, 22, 1129-1139. https://doi.org/10.1016/j.envsoft.2006.03.003
Volchko Y., Norrman J., Rosén L., Bergknut M., Josefsson S., Söderqvist T., et al. (2014). Using soil function evaluation in multi-criteria decision analysis for sustainability appraisal of remediation alternatives. *Science of the Total Environment, 485*, 785-791. https://doi.org/10.1016/j.scitotenv.2014.01.087
Wafula J., Karimjee Y., Tamba Y., Malava G., Muchiri C., Koech G., De Leeuw J., Nyongesa J., Shepherd K., & Luedeling E. (2018). Probabilistic Assessment of Investment Options in Honey Value Chains in Lamu County, Kenya. *Frontiers in Applied Mathematics and Statistics 4*, article 6, 1-11. https://doi.org/10.3389/fams.2018.00006
Whitney C. W., Lanzanova D., Muchiri C., Shepherd K., Rosenstock T. S., Krawinkel M., Tabuti J. R. S., & Luedeling E. (2018). Probabilistic decision tools for determining impacts of agricultural development policy on household nutrition. *Earth's Future*, 6, 359–372. https://doi.org/10.1002/2017EF000765
Yet B., Constantinou A., Fenton N., Neil M., Luedeling E., & Shepherd K. (2016). A Bayesian network framework for project cost, benefit and risk analysis with an agricultural development case study. *Expert Systems with Applications, 60*, 141-155. https://doi.org/10.1016/j.eswa.2016.05.005
Yokota F., & Thompson K. M. (2004). Value of information analysis in environmental health risk management decisions: past, present, and future. *Risk Analysis, 24*, 635-650. https://doi.org/10.1111/j.0272-4332.2004.00464.x
Yoshitoshi R., Watanabe N., Yasuda T., Kawamura K., Sakanoue S., Lim J. et al. (2016). Methodology to predict the spatial distribution of cattle dung using manageable factors and a Bayesian approach. *Agriculture, Ecosystems & Environment, 220*, 135-141. https://doi.org/10.1016/j.agee.2015.12.025

List of most recent Working Papers

2021

323: Opportunities for implementing improved tree seed sourcing for forest landscape restoration, agroforestry and wider tree planting at the project design stage: Findings of a survey of planters, researchers and funders. DOI: https://dx.doi.org/10.5716/WP21041.PDF

322: Multi-stakeholder platforms for cross-border biodiversity conservation and landscape governance in East Africa: Perspectives and outlook. DOI: https://doi.org/10.5716/WP21039.PDF

321: The Farmland Biodiversity Score for consistent monitoring of biodiversity based on the measurement of trees on farms. DOI: https://doi.org/10.5716/WP21038.PDF

320: Priority landscapes for tree-based restoration in Ethiopia. DOI: https://doi.org/10.5716/WP21037.PDF

319: Beyond carbon sequestration – local knowledge about tree functions. Case study from male and female Arabica coffee farmers in Vietnam. https://doi.org/10.5716/WP21025.PDF

318: Commune-level institutional arrangements and monitoring framework for integrated tree-based landscape management. Ha Noi, Viet Nam: https://doi.org/10.5716/WP21024.PDF

317: Understanding tree-cover transitions, drivers and stakeholders' perspectives for effective landscape governance: a case study of Chieng Yen Commune, Son La Province, Viet Nam. https://doi.org/10.5716/WP21023.PDF

316: Adoption of improved grain legumes and dryland cereals crop varieties: A synthesis of evidence. https://doi.org/10.5716/WP21022.PDF

315: Assessment of women's benefits and constraints in participating in agroforestry exemplar landscapes. https://doi.org/10.5716/WP21021.PDF

314: Effect of COVID-19 on rural community enterprises: the case of community forest enterprises in Cameroon. https://doi.org/10.5716/WP21007.PDF

313: Land-use Land-cover Change and Farming systems in the upland of Pagar Alam City, Indonesia. https://doi.org/10.5716/WP21007.PDF

312: The one hundred tree species prioritized for planting in the tropics and subtropics as indicated by database mining. World Agroforestry, Nairobi, Kenya. https://doi.org/10.5716/WP21001.PDF

311: Status of Perennial Tree Germplasm Resources in India and their Utilization in the Context of Global Genome Sequencing Efforts. https://doi.org/10.5716/WP2020050.PDF 2021

310: Simulating the effect of change in land cover and rainfall in Upper Citarum Watershed: calibration and sensitivity analysis of Genriver model. https://doi.org/10.5716/WP20049.PDF

2020

309: Simulasi Dampak Perubahan Tutupan Lahan dan Curah Hujan di DAS Citarum Hulu dengan Model GenRiver: Kalibrasi model dan analisa sensitivitas. https://doi.org/10.5716/WP20048.PDF

308: Especies agroforestales del Perú: Lista referencial y contribución a la priorización para la conservación de recursos genéticos agroforestales. Documento de Trabajo número 308. Centro Internacional de Investigación Agroforestal. https://doi.org/10.5716/WP20041.PDF

307: Charcoal value chains in Kenya: A 20-year synthesis. https://doi.org/10.5716/WP20026.PDF

306: An exploratory analysis of cost-benefit analysis of landscape restoration. https://doi.org/10.5716/WP20014.PDF

305: Agroforestry species of Peru: Reference list and contribution to prioritization for the conservation of agroforestry genetic resources. https://doi.org/10.5716/WP20013.PDF

304: From Tree Planting to Tree Growing: Rethinking Ecosystem Restoration Through Trees. https://doi.org/10.5716/WP20001.PDF

World Agroforestry (ICRAF) is a centre of scientific and development excellence that harnesses the benefits of trees for people and the environment. Leveraging the world's largest repository of agroforestry science and information, we develop knowledge practices, from farmers' fields to the global sphere, to ensure food security and environmental sustainability.

ICRAF is the only institution that does globally significant agroforestry research in and for all of the developing tropics. Knowledge produced by ICRAF enables governments, development agencies and farmers to utilize the power of trees to make farming and livelihoods more environmentally, socially and economically sustainable at multiple scales.

World Agroforestry

United Nations Avenue, Gigiri • PO Box 30677 • Nairobi, 00100 • Kenya
Telephone: +254 20 7224000 or via USA +1 650 833 6645
Fax: +254 20 7224001 or via USA +1 650 833 6646
Email: worldagroforestry@cgiar.org • www.worldagroforestry.org