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Stochastic simulation of restoration outcomes for a dry afromontane forest landscape in northern Ethiopia

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ABSTRACT

Forest and Landscape Restoration (FLR) is carried out with the objective of regaining ecological functions and enhancing human well-being through intervention in degrading ecosystems. However, uncertainties and risks related to FLR make it difficult to predict long-term outcomes and inform investment plans. We applied a Stochastic Impact Evaluation framework (SIE) to simulate returns on investment in the case of FLR interventions in a degraded dry Afromontane forest while accounting for uncertainties. We ran 10,000 iterations of a Monte Carlo simulation that projected FLR outcomes over a period of 25 years. Our simulations show that investments in assisted natural regeneration, enrichment planting, exclosure establishment and soil-water conservation structures all have a greater than 77% chance of positive returns. Sensitivity analysis of these outcomes indicated that the greatest threat to positive cashflows is the time required to achieve the targeted ecological outcomes. Value of Information (VOI) analysis indicated that the biggest priority for further measurement in this case is the maturity age of exclosures at which maximum biomass accumulation is achieved. The SIE framework was effective in providing forecasts of the distribution of outcomes and highlighting critical uncertainties where further measurements can help support decision-making. This approach can be useful for informing the management and planning of similar FLR interventions.

1. Introduction

According to the United Nations Environmental Programme, degradation of terrestrial and marine ecosystems undermines the well-being of 3.2 billion people and costs about 10% of the annual global gross product in loss of species and ecosystem services (UNEP, 2019). In Ethiopia, land and forest resource degradation across the different production systems of the country is considered a major impediment for sustainable development, causing considerable negative impacts on the national economy (Gashaw et al., 2014). A rapidly growing population, combined with increasingly frequent droughts, prevalent poverty and lack of alternative employment opportunities, is leading to over-exploitation of the country's natural resources (Tesfaye et al., 2014). The traditional customary resource management systems that communities have relied on for generations are therefore being challenged (Scull et al., 2017). Novel approaches to restoration, such as forest and landscape restoration (FLR), may offer effective and integrated strategies for sustainable and integrated landscape management.

FLR is a planned process where forest landscapes are restored with the goal of ecological integrity and improved human well-being. In practice, FLR projects follow guiding principles that dictate a focus on landscapes and natural ecosystems, participatory governance, context-specific approaches, adaptive management and restoration of multiple functions for multiple benefits (Gitz et al., 2020). The definition of FLR is broad, allowing for flexibility in how the process is implemented in local landscapes, while the underlying set of guiding principles were developed to ensure restoration quality. Despite being adopted as a vehicle for transformation in multiple initiatives that target degraded landscapes (such as the Convention on Biological Diversity (CBD, 2010), the United Nations Framework Convention on Climate Change's REDD+ goals (COP 16, 2011), the United Nations Conventions to Combat Desertification (Chotte et al., 2019), and the United Nation's Decade of

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Ecosystem Restoration (FAO, 2019), there is still a need for empirical evidence to support scaling-up efforts. Case studies that meet all the criteria of FLR are few due to the recency of the concept, and the lack of a standard method for assessing FLR outcomes (Stanturf et al., 2019). A variety of methods have been developed to address the need for scientific tools to support decision-making on specific components of restoration outcomes, such as soil health (land degradation surveillance framework; (Vågen et al., 2013), soil nutrient deficiencies (Munialo et al., 2019), soil organic matter content (Zomer et al., 2017), biomass accumulation (Romijn et al., 2019), rangeland/grazing management and governance (Sircely et al., 2019), as well as the economics of land degradation (Nkonya et al., 2015). However, assessment metrics that integrate both socioeconomic and biophysical outcomes are still lacking (Chomba et al., 2020).

In Ethiopia, there have been several interventions that meet the FLR criteria of sustainable land management, including the Integrated Food Security Project and, more recently, the landscapes for people, food, and nature initiatives (Nigussie et al., 2017; Weldesemaet, 2015). Substantial investment is required but often cannot be secured due to evidence gaps that threaten the success of management strategies. Another reason for limited investments is the long-term planning horizon of FLR, which dampens enthusiasm for funding (Kusters et al., 2018; McGonigle et al., 2020; Pistorius et al., 2017). To evaluate and justify investments in sustainable land management, development practitioners commonly employ deterministic cost-benefit analysis approaches that are hinged upon precise models of system functions, such as the Restoration Opportunities Assessment Methodology (ROAM) manual and the Restoration Diagnostic (IUCN and WRI, 2014; World Resources institute, 2015). However, deterministic models often fall short of adequately supporting decisions when data are scarce or of low quality (Wendt, 1975), or where complex system functions introduce risk and uncertainty (Luedeling and Shepherd, 2016). Effective planning and prioritization of interventions may be compromised by uncertainty in the definition of restoration objectives, failure to identify the most efficient practices and failure to identify the socio-economic and cultural drivers of deforestation (Cortina et al., 2011; McGonigle et al., 2020; Yet et al., 2020). Attempts by managers to value restoration outcomes also face difficulties when assigning monetary values to ecosystem services with low market values, such as carbon sequestration, regulation of hydrological cycles and improved micro-climates (de Groot et al., 2010).

Decision support approaches that holistically evaluate decision options based on plausible ranges of costs and benefits while accounting for uncertainties and risks could overcome these knowledge barriers. Furthermore, they could strengthen the capacity of managers to use continuous learning and monitoring systems to track their progress towards their goals (Rumpff et al., 2011). It is also possible to take stock of the successes and failures of restoration policies and efforts undertaken and to learn lessons for improved natural resource management and protection (Cronkleton et al., 2018). Through these approaches, we can prioritize critical uncertainties where targeted research could enhance clarity on expected outcomes. In this study, we demonstrated the application of a stochastic impact evaluation (SIE) framework to (i) predict bio-physical and socio-economic outcomes of FLR practices, (ii) identify knowledge gaps that constrain effective decision making and, (iii) provide insights that aid in adaptive management of FLR efforts.

2. Materials and methods

2.1. Study area

Desa'a forest is one of the oldest remaining dry Afromontane forests along the western escarpment of the Great Rift Valley in northern Ethiopia (Lat. 13° 53′ – 13° 56′ N and Long. 39° 48′ - 39° 51′ E) (Fig. 1). It lies between 900 and 3100 m above sea level. Based on rainfall data from the Ethiopian Meteorological Agency for 2006 to 2015, the mean annual rainfall was about 602 mm (Mokria et al., 2015). Desa'a is an even-aged secondary forest, hosting about 90 tree and shrub species, and dominated by Wild African wild Olive (*Olea europaea* subsp. *cuspidata*) and African Juniper (*Juniperus procera*) (Aynekulu et al., 2009). The forest is of high ecological and socio-economic importance as it has the potential to conserve biodiversity and soils, supply biomass for fuelwood and construction, regulate water and carbon cycles and offer a host of other ecosystem services (Teklay et al., 2013). Despite its protected status as a state forest, about 70% of dense forest, with a canopy cover of more than 40%, has been deforested and degraded since the 1970s (WeForest, 2018). This is mainly due to forest land conversion to agriculture land and settlements, over-extraction of woody biomass for fuel and timber, fire, and free grazing (Aynekulu et al., 2011).

2.2. Methods

2.2.1. FLR interventions

To restore the degraded Desa'a forest, WeForest, a non-profit organisation with support from the Ethiopian government, launched a long-term FLR programme that proposed investments in a portfolio of scalable restoration and livelihood interventions. The interventions are expected to achieve socioeconomic benefits by promoting economic resilience of vulnerable communities and incentivizing improved natural resource governance. The targeted beneficiaries of the interventions were subsistence farmers. The following FLR interventions aimed to restore degraded forest functions:

- Assisted natural regeneration (ANR) of degraded forest. The ANR intervention involved restricting access to the forest products through social fencing facilitated by local by-laws and governance structures in a process termed "exclosure". Social fencing was enforced by community members trained as forest guards, and community participation was encouraged through livelihood development interventions.
- Enrichment planting and assisted natural regenertation of up to 1000 native trees per hectare in the open forest areas with canopy cover of less than 40% but more than 10%, where assisted natural regeneration has low potential to restore vegetation.
- Grazing land exclosure, where communally owned grasslands were protected from free grazing to encourage natural regeneration of woody vegetation. The community was allowed access to harvest grass for livestock feed (cut and carry method).
- Soil and water conservation, where gully restoration and *in-situ* water harvesting structures were established to reduce soil erosion and improve water infiltration.

The project also implemented a set of livelihood improvement interventions:

- Beekeeping, where two to three modern beehives were distributed among 3280 beekeepers to establish apiaries around their homesteads with the aim of promoting non-timber forest products.
- Sheep rearing, where three to five sheep were distributed among 7650 female-headed households to provide alternative sources of income to forest products. Small ruminants were chosen due to their resilience to harsh climatic conditions, ease of liquidity to meet household financial needs and the proximity of animal feed in the form of fodder from exclosures established on communal grazing lands.
- High-value fruit trees, where eight to thirteen apple tree seedlings were distributed among 5465 targeted farmers (whose farms were located within the FLR restoration project area) with the aim of diversifying incomes and reducing demand for forest commodities.
- Poultry farming, where ten poultry birds were distributed among 7650 impoverished female-headed households to provide livelihood benefits through sale and consumption of poultry products.

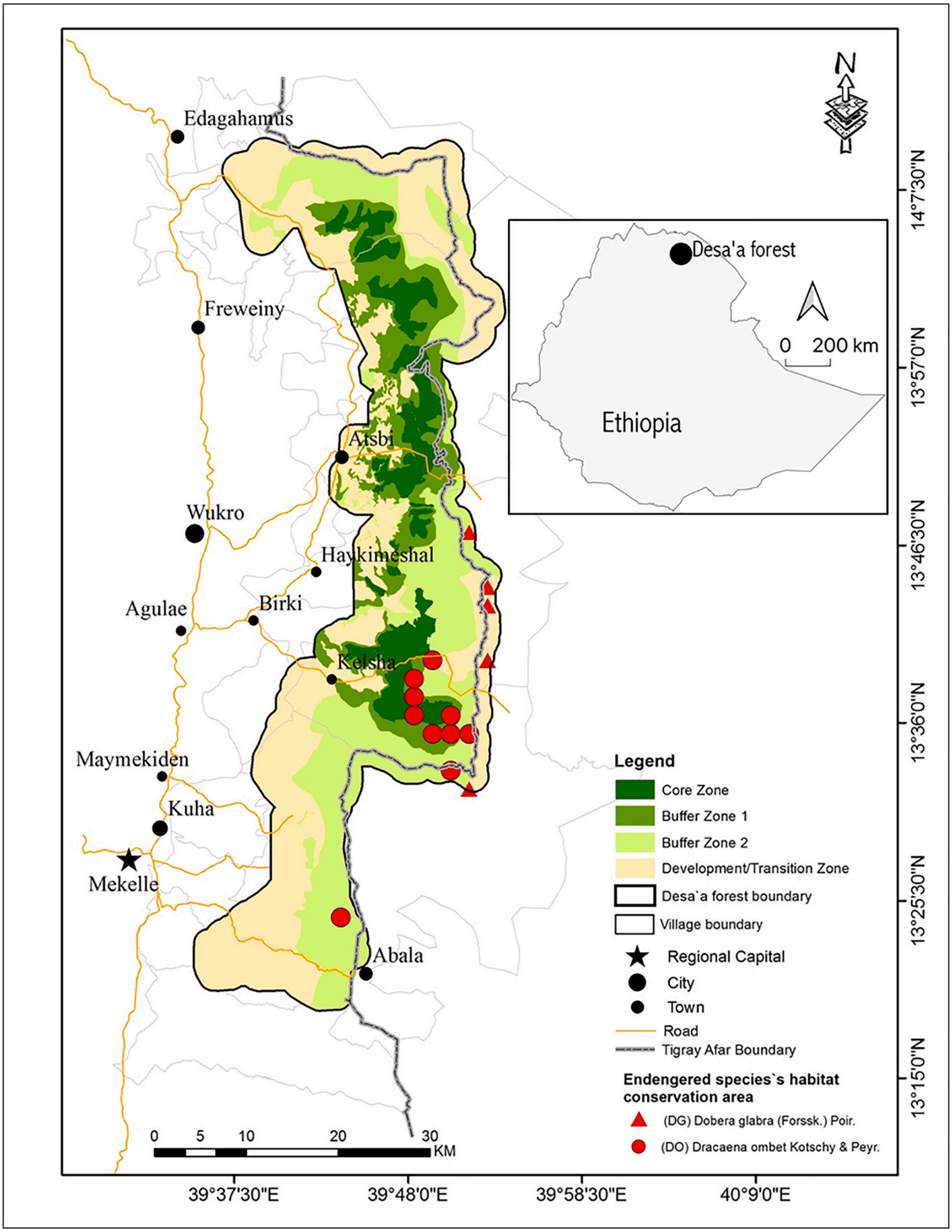

Fig. 1. Map of Desa'a state forest in Ethiopia (adapted from WeForest, 2018). Forest zones are demarcated based on vegetation density and human influence. The core zone is an area of dense forest with canopy cover ≥40%. Buffer zone 1 includes areas categorized as open forest where vegetation cover is greater than 10% but less than 40%. Buffer zone 2 denotes areas that are communally owned and made up of fragmented open forests and grazing lands where vegetation cover is ≤10%. Development zone denotes areas covered by community settlements.

- Energy efficient stoves that reduce demand for fuelwood from the forest were distributed among 10,390 households to promote alternative energy sources.

2.2.2. Stochastic simulation of FLR outcomes

We used the SIE framework (Fig. 2), based on Luedeling and Shepherd (2016) to simulate FLR outcomes. SIE is a mixed methods approach that has been widely used to simulate outcomes under uncertainty and risk for investments in honey value chains (Wafula et al., 2018), water supply (Luedeling et al., 2015), irrigation development (Yigzaw et al., 2019), management of reservoir sedimentation (Lanzanova et al., 2019), and to determine the value of ecosystem services in rangelands (Favretto et al., 2017). In this study, we applied SIE as an iterative five-step process that supports decisions by integrating evidence and expert opinion in quantitative simulations of decision impact pathways (Fig. 2).

Step 1: Decision framing

Decision framing is a crucial step where decision-makers need to explicitly define their problem and target outcomes. This first step addresses questions regarding the short-term and long-term outcomes, the targeted beneficiaries and the type of decision under consideration (prioritizing vs planning) (Luedeling and Shepherd, 2016). To clearly define the intervention's social, economic and biophysical impacts, we carried out semi-structured interviews with representatives from the implementing agency. The interviews provided insights on the objectives of the FLR project, implementation strategies and the targeted outcomes. A 25 year horizon was chosen to support long-term planning that incorporates key uncertainties. Through these interactions, the decision problem that emerged was whether the selected FLR interventions will be able to restore the degraded forest to provide sustainable socioeconomic and biophysical benefits.

To further clarify the decision context, we conducted semi-structured interviews with five government officers, seven development practitioners and one academic staff of Mekelle University. We applied purposive sampling to identify interviewees who had expertise in environmental management, forest resource management and agricultural value chains. We also held a focus group discussion with 12 male and eight female members of the local community, two development agents and two community leaders in the project area. The objective of the discussion was to elicit perspectives from members of the community on the historical trends in land use and land cover in the forest landscape, how the community expected the FLR interventions to change the trends in use of forest resources, and the potential barriers to implementation that they could foresee.

Step 2: Conceptual modelling

We followed a participatory model development process with the aim of conceptualizing the decision's impact pathways and identifying the cost, benefit and risk variables that would be parameterized in a simulation model. We held a workshop with 17 stakeholders from six development agencies, five representatives of state agencies and two researchers from Mekelle University, Ethiopia and elicited relevant variables. We then consolidated the resulting impact pathways and causal relationships between costs, benefits, and risks to generate the overall conceptual structure of the decision model (Do et al., 2020) (Fig. 3).

The variable estimates (Tamba et al., 2020) were used to feed the mathematical model, which was then run as a Monte Carlo (MC) simulation with 10,000 iterations using the *decisionSupport* package (Luedeling and Whitney, 2018; Luedeling et al., 2020) in the R programming language (R Core Team, 2017). For each run, the model produced a projection of the NPV, computed by adding up discounted net benefits over a 25-year simulation period.

Step 3: Developing a mathematical model

In the third step, the conceptual model was translated into a mathematical model to quantify the impact of nine FLR interventions as the

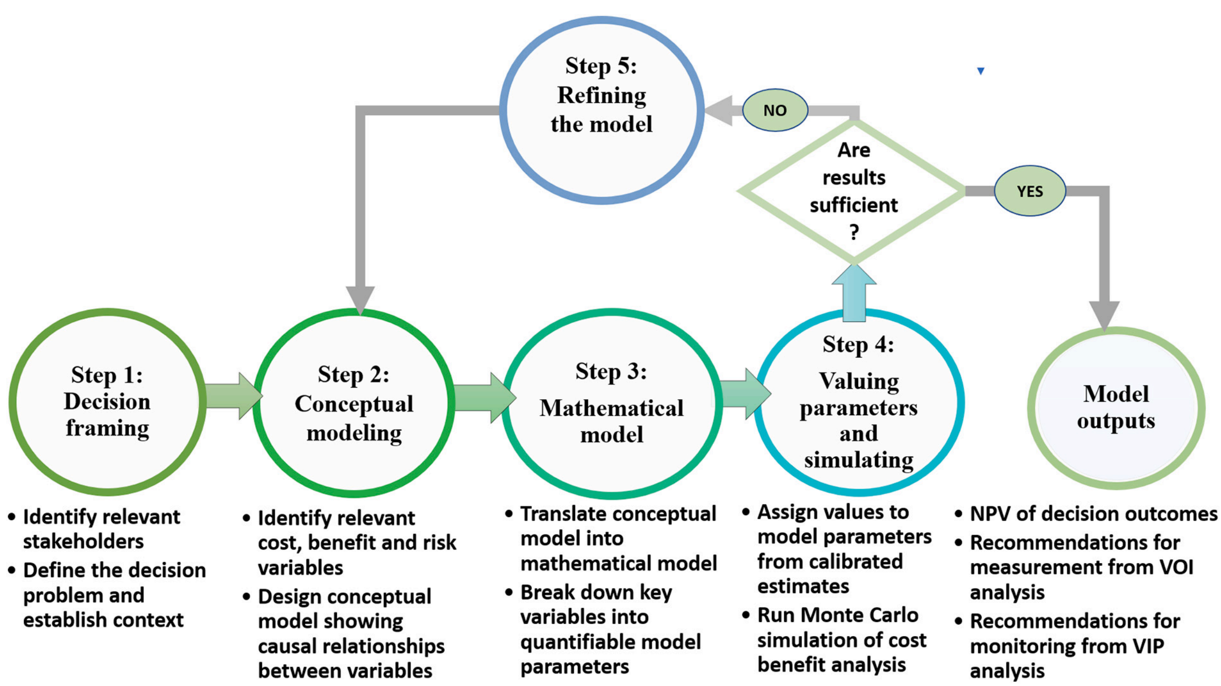

Fig. 2. Sequence of activities in the Stochastic Impact Evaluation approach (adapted from Yigzaw et al., 2019). Step 1 defines the decision context by identifying stakeholders and engaging them in a participatory research process. Step 2 creates a conceptual model of the decision's impact pathways and describes the relationships between the cost, benefit and risk variables identified by stakeholders. Step 3 translates the conceptual model into a mathematical model with causal relationships between variables rewritten as equations. In step 4, the values of model parameters are estimated by calibrated subject matter experts, and a Monte Carlo (MC) simulation of the cost-benefit analysis is run to project the distribution of returns. To analyse the sensitivity of the model, the Variable Importance in the Projection (VIP) is computed based on the results of a Partial Least Squares regression analysis. Expected Value of Perfect Information (EVPI) analysis serves to identify variables with high information value for the specific decision. Step 5 is where the model is refined when necessary. The process is iterative and allows for multiple cycles until the decision maker has sufficient information to make a decision.

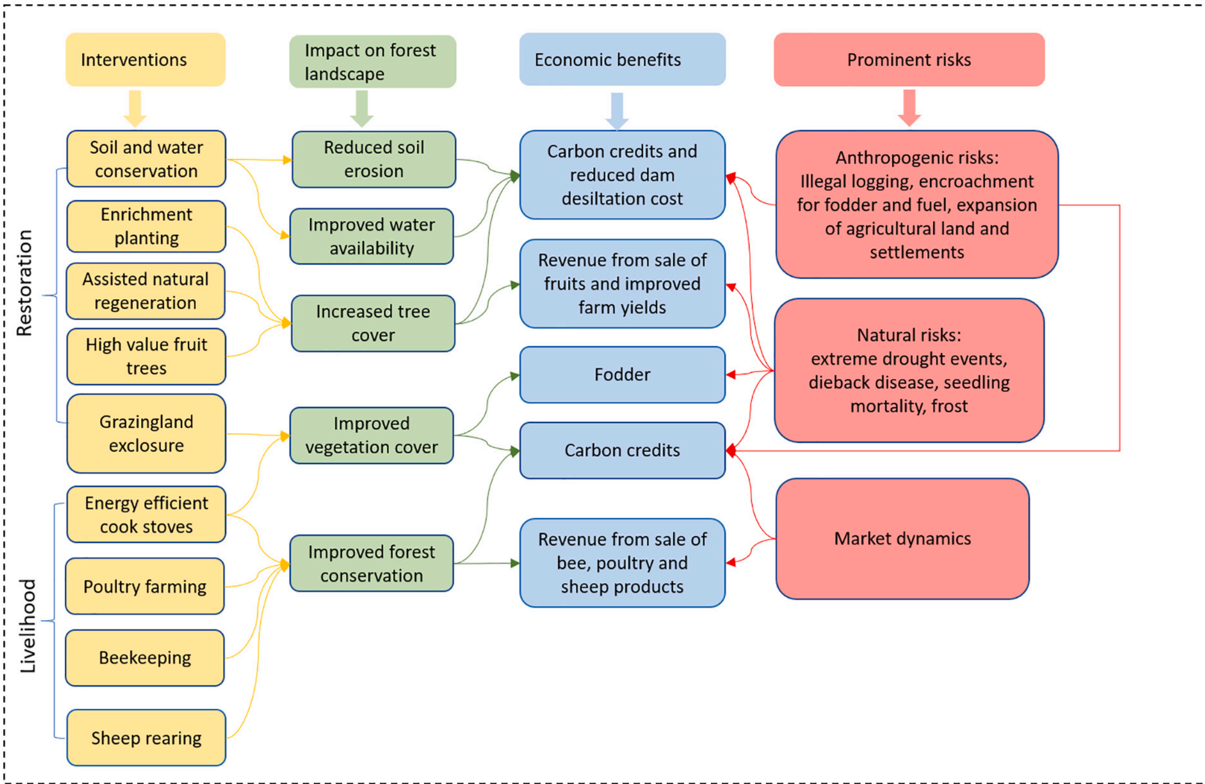

Fig. 3. Conceptual model developed by stakeholders showing the expected costs, benefits and risks of programme activities. We collected estimates of model variables (yellow bubbles) from calibrated subject matter experts and passed the inputs through the model to arrive at the value of outcome variables (blue bubbles) under risk and uncertainty (red rectangles). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

change in outcomes with intervention relative to existing land use systems.

Risks: Risk factors were considered as the probability of occurrence of risk (used to generate a binomial distribution describing whether the respective events occur or not in the simulations) and the magnitude of impacts on expected benefits, if these events occur. We identified two classes of risks. The first was a class of risks that had a random chance of occurring in any given year (random risks). These were simulated by computing the annual likelihood of occurrence and the impact on outcomes when the risks do occur using the *chance_event* function of the *decisionSupport* package. For example, for anthropogenic risk, we computed the chance that community members would encroach into the forest (for various reasons, such as illegal logging, charcoal burning, fuelwood harvesting). We then estimated the magnitude of loss of previously computed benefit streams. The second class of risk factors was conditional risks. For these, the risk events were associated with other events whose occurrence was uncertain. For instance, the risk of the community encroaching on the forest to graze their livestock was determined by the probability that exclosures were ineffective given the community's demand for fodder and the probability of poor implementation of social fencing.

Costs: We categorized costs into 'individual costs' incurred by beneficiaries and 'program costs' incurred by the implementing agency. For the livelihood development activities, the cost of acquiring assets was borne by the implementing agency and calculated only for the first year, while operating costs were borne by the individuals and considered annually over the 25-year period. Opportunity costs were added to the cost per individual. The cost of restoration interventions included the cost of acquiring materials (which was a one-off investment) and recurrent expenditure on technical labour and maintenance. As some labour was provided as in-kind payment by the community, we considered that only a part of the labour costs was paid in cash.

Benefits: For livelihood interventions, we quantified the expected increase in income per household as the main benefit. The beekeeping intervention would provide revenues from the sale of honey. For energy-efficient cookstoves, we accounted for the benefits indirectly as household health cost savings and reduced dry wood harvesting costs. Sheep rearing would mostly provide revenues from the sale of sheep. Poultry farming would provide revenues from the sale of poultry products. Apple trees would generate revenues from the sale of fruits.

For restoration interventions, the benefits were expected to accrue to the entire community and therefore quantified as communal benefits. This assessment targeted provisioning and regulating ecosystem services, since these have direct use values. We then applied a mix of market and non-market pricing strategies. The main benefit expected from ANR and enrichment planting would be the increase in carbon stocks as vegetation regenerates. In addition to regeneration, there would be agricultural benefits from a favourable microclimate, resulting in improved yields for surrounding farmers. To simulate the carbon sequestration benefit of enrichment planting, ANR and exclosure establishment, we used the gain-loss method that sums up changes in biomass stock for the specific land-use category (IPCC, 2006). We determined biomass stocks using two approaches:

-An exponential function adapted from guidelines from the Intergovernmental Panel on Climate Change was used to simulate the annual increment in biomass per replanted tree.

$$biomass\ per\ tree = \frac{a}{1 + exp - (BCEF^{*}(b - c))} \tag{1}$$

where a = maximum marketable volume, BCEF = biomass conversion and expansion factor, b = simulation period, c = stem maturity age.

-We computed biomass growth as a function of the mean annual increment per hectare of regenerated forest area and exclosure:

$$biomass\ per\ ha = mean\ annual\ increment * mean\ biomass\ per\ ha \quad (2)$$

We then quantified the change in carbon stocks that would result from restoration activities (ANR, enrichment planting, and exclosure) using the gain-loss method. Emphasis was placed on gains to estimate the impact of successful restoration. With this approach, we determined the change by the product of the area of land and the incremental biomass stock per unit of land area. The impact of social fencing was used as a proxy for forest areas gained from avoided deforestation and degradation (Eqs. 3& 4).

$$\Delta Carbon\ gain\ from\ avoided\ deforestation\ and\ degradation = biomassstock\ per\ ha * \Delta area_{socialfencing+enrichment} * carbonfraction \quad (3)$$

Where carbon fraction of dry matter = 0.47 (IPCC, 2006)

$$\Delta area_{social\ fencing+enrichment} = avoided\ loss\ in\ forest\ area\ due\ to\ agricultural\ and\ settlement\ expansion + avoided\ loss\ in\ forest\ area\ due\ illegal\ commercial\ logging \quad (4)$$

We also quantified carbon losses from random events of fire and disease outbreaks and calculated carbon accumulation per hectare of restored and conserved forest based on the mean annual increase in carbon stocks (Eqs. 1, 2). We then used the benefit transfer method to determine the market price for carbon.

The impact of exclosure establishment was assessed by valuing the change in the quantity of grass produced when land use shifted from communal grazing to exclosures with cut-and-carry harvesting. The use value of establishing exclosures was determined by the amount of fodder produced in exclosures relative to the amount produced by grazing lands. The non-use value of carbon sequestration was found by calculating the mean annual increment of above- ground biomass (Eq. 2). For investments in soil and water conservation, the avoided-cost method was used to quantify the primary benefit of reducing costs to the community related to removal of sediments from a community dam (Panagos et al., 2015; Cheboiwo et al., 2018).

For each intervention, we quantified the expected net benefits by subtracting the aggregate costs from risk-adjusted benefits (Eq. 5) and then discounted the net benefit to find the net present value (Eq. 6).

$$risk\ scaler = probability\ of\ risk\ occuring \times impact\ of\ risk \quad (5)$$

$$Net\ Benefit_i = \sum_{1}^{n} \sum_{1}^{t} [Total\ Benefit_i \times (1 - risk\ scaler)] - Total\ costs_i \quad (6)$$

where n = number of targeted beneficiary households,
t = number of simulation years.

$$\mathrm{NPV_i} = \frac{\mathrm{NetBenefit_i}}{(1+\mathrm{r})^{\mathrm{t}}} \quad (7)$$

where NPV = Net present value, r = discount rate, and t = year

Step 4: Model parameterization and simulation

We used expert knowledge elicitation and literature review to assign probability distributions for all model variables and operationalize the model. However, expert opinion can be subjective and susceptible to biases such as overconfidence or under-confidence (Hubbard, 2014; Yet et al., 2016). To reduce these biases, we conducted a calibration training of subject matter experts during a model validation workshop. The training aimed to improve the capacity of subject matter experts to make estimates for which they are 90% confident that the actual values lie within the provided ranges. We used Klein's Pre-mortem (Klein, 2007) and the equivalent-bet technique, which have been proven to measurably improve an expert's ability to provide accurate estimates (Hubbard, 2014).

Step 5: Model Refinment

We used Value of Information (VOI) analysis to identify important knowledge gaps where further measurement efforts could provide clarity on the best decision (Wilson, 2015). We did this by computing the expected value of perfect information (EVPI). EVPI represents the opportunity loss that could be incurred by a decision-maker due to lack of information on a specific variable (Felli and Hazen, 1998; Hubbard, 2014). Applied in this way, the EVPI computation can help to determine where further measurements may help reduce uncertainty on decision outcomes. We also applied Partial Least Squares (PLS) regression analysis to the MC simulation results and used Variable-Importance-in-the-Projection (VIP) sensitivity analysis to assess the input parameters (Luedeling and Gassner, 2012). The VIP statistic represents the direction and strength of each input variable's relationship with the output variable (Wold et al., 2001).

3. Results

3.1. Returns from livelihood interventions

Model results for livelihood interventions showed that most interventions would have positive NPVs for the 25-year simulation period. Returns on investments in fruit trees and beekeeping had a 0.4% chance of loss but beekeeping had a wider range of returns than fruit trees (Table 1). Poultry farming and efficient cooking stoves both had no chance of loss but were less profitable than fruit trees and beekeeping. The net present value of returns to sheep rearing had the highest possibility of loss (60%) and the lowest profits of all livelihood interventions.

3.2. Return from restoration interventions

The simulated NPV of ANR cashflows had a possibility of negative returns (Table 1). The distribution showed minor variation over time, with the median return for each year progressively increasing but never exceeding 4000 USD ha^{-1}. VIP analysis of outcomes revealed 9 variables that the projected returns were sensitive to. The impact of ANR on yields in the surrounding agricultural area, market price of carbon, annual rate of deforestation, and viability of carbon marketing were the 4 most highly ranked variables correlated with ANR outcomes (Fig. 4d). VOI analysis revealed that there were no critical knowledge gaps to be filled (Fig. 4b).

The model simulated positive returns on the enrichment planting intervention in 89.8% of model runs. Annual outcomes varied significantly with a high likelihood of losses in the first 5 years after planting. If further clarity on this outcome is needed, priority should be given to reducing uncertainty related to carbon markets (Fig. 5b). VIP analysis highlighted 13 variables with a coefficient value above the threshold of 0.8 (Fig. 5d). The most sensitive variables in this case were strongly related to carbon markets (cost of carbon and risk of lack of carbon markets) and the tree population (annual rate of deforestation, number of replanted trees per ha and risk of wildfires) (Fig. 5d). Grazing land exclosure was the riskiest restoration intervention with a 77.2% likelihood of positive returns. Annual cashflows (Fig. 6c) revealed possibilities of net losses in the initial years and and expectation of breaking even in the 10_{th} year.

Table 1
Summary of returns on Forest Landscape Restoration (FLR) interventions. The range represents the 90% confidence interval of the total Net Present Value (NPV), considering a 25-year simulation period. Also shown are the chance of loss for each intervention and the value of information (VOI) for further measurement for each intervention, expressed as the Value of Perfect Information (EVPI).

NPV in USD (n = 10,000, 90% C.I.)					VOI	
Intervention	Lower bound	Median	Upper bound	Chance of loss	EVPI (USD)	Critical knowledge gap
Beekeeping	1594	4517	10,961	0.1%	0.4	Honey yield per hive
Cookstoves	1165	2008	3140	0%	0	–
Sheep rearing	−1258	−165	1013	60.0%	209	Cost of Labour
Poultry farming	624	1053	1569	0.0%	0	–
High Value trees	1482	4292	8023	0.2%	0.4	Max. fruit yield potential
Grazing land exclosure	−13,119	9800	50,785	22.9%	2000	Biomass maturity age
Assisted natural Regeneration	13,231	20,215	30,286	0%	0	–
Soil water conservation	1104	4141	7401	1.2%	7.9	Rate of soil loss
Enrichment planting	−492	3212	13,852	10.2%	56	Market price per ton of carbon

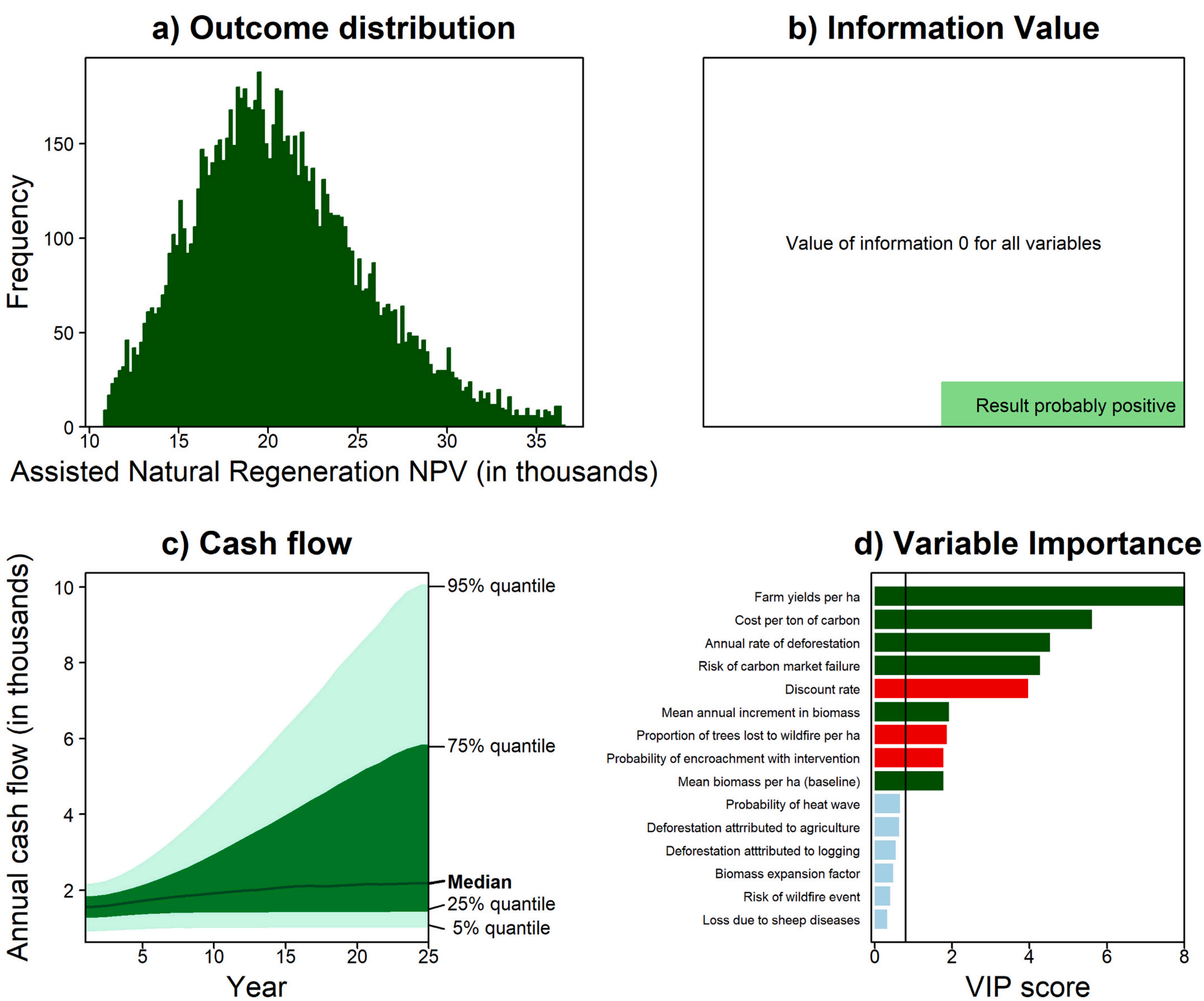

Fig. 4. Projected outcome of the decision to implement ANR in Desa'a (a), high decision-value variables (b), the respective cashflows (c) and important variables (determined by VIP analysis of PLS regression models) (d). The results were produced through MC simulation (10,000 model runs) of ANR performance over 25 years. In the PLS plot, green bars indicate positive correlations of uncertain variables with the outcome variable, while red bars indicate negative correlations. Blue bars indicate variables that did not meet the threshold of the model sensitivity analysis. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

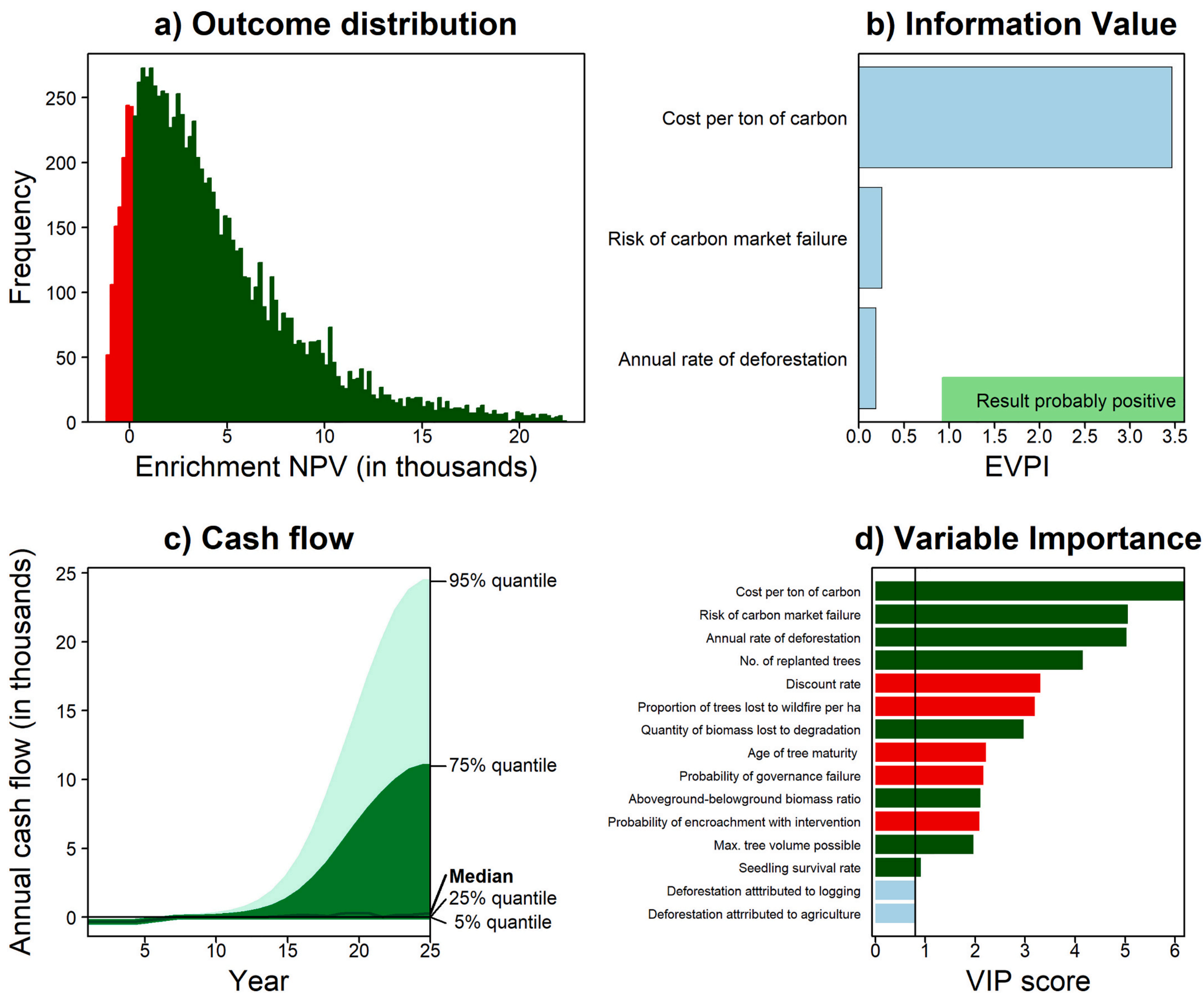

Fig. 5. Projected outcome of the decision to undertake enrichment planting in Desa'a (a), high decision-value variables (b), the respective cashflows (c) and important variables (determined by VIP analysis of PLS regression models) (d). The results were produced through MC simulation (10,000 model runs) of enrichment planting outcomes over 25 years. In the PLS plot, green bars indicate positive correlations of uncertain variables with the outcome variable, while red bars indicate negative correlations. Blue bars indicate variables that did not meet the threshold of the model sensitivity analysis. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Further measurements to pinpoint the maturity age of woody biomass in exclosures (EVPI = 1330 USD) and, to a lesser extent, the maximum carbon stock that can be accumulated in the exclosures and the rate of deforestation would reduce ambiguity for the decision-makers (Fig. 6b). The NPV for soil water conservation efforts had a 98.84% chance of positive outcomes (Fig. 7a). If further clarity is necessary, the analysis identified the rate of soil loss in the forest as a source of uncertainty (Fig. 7b). Despite this uncertainty, outcomes are most likely to be positive. Sensitivity analysis revealed five variables with a significant correlation with the projected outcomes (Fig. 7d).

4. Discussion

4.1. Livelihood interventions

Beekeeping is the most profitable among the livelihood interventions that were investigated. Energy-efficient cookstoves are also promising, although this intervention would not provide direct income, but save on the cost of extracting fuelwood from the forest, improve health and reduce carbon emissions from forest degradation (Grieshop et al., 2011). Indirect income from reduced fuelwood needs and savings on health costs might not be enough financial incentive to encourage community members to adopt energy-saving stoves (Okuthe and Akotsi, 2014). For households targeted for sheep rearing, the enterprise is risky with a 60% chance of incurring losses. This outcome indicates uncertainty, as it does not offer sufficient evidence to support the decision to roll out the intervention. Measurements to gain a better understanding of labour requirements of sheep rearing can help eliminate uncertainty about this outcome. Identifying the ideal number of sheep to distribute to community members for the intervention to make economic sense and the effect of a drought event on sheep rearing ventures can also help to gain clarity on outcomes. Poultry farming is profitable and could effectively provide an alternative source of income for the most resource poor households (Pica-Ciamarra and Otte, 2010). Investment in planting of fruit trees would also generate positive returns, but these returns will not be realised in the first few years, since apple trees take several years to

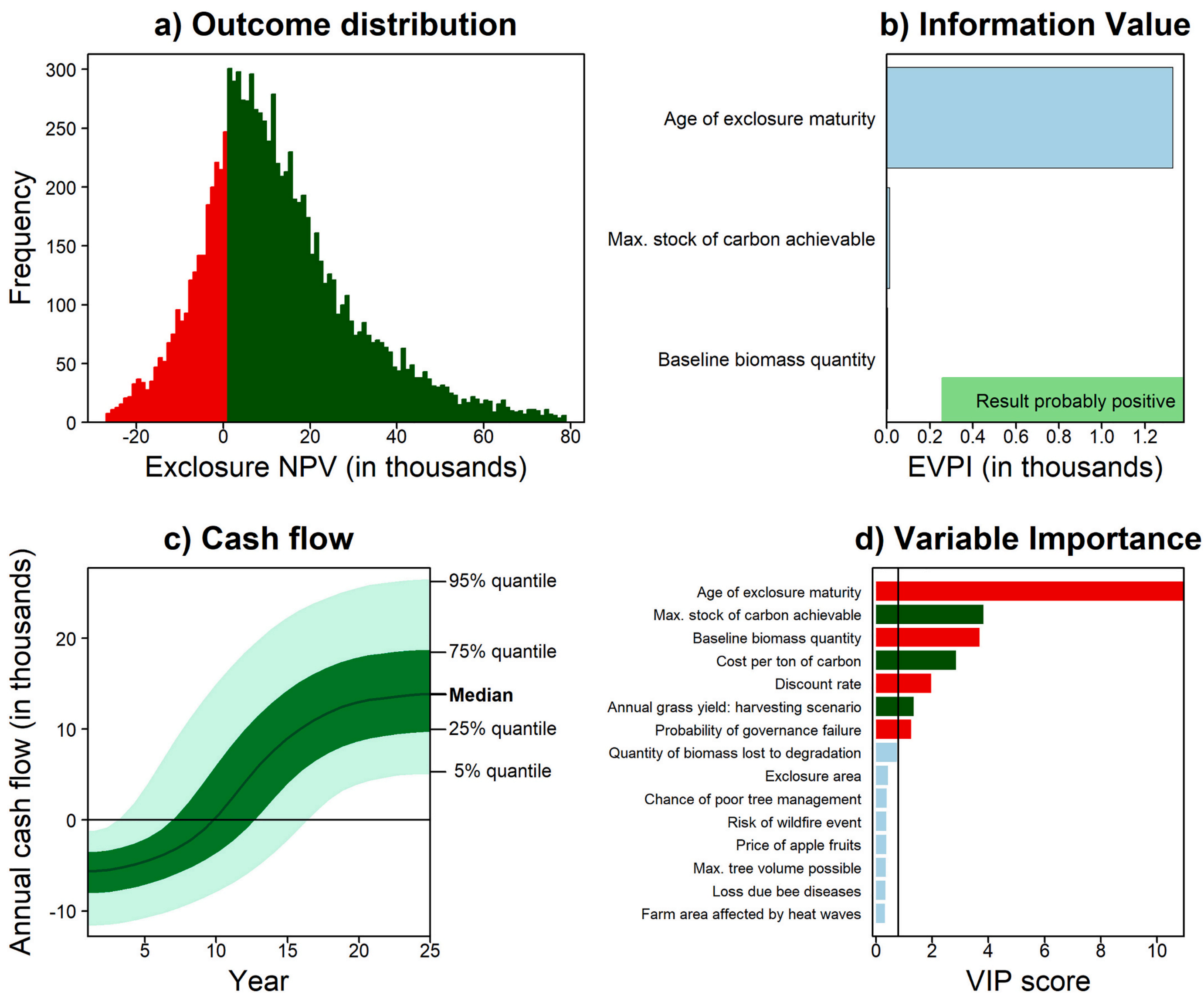

Fig. 6. Projected outcome of improved exclosure management on the economic value of ecosystem goods and services in exclosure (a), high decision-value variables (b), the respective cashflows (c) and important variables (determined by VIP analysis of PLS regression models) (d). The results were produced through MC simulation (10,000 model runs) of 25 years of exclosure performance. In the PLS plot, green bars indicate positive correlations of uncertain variables with the outcome variable, while red bars indicate negative correlations. Blue bars indicate variables that did not meet the threshold of the model sensitivity analysis. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

reach their maximum production potential.

4.2. Restoration interventions

Model results showed that the restoration strategy with ANR accelerates recovery of natural forest by reducing disturbance. Enrichment planting achieves the same outcome but through active replanting in the fragmented forest zones. While our simulations showed that both interventions were likely to have promising outcomes, the likelihood of positive monetary returns was higher with ANR than enrichment planting. This agrees with the results of a meta-analysis of forest restoration interventions in tropical forests. Crouzeilles et al. (2017) report that restoration outcomes measured by vegetation structure and biodiversity were higher for natural regeneration than for tree planting. Our findings on the differences in quantities of sequestered carbon for replanting compared with regeneration are explained by slower rates of accumulation in replanted trees and high quantities of sequestered carbon in old trees (Köhl et al., 2017). Furthermore, the difference in projected returns on enrichment planting relative to ANR is also explained by the differences in costs, as lower implementation costs are incurred with ANR as compared to enrichment planting (Chazdon et al., 2016; Shono et al., 2007). Nevertheless, projected NPVs per ha for both interventions were higher than those of most alternative land uses. This makes both interventions effective and profitable to achieve biophysical outcomes (Pistorius et al., 2017).

VOI analysis revealed that there were no high value variables for the ANR intervention. However, there were variables of importance that would determine the magnitude of positive cashflows. When the effect of restoration on yields in adjacent agricultural lands was considered, we found that the projected returns increased.A study on the effect of increased tree cover on agriculture in southern Ethiopia simulated a 5% increase in wheat production on lands adjacent to reforested forests and hedgerows (Yang et al., 2020). This result is attributed to improved soil moisture, temperature regulation and increased soil nutrient availability for agricultural lands bordering forest.

Exclosure establishment would also generate substantial benefits

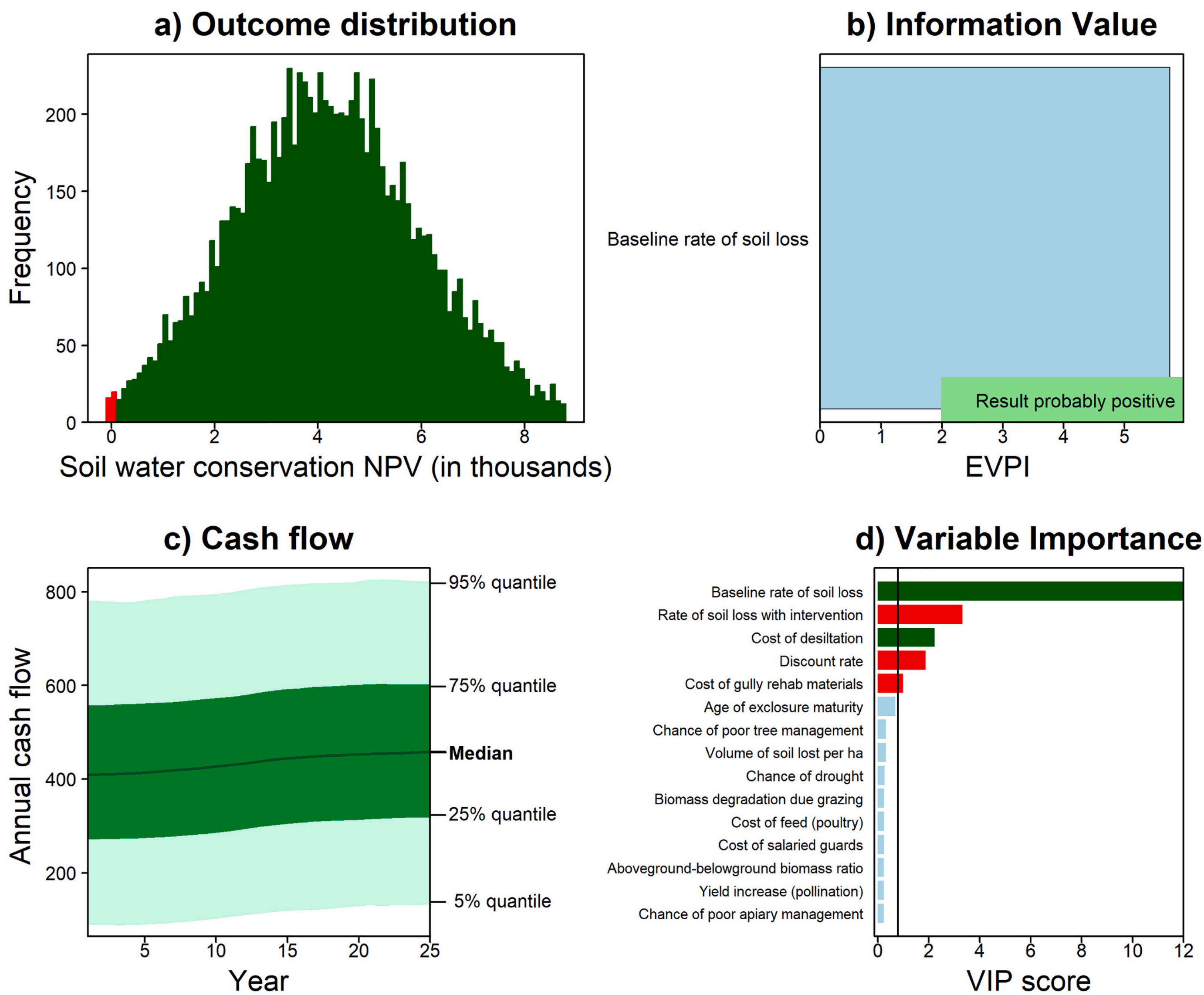

Fig. 7. Projected outcome of introducing soil and water conservation measures in Desa'a. (a), high decision-value variables (b), the respective cashflows (c) and important variables (determined by VIP analysis of PLS regression models) (d). The results were produced through MC simulation (10,000 model runs) of the performance of conservation structures over 25 years. In the PLS plot, green bars indicate positive correlations of uncertain variables with the outcome variable, while red bars indicate negative correlations. Blue bars indicate variables that did not meet the threshold of the model sensitivity analysis. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

when compared to the alternative, a communal free grazing land use system. However, while regulating services are expected to improve with the establishment of exclosure, the impact on feed resources will be negative. Exclosures could create competition for livestock feed resources among community members by restricting access to grazing land (Birhane et al., 2018). Results of VOI analysis showed that achieving greater precision in estimating the time required to achieve maximum biomass accumulation should be prioritized. This knowledge could potentially improve management of exclosures by making the valuation of carbon stock more precise. Nonetheless, the range of outcomes projected by the model brackets the deterministic result projected by Mekuria (2013) (about 3000 USD ha^{-1}) when assessing the changes in regulating ecosystem services following establishment of exclosure on communal grazing lands in Ethiopia. The trend in returns showed that over time, the cash flows increase with exclosure age and level off after the exclosure reaches its production potential. This was also found by Mekuria (2013), who compared biomass productivity in five, ten, fifteen and twenty-year old exclosures with communal grazing land, finding the greatest difference in older exclosures.

4.3. Implications for FLR actors and policy-makers

While FLR is widely expected to have positive socioeconomic outcomes, measurements of ecosystem benefits are sorely lagging behind the recognition that they exist (Matzek, 2018). This is the result of a shortage of technical experts who can address the methodological concerns and philosophical objections that come up when attempting to monetize nature's services. Uncertainty in measurement results from practical challenges in monitoring ecosystem services (de Groot et al., 2010), and the acknowledgement that restoration efforts cannot fully recover the natural 'pre-disturbance' ecosystem functions (Crouzeilles et al., 2016).

For long-term planning of FLR, managers and policy-makers should pay more attention to biological factors. The time lag to production will affect the distribution of returns, hence low returns should be expected in the first few years and greater returns towards the end of the simulation period. Managers therefore need to be prepared to evaluate the outcomes of their interventions during the early phase of their project where implementation costs are incurred, and net losses are likely. A portfolio analysis to identify the best combinations of interventions could help buffer against the risk of losses in the first few years. Also, varietal selection to prioritize tree species that accelerate ecosystem recovery can help minimize losses. It is important for managers and policy-makers to note that socioeconomic factors, i.e. the drivers of deforestation and the viability of carbon trading were more likely to determine whether actual returns matched desired outcomes than the biophysical determinants of returns. Without strategic management, exclosures are expected to lead to a resource constraint for livestock farmers, as they reduce availability of feed resources, but may not be able to offset this effect through positive revenues from carbon credits. Even when paired with cut-and-carry harvesting, this intervention may lead to a net reduction in fodder supply, which may discourage community participation. Incentivizing pastoral communities by providing a livestock insurance policy against drought could help achieve community buy-in and improve revenues from carbon credits. There is also no doubt that successful implementation of FLR programmes requires key socioeconomic mechanisms be put in place to ensure there are clear rights, roles and benefit sharing arrangements between different stakeholders and community members (Yami et al., 2013).

Holistic and stochastic valuation of forest restoration costs and benefits can provide realistic estimates of the plausible ranges of returns of interventions, considering all outcome dimensions that are relevant in a particular context. Since the objectives of FLR programmes can thus be better captured than in traditional evaluations that rely on precise measurements, this method is suitable for accounting for costs and benefits of such programmes. To realistically value ecosystem benefits, FLR actors should base their predictions on expert knowledge of the local context rather than on benchmark estimates carried over from different contexts (Stålhammar and Pedersen, 2017). The use of distributions when estimating the value of variables rather than best-bet estimates avoids overly hopeful predictions that could misguide planning (Luedeling et al., 2019).

The outcomes of this study indicate positive returns for most investments. This is a clear indication that investments in FLR programmes can succeed in reversing degradation in the long term. However, initial costs incurred to establish livelihood interventions, mobilize communities, strengthen social governance structures, and provide capacity building and training can result in net losses in the first few years. Therefore, FLR actors may need significant financial support to see their interventions through to the medium and long term (Pistorius et al., 2017).

4.4. *Limitations of the study*

The study did not explicitly consider the overall socio-economic environment and the challenges that social factors present to implementers of participatory forest management. Insecure land tenure, low levels of technical and technological capacity and a lack of benefit-sharing agreements pose an additional risk to restoration outcomes (Chazdon et al., 2016; Lemenih et al., 2014). For instance, in the case of land tenure, landless individuals may not have access to economic incentives that would discourage over-harvesting of forest resources. Incomplete consideration of land rights may mean that the returns presented here are only applicable to households that own land and have direct access to the benefits. Further consideration of biotic factors may also be warranted. The effectiveness of restoration and choice of restoration approach are linked with the regeneration potential of the species considered. While our analysis did not differentiate between regeneration potentials of the two climax tree species, evidence from previous studies indicated that *J. procera* has low potential for ecosystem recovery and might not be effectively restored by the ANR approach (Aynekulu et al., 2009).

5. Conclusions

Predicting FLR outcomes is a difficult endeavour, since outcomes are often achieved through complex mechanisms with many uncertainties and risks preventing robust decision making. Development practitioners, landscape restoration programme managers and researchers can overcome these challenges by applying stochastic methods and participatory research approaches. Decision analysis tools that apply stochastic impact evaluation are suitable for decision makers who are not only constrained by imperfect knowledge of complex systems, but also need to consider a range of social, economic, and biophysical factors to predict project impacts. The SIE framework enabled us to clearly define the objectives of FLR activities and quantify the expected impacts on land use and land cover trends.

Engagement of subject matter experts, decision-makers and community members enabled us to develop a decision model that incorporated priorities and beliefs of stakeholders and decision-makers. The process provided an avenue for stakeholders to express their uncertainty about the relevant variables, including those considered difficult to measure. Thus, we conducted a robust cost-benefit analysis and presented distributions of plausible decision outcomes to decision-makers. In this way, research outcomes were translated into economic impacts for easy integration into decision-making processes. Future studies may benefit from considering the impact of social governance structures on FLR interventions.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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