Prioritizing Tanzania's agricultural development policy to build smallholder climate resilience

Final report for the Bill & Melinda Gates Foundation Grand Challenges Explorations 22: Risk-explicit and Evidence-based Policy Prioritization (REAP)

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EXECUTIVE SUMMARY

Faced with myriad options, Sub-Saharan Africa policy makers struggle to prioritize actions. Commonly used modeling approaches perform poorly in data scare conditions or focus intently on tools at hand. Policies, by consequence, report 'wish lists', making them a challenge to implement given resource constraints. Here, we evaluate the potential of using an alternative approach, Bayesian Networks (BNs), to prioritize agricultural policy actions, specifically modeling seven 'Investment Areas' listed in Tanzania's Agriculture Sector Development Programme II.

Our probabilistic model generates information that can help prioritize agricultural policy actions in the face of multiple risks. To begin with, it calculates standard performance measures including return on investment (ROI) and net present value (NPV) based on the benefits accrued to smallholders. In our case study, all seven modeled investment areas are predicted to have positive ROIs on average. However, the shape of the ROI distributions across model runs differs among investments and no investment has zero probability of a negative outcome providing information on the likelihood of outcomes and downside risk, respectively. The analysis also delivers information on the investments' resilience by calculating performance metrics under no risk, only climate risk, and climate and social risk scenarios. We found that five of seven investments see an increased ROI under the climate risk scenario compared to the scenario with no risks. Measures of the relative performance under various scenarios helps policy makers prioritize according to their appetite for risk. Such results that evaluate investment performance amongst diverse investment types and assumption of future conditions, indicate BNs are a suitable tool for policy prioritization.

User perceptions were our primary measure of success provided our design objective. Fifteen representative stakeholders verified the results' utility and expressed appreciation for inclusion of oft-ignored concerns such as political risks, though feedback from some was more tempered. Potential users suggested future model iterations should include market shocks, the ability to disaggregate beneficiaries, and non-economic outcomes. Our own reflections mirrored these responses and we identified six additional lessons such as defining a default, but adaptable, model structure and parameter values to lower the bar for use. These reflections together lay out a roadmap to ready this approach to scale broadly in support of policy prioritization.

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1 NEW APPROACHES TO POLICY PRIORITIZATION

Agriculture is the backbone of the economy and the main livelihood activity in most developing countries. In Sub-Saharan Africa, agriculture contributes an average of 20% of the gross domestic product (GDP) and employs more than 50% of the population, often as smallholder farmers (World Bank 2019a). Women comprise 25-60% of the agricultural labor force (Palacios-Lopez et al. 2017) but women-headed households tend to have small farm sizes and own fewer livestock than male-headed households (Tavenner et al. 2019). Agricultural production is also susceptible to climate change, with yields of the majority of agricultural crops in the tropics projected to decrease by 8% to nearly 30% by 2050 (Wheeler and von Braun 2013), even as demand for food will increase by 2050 (Lobell et al. 2008). Thus, agriculture is a key lever for achieving diverse development goals, such as food and nutritional security, decent livelihoods, gender equity, and adaptation.

Many options exist for catalyzing inclusive agricultural transformation. Decision makers could, for example, choose to prioritize:

- Building infrastructure such as irrigation schemes, road networks, or electrification.
- Bolstering the availability of information to farmers through improved extension systems and digital tools.
- Reducing the impact of shocks on livelihoods through services such as social safety nets, agricultural insurance, microloans, and early warning systems.
- Increasing yields and reducing emissions intensity in the face of climate change by developing and incentivizing adoption of adaptive on-farm management practices.

The diversity of options and the complexity of intervention-to-outcome pathways makes prioritizing agricultural policy development and implementation difficult. Decision makers often include all possible priorities in policies, ultimately resulting in unwieldy strategies that cannot be effectively implemented given the limited financial and human resources available. Policy makers need to prioritize. Many modeling frameworks are available to help, but agricultural policymakers in Sub-Saharan Africa rarely utilize them because data are scarce, assumptions are non-transparent, and most models require specific technical capacity (Table 1, Annex A).

The Bill & Melinda Gates Foundation Grand Challenge New Approaches for Strategic Prioritization of Agricultural Development Policies aims to address these difficulties by developing new methods to assist policy makers and implementers in analyzing their options and choosing the most promising approaches to achieving development objectives. In response to this challenge, we propose testing the utility of BNs for agricultural policy prioritization using a participatory, evidence-based, and risk-explicit model. We hypothesize that (i) BNs will allow users to compare various policy options or development interventions, (ii) the incorporation of risk and uncertainty in the modeling will result in more realistic and useful results information to inform decision making shape prioritization, and (iii) the participatory process will increase make stakeholders feel personal investment ed and engagement in this approach. To undertake this test, we focus on the case of agricultural policy for climate change resilience in the United Republic of Tanzania (hereafter 'Tanzania').

Table 1 | Summary comparison of select modeling frameworks. Modeling frameworks differ across important attributes that affect their relevance and likelihood of use for policy prioritization. A more in-depth discussion of the pros and cons of these approaches can be found in Annex A. The REAP project - reported on here - develops and evaluates the use of Bayesian Networks specifically.

Approach	Scale of analysis	Appropriate level of intervention	Model structure	Data needs	Non-economic outcomes	Risk and uncertainty
Bayesian Networks	Complex systems with many actors or characteristics	A wide range, from projects for households and individuals to national policy	One-way or non-recursive, no feedbacks unless in multiple timesteps	Qualitative data and expert opinion can be exclusively used; more complex models require quantitative data; Users can help define model structure	Easy to include and model, often as unobserved or latent variables	Included as probability distributions
Fuzzy Cognitive Maps	Complex systems with many actors or characteristics	A wide range, from projects for households and individuals to national policy	Feedback loops allowed; dynamic and recursive	Only qualitative data can be used; users assign values and define model structure	Easy to include and model	Yes, but uncommon
Agent-based models	Simulated at the agency level to understand system as a whole	A wide range, from projects for households and individuals to national policy	Dynamic and recursive; provides dynamic results	Data resource-intensive; Users define the agents	Yes, but not standard	Yes, but not standard
Household agricultural models	Individuals and households	Projects for households and individuals	No feedbacks; unidirectional relationships	Require extensive empirical data	Can be included; good for gender-disaggregated analysis	Error terms are potentially large with scant data
Computable generalizable equilibrium	Markets within regional or national economies	Regional, national, or international policy change or market shocks	Static results; no solid econometric foundation	Entail significant data demand are technical modeling-centric	Not usually included	Sensitivity analyses
Multi-criteria analysis	Complex systems with many actors or characteristics	A wide range, from projects for households and individuals to national policy	No feedbacks; unidirectional relationships	Data and expert knowledge can be used in combination, though data are not required	Easy to include	Included as probability distributions

2 THE TANZANIA CONTEXT

Tanzania's agriculture and climate change context is indicative of countries across the continent. The economy depends heavily on agriculture: in 2020, agriculture contributed 28% of Tanzania's GDP and employed 65% of its workforce (Chuwa 2020). Approximately 7.8 million households are directly engaged in agriculture, the majority of which are smallholder farmers producing crops or livestock. Smallholder farms account for 90% of the cultivated lands in Tanzania and their use of inputs remains low; inorganic fertilizers are applied to only 8% of the nation's cropped area, and improved seeds are grown on about 21%. Fully irrigated areas are virtually non-existent among smallholders and comprise less than 0.7% of total national agricultural land (FAO 2016). As such, the Tanzanian national economy and the livelihoods of the majority of its population are directly reliant on the natural resource base, which are threatened by climate change.


Photo: C. Schubert (CCAFS)

Climate change impacts in Tanzania will largely be felt in changing rainfall patterns across the country. Although changes in mean annual rainfall are likely to be relatively modest (Luhunga et al. 2018), variability in the timing and intensity of rainfall will increase (Chamberlin et al. 2009). Increased variability in rainfall impacts the livelihood of Tanzania's smallholder farmers, fishers and pastoralists through uncertainty in planting dates and failed harvests, changing lake levels, and difficulty in managing traditional grazing regimes (Conway et al. 2005). Climate change is also increasing the frequency and severity of extreme events in the region, including both droughts and heavy rainfall (Wainwright et al. 2020), as well as climate-related pest outbreaks such as the 2020 locust plague (Meynard et al. 2020). Adapting to and planning for climate change impacts is thus of critical importance for Tanzania's agricultural sector.

The importance of agriculture to Tanzania is evident in its policy. Tanzania's Vision 2025 (1995) identifies agriculture as a key development priority. The Ministry of Agriculture (MoA) created the Agricultural Sectoral Development Strategy (ASDS - 2001) and the Agricultural Sector Development Programme (ASDP - 2006) to guide growth in line with Vision 2025 (Figure 1). Furthermore, Tanzania became a signatory to the international Comprehensive African Agricultural Development Programme (CAADP) compact in 2010, which sets out targets for agriculture sector spending and development on the continent.

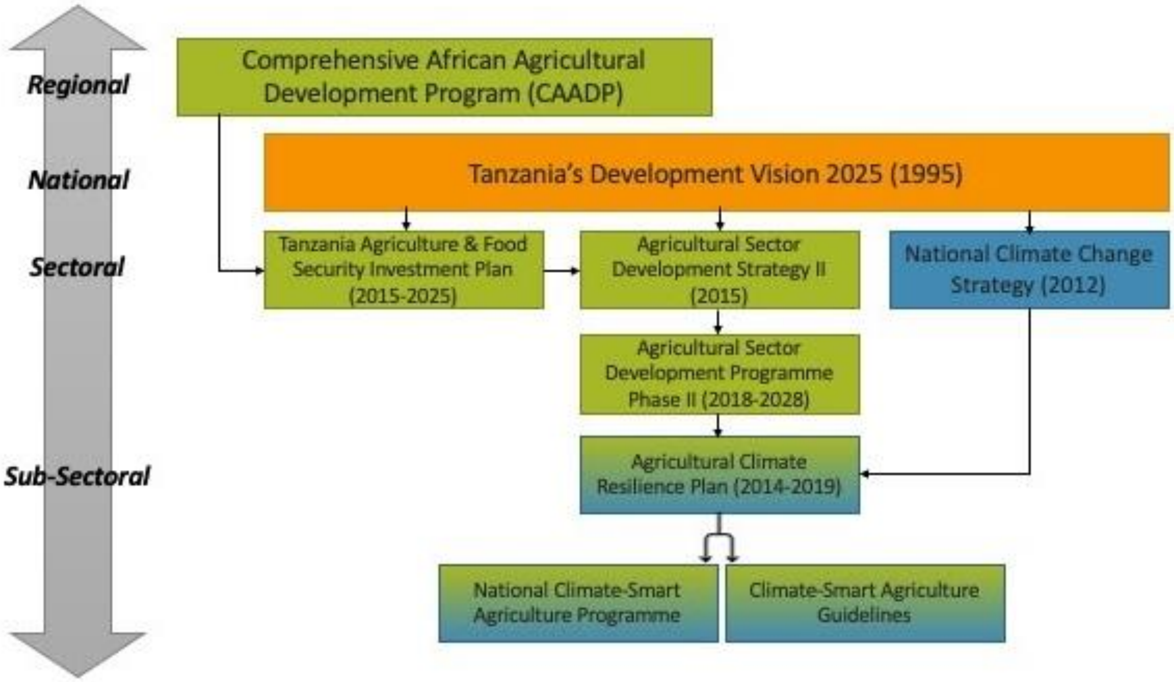


Figure 1 | Tanzanian policies and strategies relating to climate change (blue) and agriculture (green) across scales. Arrows indicate where policies explicitly support implementation of a higher-level policy or program.

Climate change is becoming increasingly prominent in Tanzania's governance. Climate change issues in Tanzania are the responsibility of the Division of Environment (DoE) within the Vice President's Office. Tanzania does not yet have an explicit national climate change policy, but several overarching strategies have been established. The 2012 National Climate Change Strategy (NCCS) aims to support the national Vision 2025 objectives via climate change adaptation and mitigation action, as well as support Tanzania's commitments to the UNFCCC. The NCCS outlines broad adaptation options for each vulnerable sector in the country. Within the agricultural sector, the NCCS promotes resilience to climate change through adaptive crop varieties and agricultural practices.

In response to the NCCS, the MoA put forth the 2014 Agricultural Climate Resilience Plan (ACRP) to provide a roadmap for meeting the objectives of the NCCS, the ASDS, and Vision 2025. The ACRP prioritizes four action areas:

Action Area 1: Improving agricultural land and water management
Action Area 2: Accelerating the uptake of climate-smart agriculture (CSA)
Action Area 3: Reducing the impact of climate-related shocks
Action Area 4: Strengthening knowledge systems

Several sub-sectoral documents were subsequently developed under the auspices of the ACRP to guide implementation of these action areas, particularly Action Area 2. In 2017, the National Climate-Smart Agricultural (CSA) Programme and Climate-Smart Agriculture Guidelines were issued to support the implementation of CSA in the country. The ACRP also greatly influenced the development of the 2015 Agriculture Sector Development Strategy II and the Agricultural Sector Development Programme Phase II (2018-2028); several of the ACRP Action Areas became strategic investment areas within the ASDP II (Table 2).

Table 2 | Key agricultural climate resilience topics in Tanzanian policy development. Dark green indicates a main strategic area, light green indicates one or more mentions of the topic, and gray indicates unmentioned topics.

			Agricultural climate resilience topics					
Title	Year	Dom ain	Land & soil manage-ment	Irrigation & water harvesting	Climate-smart agriculture	Improved varieties	Climate information services	Climate risk reduction
ASDS	2001	MoA						
NCCA	2012	DoE						
ACRP	2014	MoA						
ASDP II	2018	MoA						

At the close of the ACRP in 2019, stakeholders convened to determine the need for a second phase of the ACRP to continue addressing climate change in the agricultural sector. The ability of the ACRP to set priorities and channel donor interest was a standout achievement of the policy, particularly evidenced by the growth of CSA projects in the country (MoA 2021). The ACRP successfully influenced the development of the Phase II ASDP, which included nearly all of the climate-resilient topics identified in the ACRP. In light of this, stakeholders opted to conduct an analysis of the ASDP II policy to determine whether it alone was sufficient to address climate change adaptation and resilience in the agricultural sector.

The ASDP II identifies 23 Priority Investment Areas for agricultural development in Tanzania. Seven of these priority areas align with opportunities promoted for climate resilience in Sub-Saharan African agriculture (Table 3). The presence of these seven widely promoted opportunities implies that the analysis results are likely generalizable to African geographies and policies outside of Tanzania. Therefore, the model developed here while specific for ASDP II and Tanzania is likely widely relevant to additional geographies and agricultural policies.

Table 3 | ASDP II Priority Investment Areas relevant to climate change.

Priority Investment Area	Technologies or interventions discussed	Target value chains or regions	Five-year budget (millions)
1.1 Land and water management	Conservation agriculture, reduced tillage, fertilizers, afforestation, agroforestry, fodder trees, mixed crop-livestock systems, early warning systems	None specified	TSh 196,725 USD 87
1.2 Irrigation development	Irrigation, water harvesting, conservation agriculture, enhanced soil cover, run-off management, reduced tillage, organic mulching	Crops	TSh 976,703 USD 434
1.4 Water for livestock and fisheries	Charco dams, aquaculture ponds and cages, pasture improvement, seaweed cultivation	Livestock, fisheries	TSh 788,782 USD 351
1.5 CSA Climate-smart agriculture	Improved seeds and breeds, early warning systems, conservation agriculture, weather forecasting, Good Agricultural Practices (GAPs), capacity building	None specified	TSh 52,331 USD 23
2.1 Agricultural extension system	Conservation agriculture, Good Agricultural PracticeGAPs, integrated pest management, improved seeds, fertilizers, improved feeds, vaccines	All	TSh 4,734,493 USD 2,104
4.9 Agricultural information services	Mobile agricultural advisory services, call numbers, early warning systems, capacity building	None specified	TSh 6,373 USD 2.8
4.10 Microfinance	Access to microcredit, microfinance, farmer cooperatives, warehouse receipt systems	None specified	TSh 7,067 USD 3.1

3 DEVELOPING A BAYESIAN NETWORK

A BN is a probabilistic modeling framework commonly used in financial and risk analysis, computer science, and natural resource management because of their flexibility to represent the world, their ability to formally integrate qualitative expert opinion and quantitative data, and their handling of uncertainty (McCann et al. 2006). Essentially, Bayesian networks are directed acyclic graphs (DAGs) that represent the relationships among variables as conditional probabilities. The graphical model defines the model's structure and our assumptions about how the variables (i.e., nodes) in the model relate to each other. The arrows between the nodes represent a direct influence of one node on another. Each node is parameterized based on the probabilities of events given the variable(s) that influence it (i.e., its parents) and distributions of the outcomes.

For a BN to be used for policy prioritization, it must represent the causal relationship between policy options and desired outcomes. The primary goal of the ASDP II is "increased and sustainable productivity of agricultural commodities to improve Tanzanian livelihoods," while the goal of the ACRP is to mitigate climate risks in the agricultural sector. Both policies target the activities of smallholder farmers through both on-farm practices and service provisions to achieve these outcomes. The basic policy-outcome pathway we modeled is through changes in smallholder farmer incomes, resilience and greenhouse gas emissions from adoption of technologies and/or services promoted by policy options.

The ASDP II policy options are presented as Priority Investment Areas. Therefore, we used an existing probabilistic investment model, which predicts project benefits (e.g., return on investment) according to implementing risks as our starting point (Yet et al. 2016). The model's structure is based on financial project evaluation methods that describe causal relationships among project activities and monetized benefits (e.g. increased yield for farmers, desired externalities). The model also includes realities of project implementation in its estimate of project value, including risks of budget overruns or project mismanagement. We extended this model to deal specifically with the climate hazards targeted by the ACRP (e.g., droughts, floods, and pests and diseases) as well as including valuation of climate change mitigation benefits (Yet et al. 2020). The resulting model is therefore able to address the goals of productivity, resilience, and climate change mitigation of ASDP II investment areas.

The REAP model elaborates the policy-impact pathway with five main components: impacts, adoption, costs and budget, risks, and outcomes (Figure 2 and more detailed Figure B1). Each model component and its data requirements are described in detail below, and data sources are listed in Table 4.

Impact

Each Priority Investment Area in the ASDP II specifies a portfolio of interventions meant to increase agricultural productivity and climate change resilience in Tanzania (Table 2). The monetized productivity impact is calculated as the changes in farming household income due to adopting these interventions multiplied by the number of adopting households over time. Potential changes in yields for targeted households were estimated using the Evidence for Resilience Agriculture (ERA) database, which collates data from more than 2,000 peer-reviewed research papers that assess the impact of climate-resilient agricultural practices on productivity, resilience, and mitigation outcomes at the farm level in Africa. For each targeted farming system, such as livestock, semi-arid, maize, or a combination of systems, the mean and variance of the change in yields were computed according to best practices for meta-analysis (Rosenstock et al. 2015). This distribution of outcomes was then used to assess how income changed for adopters as well as the level of uncertainty around that change, assuming that in smallholder farming households, the majority of income is derived from on-farm activities.

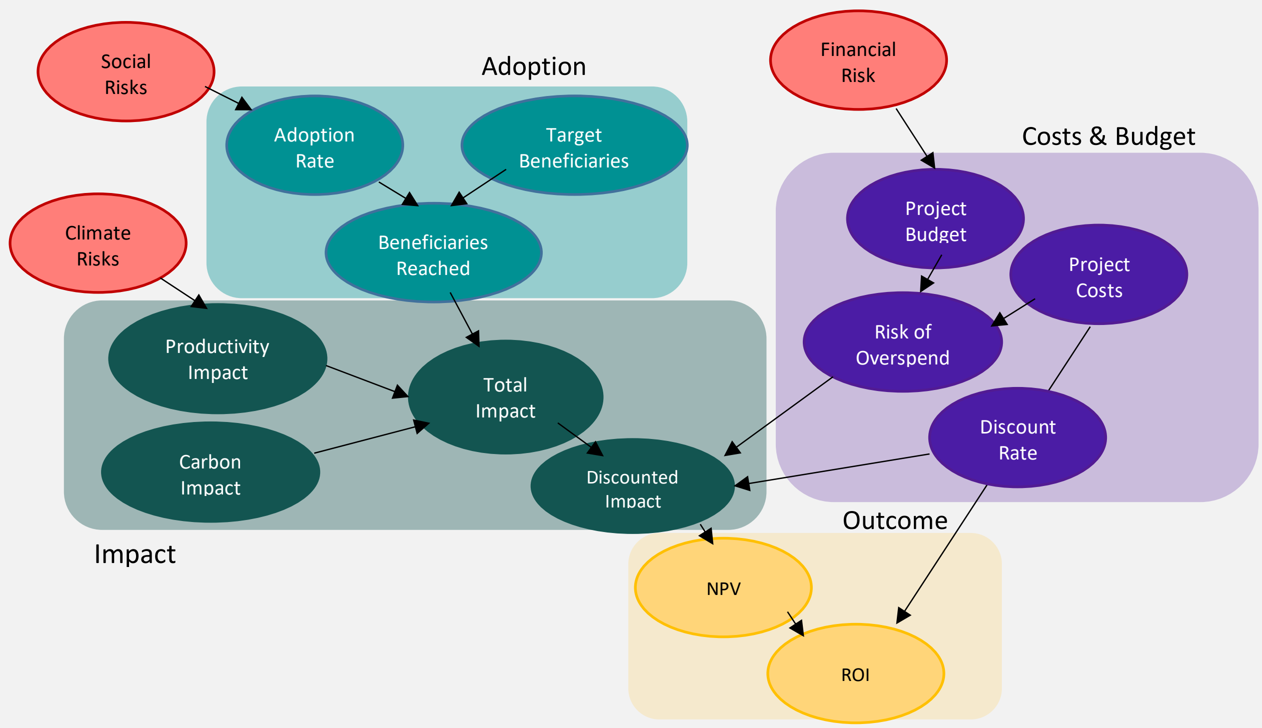


Figure 2 | A simplified Bayesian network model of impacts on the Agricultural Sector Development Programme Phase II Priority Investments

In addition to changes in agricultural productivity due to the implementation of policy options, we also estimated climate impacts in the form of carbon dioxide equivalents and monetary benefits. We determined changes in the greenhouse gas balance at the farm level for the technologies and targeted systems identified for each priority investment area in the ASDP II using the Ex-Ante Carbon-balance Tool (FAO 2019). Resulting changes in carbon emissions were then monetized using a distribution of possible values per ton of carbon dioxide to account for the social costs of carbon and uncertainty in the future carbon markets (World Bank Group 2017).

Adoption

The number of adopting households over the lifetime of the ASDP II investment was modeled using the Bass model (Yet et al. 2020, Bass 1969). The Bass model estimates the diffusion of innovations in a society and approximates the adopters at each time step, which in this case is a year. The model includes three key parameters: the saturated number of adopters, a coefficient of innovation (P), and a coefficient of imitation (Q). The saturated number of adopters counts the target beneficiaries. To calculate the potential number of target beneficiaries, we divided the total budget of the investment in the ASDP II by an estimated cost-per-beneficiary in US$ per household based on similar agricultural development projects (World Bank 2019b). The coefficients of innovation and imitation were assigned according to a typology of anticipated functional responses of adoption (Annex C). For example, projects that can quickly and directly reach numerous target beneficiaries will have a high coefficient of innovation, whereas those that take longer to start like infrastructure projects will have a lower coefficient of innovation. Technologies or practices that can be transmitted horizontally between potential beneficiaries receive a high coefficient of imitation. Technologies such as agricultural insurance, digital extension, improved seeds, and other 'single change' options are thought to have a high likelihood of indirect adoption, whereas those that involve many changes, such as conservation agriculture or a system of rice intensification, have lower coefficients of imitation. Varying these parameters affects the adoption curve, the number of beneficiaries each year, and hence the policy's overall impact.

Costs and budget

Two main financial factors affect an investment's impact: budget and costs. The project's budget is the amount of money to be spent per year as stated in the ASDP II. For simplicity, we assumed that annual spending was the same across the five-year duration of each investment, although more complex budgeting cycles could be accommodated. Annual costs were modeled as having the same mean as the project budget, but a higher variance to account for fluctuating spending across project years. If costs exceed the project budget, the monetized benefits are reduced by this amount.

Risks

The model integrates three major risk types: climate, social, and financial risks. Climate risks included droughts, floods or heavy rainfall, and outbreaks of pests and disease, which are the main climate shocks that impact agricultural systems. For each climate risk, the frequency, or likelihood of occurrence, was estimated using the historic frequency of shocks that were significant enough to impact agricultural productivity on a national scale. In Tanzania, significant droughts occur about once every five years, meaning that the likelihood of occurrence in any year is approximately 20% (Arce & Caballero 2015). Pest outbreaks, including novel pests such as the Fall Army Worm, befall Tanzania with a similar frequency, while heavy rain events that cause large-scale disruption tend to be less frequent, happening about once in 20 years.

If a climate shock occurs, smallholder farmers will be affected. The risk impact was modeled differentially for adopters and non-adopters of the policy's key interventions, with a uniform distribution of potential agricultural losses between 0%, or no loss, and 100%, or total loss. If the technologies or interventions strengthened resilience to the climate shock, the impact was lessened; for instance, the adoption of drought-tolerant crop varieties should reduce the impact of a drought on yields. If not, the risk impact was the same between adopters and non-adopters; for example, participation in an irrigation scheme would not directly decrease vulnerability to a pest outbreak. Risk impacts were assigned to each policy option according to a typology based on the magnitude of impact and the certainty around that impact (Annex D).

Social risks can also reduce the impact of policy or investment options. We included three main types of social risk in our model: political instability, social conflict, and poor project governance. Political instability, such as post-election violence, and social conflict, such as violent extremism or tensions between farmers and pastoralists, were modeled as slowing the rate of adoption of policy or project interventions due to displacement or uncertainty about the future. Poor project governance, for example because of corruption, was modeled as diminishing the total number of beneficiaries that could be reached within the investment's budget. We arrived at the frequency of these risks using data on political instability and social conflict in Tanzania as well as the relative performance of Tanzania on scores for Rule of Law and Control of Corruption in the Worldwide Governance Indicators (Kaufmann et al. 2010).

Finally, we modeled financial risk that might constrict the project's overall budget, such as altered donor objectives, donor responses to political circumstances, or changing national political priorities. For example, in 2021, the United Kingdom dramatically curtailed official development assistance (Sample 2021), disrupting funding for new and ongoing projects, and in 2016, because of the disputed Zanzibar election results, the United States government reduced development assistance to Tanzania (BBC 2016). The risk of budget cuts was modeled as a normal distribution with a mean of X. If a budget cut happens, the project's budget drops by an amount also modeled with a normal distribution to account for uncertainty in potential budget cuts. Project costs were not automatically reduced, increasing the risk of overspending.

Outcomes

The REAP Model evaluates policy options in terms of net present value (NPV) and return on investment (ROI). In each year of the policy implementation cycle, accrued monetized impact is reduced by any project overspend. Net returns (R) is calculated as current year's net impact (impact - costs in that year) discounted using a distribution of possible discount rates (d).

$$R_t = \frac{(Impact_t - Overspend_t)}{(1+d)^t}$$

At the end of the policy implementation cycle (t= 5 years), NPV is calculated as cumulative discounted net returns and the ROI is calculated as the ratio of the cumulative discounted benefits (NPV) to the cumulative costs.

$$NPV = \sum_{t=1}^{5} R_t$$

$$ROI = \frac{NPV}{\sum_{t=1}^{5} Costs_t}$$

The percent chance of producing a positive NPV or ROI for each scenario is also calculated.

Model implementation

The model was developed and implemented using AgenaRisk software (AgenaRisk 2020). Models were parameterized for each of the identified ASDP II climate-relevant Priority Investment areas using a combination of external data sources and expert opinion (Table 4). The models were run for a five-year investment cycle as described in the ASDP II (Figure B2).

Each policy option was evaluated in four different risk scenarios. The first scenario lacked any risks so we could compare the risk-explicit policy evaluation with conventional analyses that do not consider risks. We also evaluated each ASDP II option in scenarios considering climate risks only, social and financial risks only, and finally, with all risks.

Stakeholder Engagement

In order to assess the utility of both the modelling approach and the REAP outputs for prioritizing agricultural policy options, we engaged stakeholders directly involved in the process of formulating the Phase II Agricultural Climate Resilience Plan in Tanzania. These stakeholders participated in the December 2019 ACRP II workshop in Dar es Salaam, and then were engaged via survey instruments upon model completion (Annex E). We requested detailed feedback from 15 stakeholders, representing the government, development, research, and the private sector. Stakeholders were asked about the usefulness, adequacy, and usability of the model and its results, as well as about any conceptual or informational gaps. Of the respondents, 50% were men and 50% women. Half of respondents were involved in agriculture and climate change research, 20% were government officials, and 30% acted as donors or implementors in the development sector. All feedback was transcribed and coded for analysis of key themes related to the usefulness, adequacy, and usability of REAP.


Photo: S. Kilungu (CCAFS)

Table 4 | Parameters and data sources for the REAP Model

Model Parameter	Data type	Data Source
Costs and budget		
Project total budget	Fixed integer	ASDP II
Project yearly budget	Truncated normal distribution	ASDP II
Cost per beneficiary	Truncated normal distribution	World Bank CSAIPs (World Bank 2019b)
Evaluation period	Fixed integer	ASDP II
Yearly cost	Truncated normal distribution	ASDP II
Discount rate	Truncated normal distribution	World Bank CSAIPs (World Bank 2019b)
Adoption		
Total targeted beneficiaries	Truncated normal distribution	Calculated
Coefficient of innovation	Truncated normal distribution	Project typologies (Annex B)
Coefficient of imitation	Truncated normal distribution	Project typologies (Annex B)
Impact		
Baseline income	Truncated normal distribution	*Economic Lives of Smallholder Farmers* (Rapsomanikis 2015).
Relative impact	Normal distribution	ERA
Greenhouse gas balance	Normal distribution	ExACT and literature
Carbon price	Truncated normal distribution	*Social Cost of Carbon* (World Bank Group 2017).
Risks		
Risk of drought	Truncated normal distribution	Acre & Caballero 2015
Impact of drought	Uniform distribution	Risk typologies (Annex C)
Risk of floods or heavy rainfall	Truncated normal distribution	Acre & Caballero 2015
Impact of floods or heavy rain	Uniform distribution	Risk typologies (Annex C)
Risk of pests or diseases	Truncated normal distribution	Acre & Caballero 2015
Impact of pests or diseases	Uniform distribution	Risk typologies (Annex C)
Risk of budget cuts	Truncated normal distribution	Expert opinion
Risk of poor governance	Truncated normal distribution	Worldwide Governance Indicators
Risk of conflict	Truncated normal distribution	Worldwide Governance Indicators
Risk of political instability	Truncated normal distribution	Worldwide Governance Indicators

4 PERFORMANCE OF THE ASDP II PRIORITY INVESTMENTS

The model predicts all ASDP II priority investment areas will have positive mean ROIs across all risk scenarios. Given their total budgets, estimated number of beneficiaries, and estimated impact per beneficiary, all investments are projected to increase agricultural productivity for smallholder farmers in Tanzania on average. However, the investments differ significantly in the distribution of the potential ROIs (Figure 3). Investments with a low cost per beneficiary and a relatively small impact per beneficiary such as agricultural information services or increasing access to credit and microfinancing have wide distributions in their ROIs, whereas the ROIs of costly projects with more robust benefits for farmers such as irrigation development or enhancing the water resources for livestock have much narrower distributions. However, no investment has zero probability of a negative outcome (ROI < 0), and the investment that is least likely to yield a negative result is sustainable land and water management (Table 5).

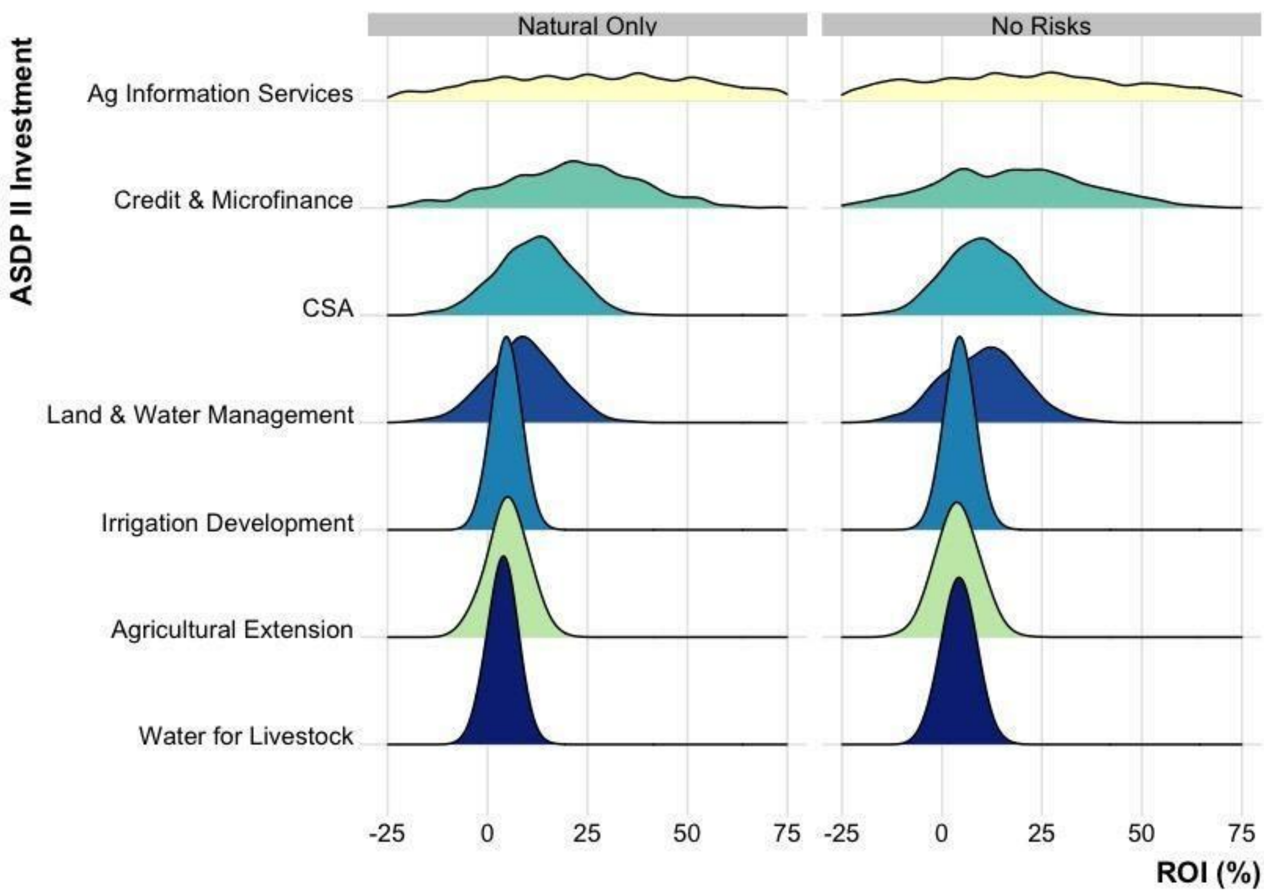


Figure 3. | Distribution of return on investment outcomes from ASDP II investments under scenarios with and without climate risks

Table 5 | ASDP II Investment performance with and without climate risk

Investment	Budget (M USDs)	Target benefici-aries	Cost per beneficiary (USD)	Change in beneficiary income (%)	ROI, no risks (%)	ROI, with climate risks (%)	Chance of a positive NPV (%)
1.1 Land & water management	87	320,000	275	40	9.9	9.5	95.0
1.2 Irrigation development	434	868,000	500	45	4.3	4.8	96.6
1.4 Water for livestock & fisheries	351	609,000	575	55	4.0	3.7	89.0
1.5 CSA	23	115,000	200	30	10.5	11.1	91.5
2.1 Agricultural extension systems	2,104	5,000,000	421	20	4.0	5.0	85.5
4.9 Agricultural information services	2.8	47,000	60	15	18.5	30.1	82.5
4.10 Microfinance services	3.1	27,000	115	20	16.8	20.5	88.8

We assessed the performance of investments for agricultural climate resilience by comparing the ROI with and without considering climate risks. Of the seven investments modeled, five see an increased ROI under the climate risk scenario compared to the scenario with no risks. Investment in agricultural information services shows the largest jump in its ROI with climate risks. In the absence of climate risks, the use of weather or planting date information is unlikely to boost the performance of smallholder farmers significantly. However, if agricultural information systems can accurately inform farmers of seasonal rainfall amounts, likely planting dates, or impending pest outbreaks, the benefits of using such systems can be dramatic. The ROIs of other investments, including the development of irrigation infrastructure, CSA, improved agricultural extension systems, and broader access to credit and microfinance services, also rise under the climate risk scenario.

All of the modeled options are likely to have positive returns. The chances of a positive NPV exceed 80% in all cases. These results contrast with investments modeled in a similar approach for Mali and Cote d'Ivoire, where multiple investments have chances of NPV below 50% (World Bank 2019c, World Bank 2019d). The results found here can be explained by the favorable assumptions used to run the simulations in Tanzania. For example, the cost per beneficiary for an agricultural information service project is only 60 USD and has the potential to change incomes by 15% on average. This would be a highly efficient and effective program by any standard. Also, the Mali and Cote d'Ivoire investment plans were much more specific about how many beneficiaries were to be targeted, in what regions and for which value chains. The lack of specificity in Tanzania's ASDP II required many more assumptions to be made by the modeling team, potentially resulting in more favorable assumptions. The leverage assumptions have on the results highlights the importance of credible and quality input data.

5 STAKEHOLDER FEEDBACK

Photo: C. Schubert (CCAFS)

Stakeholder perceptions of the modeling approach and results were the primary measuring stick, given our design objective was to create a useful and relevant model that informs and prioritizes policy. Overall, the 15 stakeholders who provided feedback on the modeling process and results found the outputs of the REAP model valuable for prioritizing ASDP II policy options. All stakeholders stated that they felt the results were useful for policy prioritization, although 25% of respondents qualified their statements by saying, for instance, “yes and no” or “possibly yes”. Stakeholders stated that the model was generally comprehensive and allowed for the comparison of diverse options related to agriculture and climate change adaptation. The key advantage of the REAP model according to stakeholders is the inclusion of risks, particularly social and political risks to policy and project implementation. Indeed, one development practitioner responded as follows:

“Political and policy instability [are main components] because these two ‘big fish’ do significantly affect any investment, especially demoralizing donors and/or implementing project partners and often the beneficiaries, the farmers, too.”

This stakeholder was referring to the impact of political instability both within Tanzania and within donor countries on the flow of funding for agricultural development. The stakeholder pointed out that Tanzania is no longer considered a priority country for the United States Government's Feed the Future Initiative. In addition, several stakeholders stressed the importance of macroeconomic risks, such as price shocks or a lack of access to export markets, and suggested that these could be included in future versions of the model.

Stakeholders were split as to whether the REAP model is adequate to assess the climate resilience benefits of the ASDP II policy options. Approximately 25% of respondents felt the model was adequate, 25% felt it is not, and the remaining 50% felt the model falls somewhere in between. Some stakeholders felt that the model sufficiently addresses climate resilience because the policy options modeled strengthen climate resilience and show changes in NPV and ROI with and without climate risks. Others felt that the model lacks a "clear definition of resilience" and a "link between policy and enhanced resilience". While our approach to resilience focused on how policy options change economic outcomes in the face of shocks, some stakeholders pointed out that gradual changes in climate parameters are also important to model.

When asked how the model could be improved for prioritizing climate change and agricultural policies, several distinct directions emerged (Table 5). One is to **model markets** by including elements such as market availability, labor, value chains, farm gate pricing, economic shocks, and macroeconomic policy. A second emergent direction involves increasing the model's **social complexity** by disaggregating beneficiaries by gender or other social dimensions, adding context specificity in outcomes, and including more complicated adoption models that also allowed for disadoption of interventions. The final suggestion that emerged from stakeholder feedback is to include **non-economic outcomes**, particularly those with strong relevance to climate change resilience. A food systems researcher shared the following advice:

" Financial impacts alone may not necessarily be helpful in understanding smallholder subsistence farming systems. There are other impacts that are non-monetary, linked to livelihoods that promote resilience."

Suggested outcomes included impacts on ecosystem health and services, natural resource bases, and the adaptive capacity of beneficiaries.

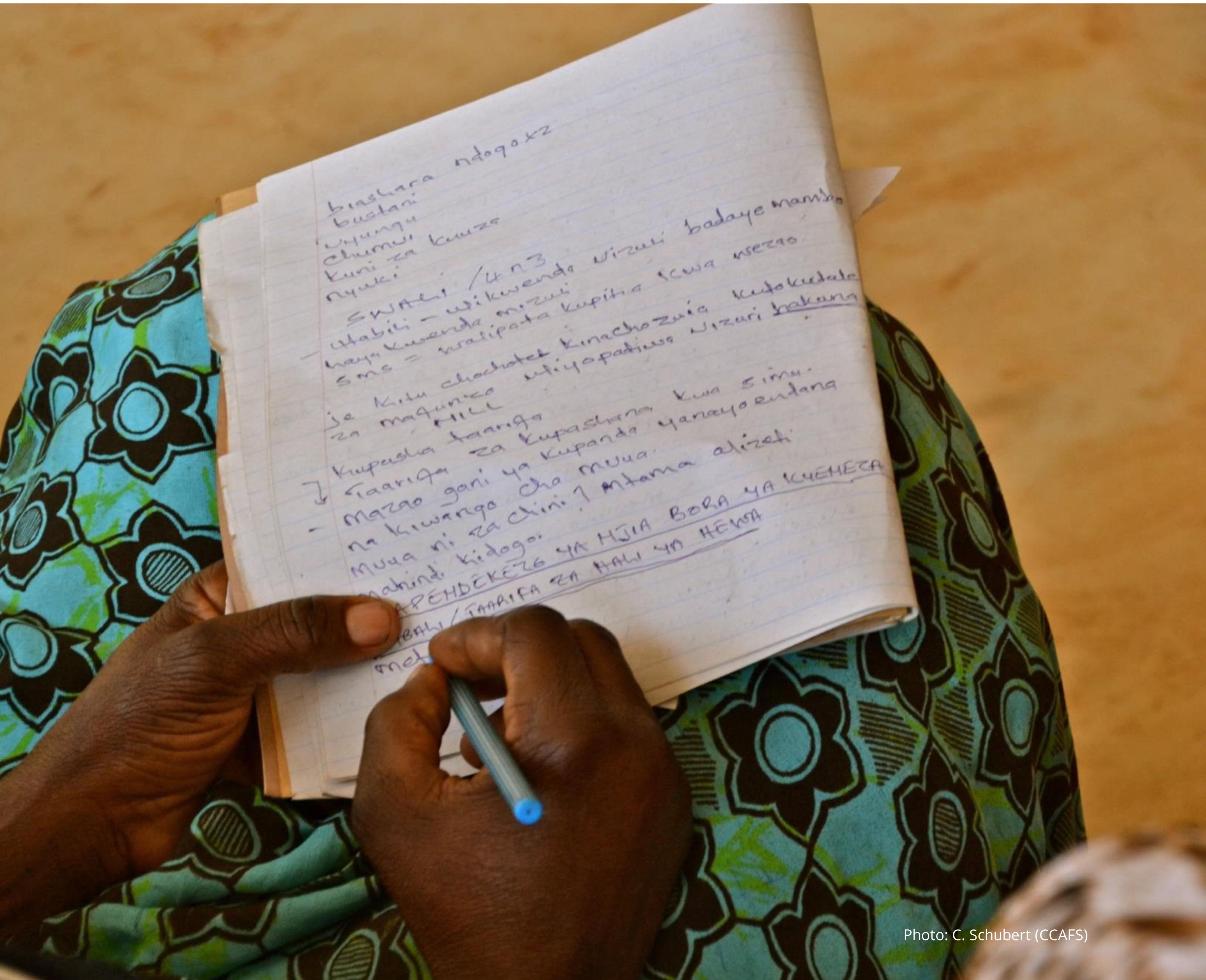
Table 6 | Perception of model parameters by stakeholders. In other words, what should be retained, expanded or removed from the model.

		Included	Not included
Stakeholder perception	Retain or add	Risk assessment, uncertainty, economic outcomes, change in NPV and ROI, mitigation, political instability, benefits to farmers, yield	Non-economic outcomes, trade-offs, disadoption, gender, economic shocks, national budget cycles, market availability, capacity building, gradual changes, value chains, labor, ecosystem services and natural resources.
	Remove	Mitigation, carbon costs, greenhouse gas emissions	

The number of parameters, complexity of relationships between policy and impact, use of quantitative distributions for model parameters, and presentation of outputs across multiple scenarios including uncertainty led some stakeholders to feel that model was difficult to understand. For example, a program officer at a donor organization shared the following reflection:

"I certainly think the model is useful and could be useful in the work of my office. However, it is not intuitive to me as someone who is not a researcher or policy maker."

For the model to be useful for policy prioritization, it may be important to increase the usability of either the model interface itself, or the way that stakeholders interact with the model outputs. Finally, several stakeholders had concerns about the data sources used to parameterize the model. Although most felt the data choices were adequate, there was a call to harmonize data inputs with data collected by national data collection systems in Tanzania to increase the usefulness of the model, particularly for future policy prioritization exercises.



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6 RESEARCHER REFLECTIONS

REAP provided an opportunity to adapt and field test a BN-based approach to policy prioritization. The application to an existing policy in collaboration with stakeholders heavily vested in the policy processes generated new insights into its relevance and how to improve. Six reflections emerged.

MIND THE RISK. Including risks in the REAP model alters modeling outcomes and hence could affect prioritization. The estimated NPV and ROI of all investments changed for each risk scenario, although the relative ranking of the investments by mean ROI did not significantly differ between risk scenarios. We believe this result is largely due to the lack of specificity in the description of the ASDP II investments, which overlapped significantly in terms of technologies mentioned and agroecosystems targeted, so the largest differences among the investments were their overall budgets and costs per beneficiary. Regardless of cause, the leverage that including risks has on the results and the prioritization highlights an existential crisis for policy makers and investors. Risks in general, not to mention climate risks, are rarely if ever considered in agricultural policy prioritization.

Lesson 1: *REAP results suggest that careful consideration of the risks needs to become commonplace going forward, irrespective of the prioritization framework used.*

APPLES TO APPLES. Our model allows a decision maker to compare diverse common agricultural and climate change policy options by assuming economic benefits accrue to smallholder farmers. This approach works well for policy options that directly target farm-level changes. Key assumptions about the number of beneficiaries, scale of impact and rate of adoption are more difficult to reasonably constrain for options with high costs and diffuse benefits, such as large-scale infrastructure projects or resource management schemes, amongst other challenges to ensure plausible comparability.

Lesson 2: *Bayesian Networks may not be appropriate to model the entire gamut of policy options affecting inclusive agriculture transformation.*

EXPERT ELICITATION. Expert elicitation of the model structure and the parameter values is central to using BNs, especially in data-scarce environments. Workshops lend credibility to the process and buy-in to the modeling effort in addition to providing expert judgments. In order to provide reasonable approximations of parameter distributions, experts must be "calibrated" to mitigate the known bias that arise from this practice such as overconfidence, bandwagoning, available heuristic, and more. Under COVID-19 restrictions, discussions typically held in person were moved online. This presented challenges under remote participation scenarios because of internet connections, lack of participation, and distraction. Unfortunately tools such as online training and surveys were relatively ineffective in calibrating stakeholders.

Lesson 3*: Unguided expert elicitation is unlikely to result in usable estimates of model parameters.*

GARBAGE IN, GARBAGE OUT. The model provided reasonable estimates of impact, such as ROIs between 4% and 30% across a diverse array of policy options. Variation among the investments was driven by assumptions and data availability pertaining to impacts, adoption, and risks. For example, investments that reach a large number of beneficiaries such as climate information tend to have the highest ROIs. There are often multiple data sources to select from; in some cases the globally accepted data are not the nationally expected data. Furthermore, experts may also have dissenting opinions. Bayesian Networks illustrate data and processes transparently helping to mitigate concerns over which data were used. However, discrepancies do arise, sometimes after modeling and seeing the results.

Lesson 4: *Assumptions and data need to be developed in collaboration with policy makers to ensure the credibility of the results.*

USABILITY IS KEY. Though typically conducted using participatory methods, our approach requires significant time investments by technical and domain experts to develop, parameterize, run, and refine models. Models require a software platform that may not be available to all users. More complex models demand large amounts of memory and computing resources, limiting the ability to run scenarios in real-time with stakeholders. This means that the BN approach, in its current format, may be challenging to practically implement at scale with many iterations. However, the REAP experience when added to previous work further lends evidence that the core structure of the policy-impact pathways is fairly consistent across contexts. Stakeholders want to adapt or change relatively small components of the model for their liking such as the risks that are modeled, the distribution of impacts, or the inclusion of carbon benefits. Non-structural changes can be accommodated more readily.

Lesson 5: *The bar for entry needs to be lowered to increase use, which suggests the opportunity to develop a Web-based tool where the model could be adapted based on drag and dropped selections and default primary data could be loaded based on selected geographies (i.e., from the Adaptation Atlas) but modifiable to users inputs.*

MULTIPLE USE CASES. In REAP, we used BN to assess existing policy options for a specific outcome - increased climate change resilience of the agricultural sector. Through our engagement with decision-makers in Tanzania, several use cases of policy prioritization models and BNs in particular emerged. In addition to policy assessment, funding prioritization and policy formulation are two other key needs. The outcomes modeled or weighting across multiple outcomes, as well as the scale of analysis can change in each specific use case. However, if the core impact pathway remains the same (in this case, impact is accrued through changes in smallholder farmer behavior), the model can be adapted to different use cases.

Lesson 6*: Multiple use cases demand a flexible modeling framework, but can be accomodated if the core impact pathway remains the same.*

7 CONCLUSIONS

At the outset of the Grand Challenge, we hypothesized that using BNs would improve policy prioritization by (i) allowing stakeholders to compare diverse policy options despite data scarcity, (ii) increase the utility of prioritization results by incorporating stochastic social and climate risks into the model and (iii) increase acceptance of model results through the utilization of participatory modeling processes. REAP was largely able to achieve these goals. The REAP model allowed stakeholders to directly compare aggregated agricultural productivity, resilience, and mitigation impacts of ASDP II options ranging from promoting climate-smart agriculture, to developing irrigation infrastructure, to improving agricultural information services and access to microfinance for smallholder farmers. Stakeholders generally felt that the model was adequate for this task, but some wanted to see non-economic impacts, results stratified by social groupings, or inclusion of more social policy options.

The inclusion of risk into policy prioritization was seen as a key advantage of the REAP approach, allowing stakeholders to get a more realistic sense of potential policy impacts. Including social and financial risks always lowered the ROI of ASDP II investments, but climate risks could sometimes increase the ROI if the investment increased resilience to that particular shock. Stakeholders especially appreciated the inclusion of political risks as many felt this was important in the Tanzanian context. However, some stakeholders felt that examining change in ROI with climate shocks was inadequate for assessing resilience benefits, and others wanted to see inclusion of market and economic shocks suggesting a need to increase the number (currently capped at six) and change the portfolio of shocks modeled in future iterations

Acceptance and use of outputs for policy prioritization remains a key challenge for all modeling approaches. For REAP, many of the participatory model design, parameter elicitation, and output validation processes were severely limited due to COVID19 safety precautions and internal political reasons in Tanzania. In the absence of face-to-face workshops, overcoming the inherent biases in human estimation of parameters is difficult. Many stakeholders felt that the model and results were highly technical and thus difficult to use in a policy prioritization process.

In conclusion, BNs provided a robust and flexible modeling approach for prioritizing agricultural policies. Further development of the model to include non-economic impacts of agricultural policies would expand its application to prioritization contexts, particularly when multiple development goals are desired. Creating an accessible web-based interface for stakeholders to design, parameterize, and analyze their results could also increase the usability and prime this approach to go to scale.


Photo: CCAFS

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ANNEXES

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Annex A. A review of select policy prioritization approaches

A plethora of modeling approaches are currently used for policy prioritization in agriculture and other sectors. These models attempt to predict, *ex-ante*, the impacts of various policy options on key outcomes that are nearly always quantitative and often economic. These modeling approaches are seen as a way to integrate impacts on various system elements into a "common currency" for easy comparison, and they vary in their scales of analysis from the household to the macroeconomic levels, in their data requirements, and in the difficulty of implementation. Below we review some of the most frequently used modeling approaches for policy prioritization, in order of increasing scale of analysis. Table 1 of the main report summarizes the review.

Household models

Agricultural household models, sometimes described as models with non-separability (DeJanvry et al. 1991) or models of peasant or semi-commercial households, are a specific microeconomic approach to understanding decision-making in agricultural households in developing-country contexts. The specification of these models arose out of observations in the mid-20th century that agricultural households in many parts of the world did not make decisions in ways that met the profit- or utility-maximizing expectations of classical economic theory. Rather than analyzing farming household behavior either from the point of view of their role as producers of economic goods or as consumers of goods, services, and leisure, agricultural household models are premised on the observation that semi-commercial agricultural households make integrated decisions as both producers and consumers (Singh et al. 1986). The relationship between production and consumption decisions can be simultaneous or recursive, which means that "production decisions are made with reference to market prices but are independent of other decisions, whereas consumption and labor supply decisions depend crucially on the income derived from the household's production" (Singh et al. 1986: 151). Many of the foundational assumptions and analytical outcomes of agricultural household models are now used as starting points for parameterizing simulation models, which will be discussed below.

Analytically, agricultural household models are specified and applied to empirical "real-world" data, and rely on standard multivariate regression techniques to assess the strength and direction of relationships and uncertainty in those estimates. This means that household models require large amounts of data to generate estimates with relatively small errors, which can be costly and often unrealistic in terms of time and effort. The assumptions that underlie agricultural household models include the fact that there are "missing markets" for either agricultural commodities or household labor, or both, in many developing-country contexts (DeJanvry et al. 1991). In addition, because agricultural households produce goods that may be consumed by the households themselves, the profit effect plays a less linear role in understanding consumption patterns, since an increase in profits from agricultural production does not necessarily decrease the household's own consumption. These assumptions generate models of household decision making that focus on estimating the elasticities of the consumption of agricultural production and other purchased goods, of household labor supply, and of marketed agricultural goods, with changes in the prices of agricultural goods (Singh et al. 1986). This emphasis on the price elasticity of agricultural goods reflects the dominant approach to agricultural policy throughout the 1970s and 1980s, when these models were being explored and refined, which foregrounded national efforts to manage the prices of agricultural goods with an eye toward both the well-being of rural households and the macroeconomic balance of accounts.

The main strength of the agricultural household model is that its structure and assumptions reflect the real-world conditions of many agricultural households in lower- and middle-income countries. These households are semi-commercial in that they both sell and consume their outputs, and they both purchase and provide their inputs, including labor. Expressing this reality in models allows for more accurate estimations of decision-making and well-being outcomes at the individual, household, and community levels, given policy changes. Agricultural household models have been used to assess the relationship between the labor supply and agricultural production and consumption, and to better understand the impacts of technologies that might free up labor previously used in household agricultural production (Singh et al. 1986; Davalos et al. 2020). Recent applications have continued to focus on the impacts of new technologies, such as the willingness of farmers to pay for new crop varietal traits (Dalton 2004) and the role that modern varieties play in overall household decision making and crop diversity (Benin et al. 2004). Another strength of the agricultural household model and its assumptions is that it can be extended to focus on the distributional and differentiated effects of changes in agricultural policies by "distinguishing structurally distinct types of households" (Brooks et al. 2008). On the other hand, one of the weaknesses of the original agricultural household model approach was its assumption of a "unitary" household with decision making and utility functions consistent across members. More recent extensions have focused on gender and age-disaggregated analyses to highlight intrahousehold differences (Doss and Quisumbing 2019).

Agent-based models

Agent-based models (ABMs) are another bottom-up or microscale approach, simulating autonomous individuals ("agents") with heterogeneous rather than "unitary" behavior to understand how their decisions shape systems as a whole. ABMs use agent-to-agent and agent-to-environment interactions to generate a dynamic representation of a system. The data requirements for ABMs are model-dependent – some can entail copious amounts of data, while others may be more abstract and parameterized using expert opinions (Auchincloss & Garcia 2015).

ABMs are frequently used in agricultural research to evaluate policy interventions. The models define individual farm households or farmers as agents. Some papers utilize ABMs to understand the effects of policies on crop choices, such as to explore which policies would be most effective in reducing poppy crop production and encouraging farmers to cultivate other crops in Afghanistan (Widener et al. 2013). In the quest to develop an agricultural system that evolves alongside climate change, ABMs have been implemented to analyze the effects of farmer subsidies on the production of crops that can handle climate variability (Berger et al. 2017). This literature also focuses intensively on policies that affect how individuals choose to farm, such as how a particular innovation changes the use of water and affects income for different types of farmers (Berger et al. 2001) or how the ability to acquire a loan affects the adoption rate of greenhouse agriculture, which enables better water usage and leads to greater incomes (Schreinemachers et al. 2009).

ABMs are advantageous because of their dynamic nature, which allows individuals to adapt and learn over time. It also provides the opportunity to observe the state of a system throughout the time period and out-of-equilibrium, rather than delivering only static outcomes (Auchincloss & Garcia 2015). ABMs have been leveraged to analyze empirical historical data, for example, to understand the drivers of land-use change in agricultural systems and its impacts on household well-being (Evans et al. 2011). Spatial structure is another strength of ABMs that is not always integrated into other analytical approaches. Spatial analysis can help account for how agents interact with the environment directly around them, which is especially relevant to agriculture given differing soil qualities or other land characteristics.

Although ABMs are useful in examining hypothetical interventions or changes in the environment, these models are not useful for predictions, and results are not precise estimates (Auchincloss & Garcia 2015). Instead, they are best interpreted qualitatively instead of quantitatively (Auchincloss & Garcia 2015), using outcomes to generate guidelines based on strong patterns within a system. Because ABMs are best used to identify such patterns, they are often implemented in research as a complement to other models (Berger and Troost 2013).

Computable General Equilibrium Models

Computable general equilibrium (CGE) models integrate the microeconomic theory of generalized equilibrium, which holds that when they are interconnected, markets are in equilibrium. CGE models utilize economic data to arrive at realistic prices and levels of supply and demand (Wing 2004). Unlike the previous two approaches, this type of model exemplifies a top-down approach in that it is analyzing a system as a whole. CGE models are useful in simulating a policy change or a shock in a particular market to observe effects within the economy as a whole, although they offer a static representation of a system rather than a dynamic one.

CGE models are used often in the literature to evaluate the impacts of agricultural policy changes at an economic level. For instance, a CGE model has been utilized to evaluate the impacts of banning the export of maize in Tanzania (Diao and Kennedy 2016). Results indicate that when exports are banned, maize producer prices decrease, which is advantageous for urban households in Tanzania but hurtful for producers. The wage rate for low-skilled labor declines, while wages for skilled workers rise, which widens the wealth gap and affects many different markets in Tanzania. CGE models also enabled analysis of the effects of planned adaptation to expected climate change impacts on agricultural productivity in Ethiopia (Yalew et al. 2019). Evaluating outcomes such as urban household welfare, income for skilled and unskilled workers, government saving, and manufacturing output enabled the simulation of trade-offs entailed in the policy change.

The primary strength of CGE models is that unlike some other models, they conduct an economy-wide analysis (Yalew et al. 2019). For example, if a particular policy change pertains to agriculture, a CGE model can analyze its effects on other markets, exposing trade-offs across the economy (Palatnik & Roson 2012). This feature gives CGE models an advantage over other models that focus only on the industry or people that the policy directly affects.

One pitfall of CGE models is that they cannot incorporate non-economic parameters. In agricultural applications, for example, non-economic characteristics of land, such as its biophysical features, may be important in policy simulation. Another weakness of CGE models is that because they typically involve numerous parameters and a complex structure, they also require many assumptions. If the assumptions are questionable and not transparent, they could drive the results and lead to invalid conclusions (Wing 2004). These models also typically require ample data. Finally, CGE models are underpinned by the tenets of neoclassical economic theory, specifically that production and consumption functions operate separately for the economically active population. However, as noted in the agricultural household models section, these tenets are often inappropriate at the household or agricultural economy scale in developing countries, where producers are also consumers of their own goods in semi-commercial or peasant households and systems.

Monte Carlo simulation models

Monte Carlo (MC) simulation models have been a popular approach for computing probabilistic risk assessments primarily due to their ease of implementation. Available for over 60 years, MC approaches have also more recently been used to evaluate agricultural development investments. MC models have been implemented to evaluate investment options in honey value chains in Kenya (Wafula et al. 2018). This approach has also been utilized to prioritize reservoir protection investments in Burkina Faso (Lanzanova et al. 2019). MC simulations repeatedly generate samples for random variables in the model and produce a statistical analysis of those samples. Difficulty in understanding the assumptions underlying large MC simulation models is a barrier to their use. Although their modeling assumptions are encoded transparently, often in spreadsheets, clarifying the relations between different parameters may be infeasible.

Fuzzy Cognitive Maps

Fuzzy cognitive maps (FCMs) are similar to BNs in that the model can be represented with nodes and directed arcs or edges to depict the relationships between different variables. Unlike BNs, however, FCMs are not acyclic, meaning there can be feedback loops or cycles. Each edge is assigned a value between -1 and 1 to represent the causal strength of one variable on the other, where a negative value represents a negative association, a zero indicates no association, and a positive value shows a positive association. Conversely, BNs utilize probability distributions at each node.

In the literature, FCMs have been implemented similarly to BNs. They have been used to predict the yield of crops such as coconuts and cotton on the basis of climate variability, weather, and soil composition (Jayashree et al. 2015, Papageorgiou et al. 2011). One study stresses the potential for FCMs as a tool for crop management (Papageorgiou et al. 2011). FCMs can also be helpful in evaluating policy and regulation, and several studies focus on the environmental impacts of agricultural policy. FCMs have also been key in analyzing how environmental regulation impacts farmers and their decisions in Scotland by enabling an evaluation of whether the policies under consideration are producing the intended results (Christen et al. 2015). FCMs facilitate identification of where a policy is breaking down, causing farmers to not comply with the regulations (Christen et al. 2015). Other studies built around FCMs evaluate the effects of programs designed to promote environmentally friendly agricultural practices in rural areas, generating results that show what types of policies may be most effective in specific communities (Satama and Iglesias 2020; Targetti et al. 2019). Scholars have also developed a tool that combines multi-agent systems and FCMs to help improve decision making at the farm level by optimizing water and fertilizer use and farmer income while also taking into account the environment and consumers in the market.

FCMs have a few major advantages over BNs: they integrate feedback loops, are more user-friendly and easily understood, and can easily be expanded to include more variables. The ability of FCMs to entertain feedback loops improves the accuracy of the model by enabling it to incorporate variables that produce a cycle (Osoba & Kosko 2019). FCMs generally require fewer details than BNs and are more abstract in terms of the strength and quality of relationships (Wee et al. 2019). In addition, new variables can be easily integrated into FCMs, and whereas with the introduction of a new variable, the complexity of a BNs would increase exponentially, that of an FCM grows linearly because in FCMs, only the new relationship needs to be defined. For BNs, however, adding a new variable will require redefining the existing conditional probability distributions because all the causal relationships in the network are affected.

However, the simplicity of FCMs comes with a trade-off. The values associated with the edges in an FCM are abstract and do not represent a physical quantity, whereas BNs use the more concrete concept of probabilities (Wee et al., 2019). This lack of formality in FCMs leads to pattern predictions rather than the precise results possible with BNs. Because of this, FCMs cannot be used to perform diagnostic analyses or to evaluate risks and uncertainty in the same capacity or with the same level of precision. Another aspect of FCMs that diminishes their precision is that they do not assign a probability to the initial variables. Bayesian Networks, on the other hand, provide a probability to the starting variables, or the variables that have no parents, which enhance the precision of the model in estimating the probability of the outcomes (Wee et al. 2019).

Bayesian Networks

Bayesian Networks, or probabilistic causal models, use graphical network analysis in tandem with Bayesian statistics to measure uncertainty. The model is represented in a directed acyclic graph, with no closed loops or cycles, that relies on nodes to convey random variables and on edges to communicate the relationship between the nodes. “Parent” nodes have an edge that leads to another node, called a “child” node. Each node is assigned a probability of being in a particular state. Conditional probabilities are used for each child node because its state depends on its parent or parents. These models can incorporate two knowledge sources -- domain experts and empirical data (Jensen 2009, Uusitalo 2007) -- which adds flexibility in model specification. Domain experts help build the structure of the network, including the states of each variable and the relationships between variables, and define the conditional probabilities of each variable. Estimates of the directionality of relationships and probability distributions can be extracted from different sources, such as directly from empirical data or from other simulation models.

The use of BNs in agricultural research is relatively new. Much of the agricultural literature implementing BNs utilizes this modeling framework to understand or predict crop yield given different seasonal climate conditions or other uncertain factors (Gandhi et al. 2016, Newland and Townley-Smith 2010, Cornet et al. 2016). Bayesian Networks have also been implemented to analyze farmer decisions and behavior, such as changes in land use (Peter et al. 2009), the adoption of conservation agriculture (Bonzanigo et al. 2016), and exiting certain markets within the sector (Gambelli and Bruschi 2010). Other papers have also expressed the potential of using BNs for policy decisions in an agricultural context. For example, BNs can be utilized to evaluate risks and uncertainties associated with pest management, an evolving issue due to climate change (Reardon-Smith et al. 2012). They may also aid in the evaluation of agricultural policy, including in rural areas of Europe; BNs are advantageous to analyze the complexity of rural agricultural systems and manage the lack of data available in these areas (Viaggi et al. 2011)

One primary strength of BNs is that they better estimate risk and uncertainty compared to other models because of their use of probability distributions rather than relying on expected values (Uusitalo 2007). This characteristic makes BNs relevant for evaluating impacts related to policy changes because they not only simulate how a policy might change the system, but also how likely that outcome is to be true. Through the inclusion of probability distributions, uncertainty is treated explicitly in conjunction with each parameter (Uusitalo 2007). Bayesian Networks also allow for ignorance and uncertainty of some causes. In developing the structure of the network and assigning probabilities, "the domain expert in BNs must estimate the total strength of a combination of multiple causal effects without a need to know and specify their individual causal strengths" (Wee et al. 2019). This aspect of BNs is advantageous because the expert can remain uncertain about details that may be required in other models, such as Fuzzy Cognitive Maps.

Another main advantage of BNs is that these models do not require much data; these networks can rely on both expert knowledge and data, a valuable capability when minimal data are available (Jensen 2009, Uusitalo 2007). Also, the expert knowledge can come from different sources, giving the modeler great flexibility (Aalders 2008, Uusitalo 2007). Though the ability to incorporate knowledge from many resources is one of the advantages of BNs, it can come with a cost: the quality may vary between these sources of knowledge, and information may be more or less reliable (Aalders 2008). The assumption in using the expert knowledge in the model is that the information accurately reflects empirical phenomena, without the benefit of mathematically confirming those estimates.

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Annex B. Model structure

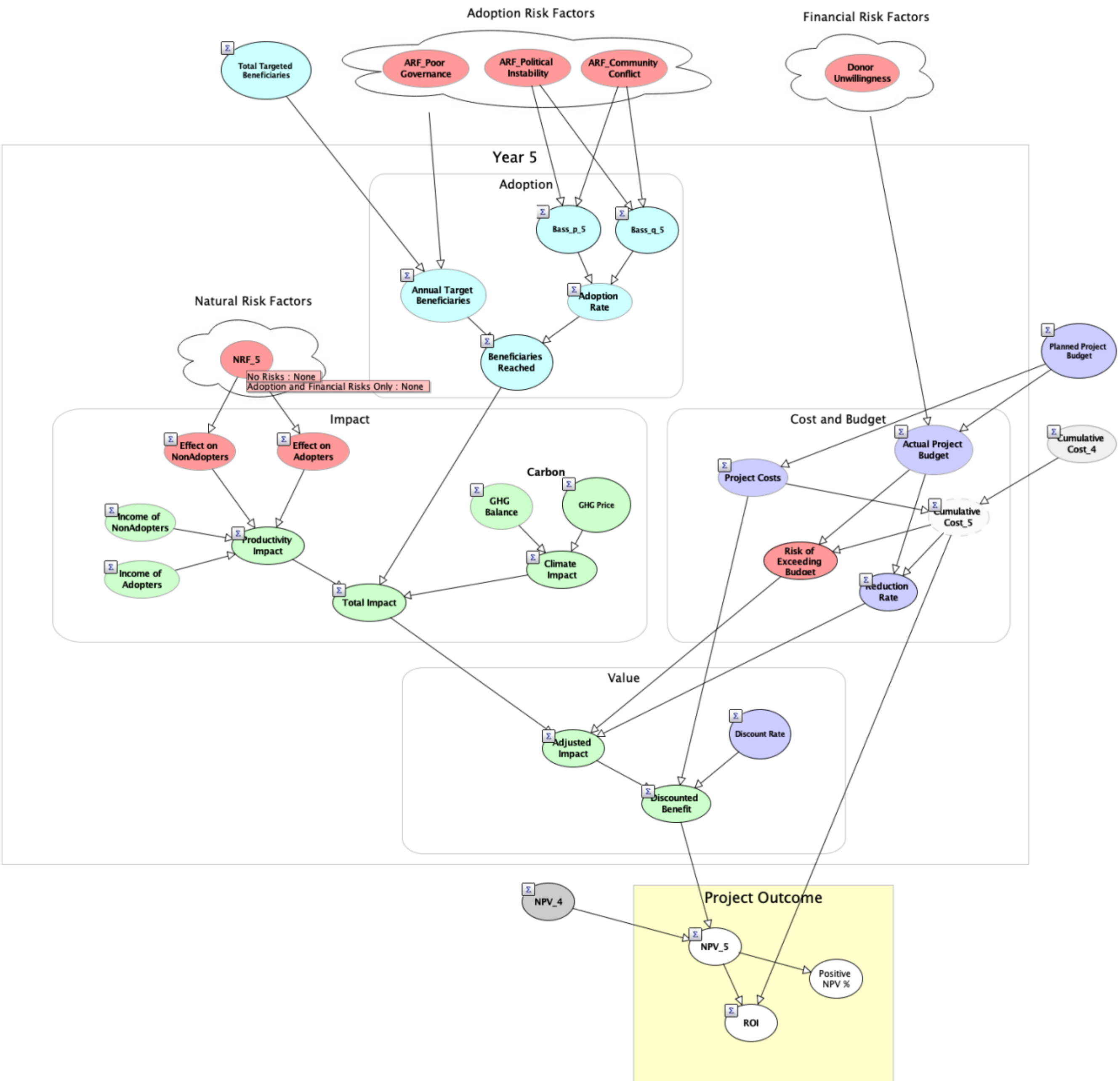

Figure B1 | A Bayesian Network model of impacts on the Agricultural Sector Development Programme Phase II Priority Investments. Impact parameters are green, adoption parameters are blue, cost and budget parameters are purple, and risk parameters are red. Note that ROI stands for "return on investment" and NPV means "net present value."

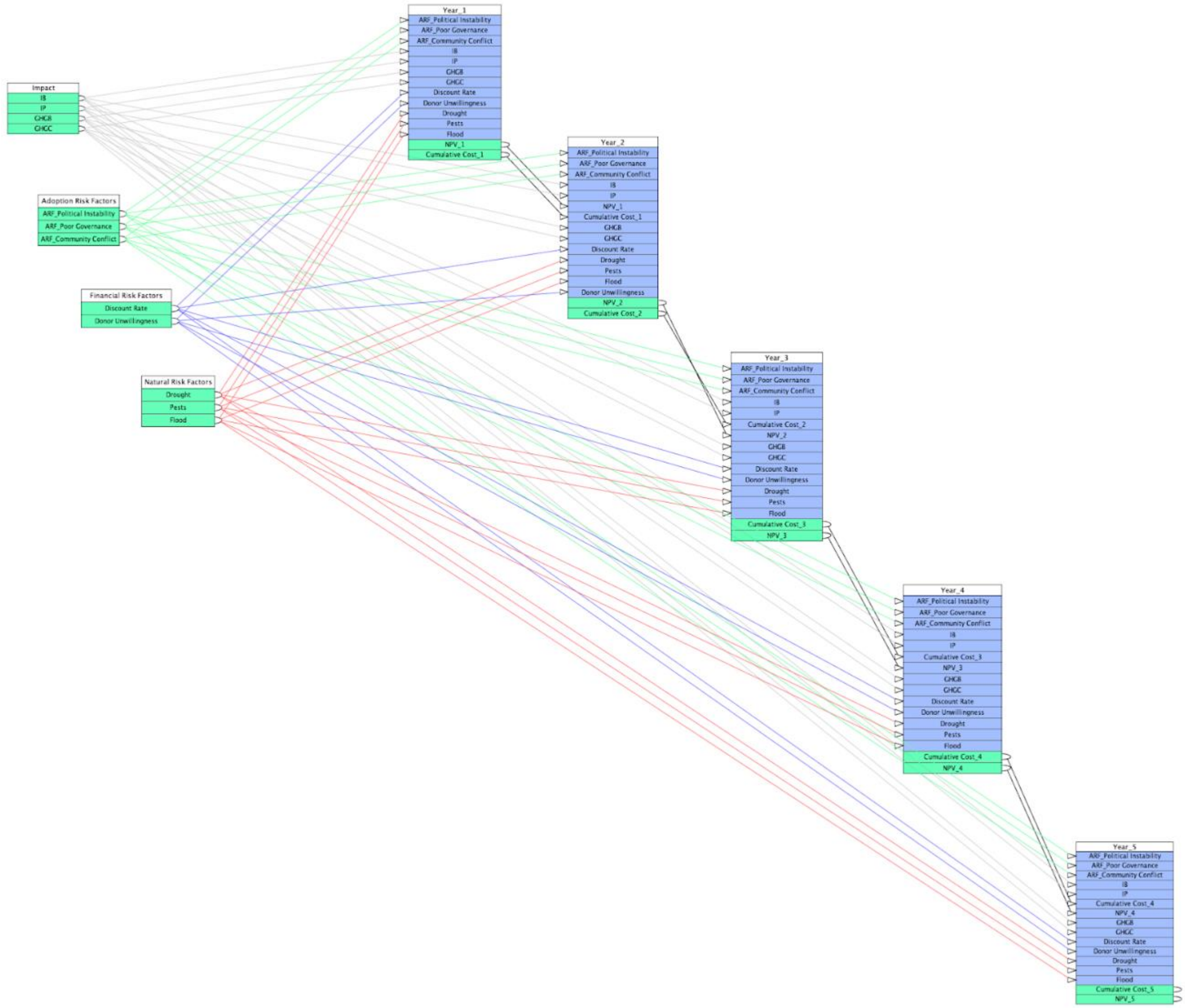

Figure B2 | Map of overall Risk Explicit Agricultural Policy Prioritization Model structure, showing how input parameters on the left are used in each year of the project cycle.

Annex C. Bass model and project adoption typologies

The Bass model of diffusion of innovations (Bass 1969) can be used to model adoption of new technologies by target beneficiaries of agricultural policy options. The Bass model gives the adoption rate (AR) as a function of three parameters: P, the rate of innovation or direct uptake of technologies by beneficiaries; Q, the rate of imitation or uptake of technologies by beneficiaries not directly reached by project staff; and t, the time in years.

$$AR_t = \frac{1 - e^{-(P+Q)t}}{1 + \left(\frac{Q}{P}\right) e^{-(P+Q)t}}$$

Parameter values used for P and Q determine the shape of the adoption curve, the expected number of beneficiaries and thus accrued benefits. Depending on the values selected, the proportion of beneficiaries reached varies between 43% and 100% depending on the choice of P and Q (Table C1). To assign values for P and Q, we developed a typology of policy options based on expert opinion of the expected shape of the adoption function promoted in each policy option (Table C2).

Table C1: Proportion of target beneficiaries reached (AR) after 5 years according to Bass model parameters

	Q - imitation						
P - innovation	0.1	0.2	0.3	0.4	0.5	0.6	0.7
0.1	0.43	0.48	0.53	0.58	0.64	0.69	0.75
0.2	0.71	0.76	0.81	0.86	0.9	0.94	0.97
0.3	0.86	0.9	0.93	0.96	0.98	0.99	1
0.4	0.91	0.94	0.96	0.98	0.99	1	1
0.5	0.96	0.98	0.99	1	1	1	1
0.6	0.99	1	1	1	1	1	1

Table C2: Project adoption typologies

Project Type	Description	P	Q	Examples
High upfront costs	Low p, Low q	0.05	0.4	Irrigation, water for livestock
Long time until investment returns	Moderate p, Low q	0.1	0.4	Agroforestry, landscape management
Farm management	Moderate p, Moderate q	0.1	0.5	CSA, extension services
Information services	High p, High q	0.15	0.6	Climate information, microfinance

Annex D. Resilience typologies

To model the impact of climate risks on beneficiaries and the associated climate resilience benefits of policy options, we developed a typology of risk impact and certainty of that impact on smallholder farmers. Impact was modeled as a uniform distribution of agricultural yield loss, meaning that any value within the bounds of the distribution was equally likely. Impact of a risk could either be high, medium, or low, modeled as a uniform distribution centered on 75% losses, 50% losses or 25% losses respectively (Table D1). Uncertainty in impact was modeled as the width of the uniform distribution. The higher the certainty, the narrower the distribution of potential losses. All uniform distributions were truncated to values between 0-100% losses.

Table D1 | Projected agricultural losses given the impact and the certainty around the impact of climate risks.

	High Impact	Medium Impact	Low Impact
High Certainty	75% +/- 25%	50%+/-17%	25% +/- 8%
Medium Certainty	75% +/- 37.5%	50% +/- 34%	25% +/- 16%
Low Certainty	75% +/- 75%	50% +/- 50%	25% +/- 25%

For each modeled climate risk and ASDP II policy option, we assigned a risk impact typology to beneficiaries of the technologies in the policy option as well as impact to non-beneficiaries in the same farming system. For example, for maize farmers in semi-arid areas, the impact of a drought is likely to be high and our certainty around that impact is also high. Risks here are considered to be climate shocks on a large enough scale to impact national level agricultural production. However, if the maize farmer is part of a sustainable land and water management scheme that promotes agroforestry and conservation agriculture, they are also likely to be highly impacted by the drought, but with much less certainty. If instead that farmer is part of an irrigation scheme, we would assign them a medium level of impact rather than a high level of impact. Expert opinion was used to categorize the risk and uncertainty for each combination of policy option and climate risk (Table D2).

Table D2 | Characterization of climate risk impact and certainty for ASDP II Investments

	Drought Impact		Flood Impact		Pests & Disease	
Policy Option	w/o Policy	w/ Policy	w/o Policy	w/ Policy	w/o Policy	w/ Policy
Sustainable Land & Water Management	High/High	High/Low	High/High	High/Low	High/High	High/Low
Irrigation	High/High	Low/Low	High/High	Med/Med	High/High	High/High
Water for Livestock	High/High	Med/Med	High/High	High/Low	High/High	High/Low
CSA	High/High	High/Low	High/High	High/Low	High/High	High/Low
Agricultural Extension	High/High	High/Low	High/High	High/Low	High/High	Med/Low
Climate Information services	High/High	High/Low	High/High	High/Low	High/High	Med/Low
Microfinance	High/High	High/Low	High/High	High/Low	High/High	High/Low

Annex E. Survey Instrument

Introduction

Thank you for agreeing to take part in this interview. We are researchers from World Agroforestry (ICRAF) and we are conducting this research as part of a seed grant from the Bill & Melinda Gates Foundation to test methods for prioritizing agricultural policy options.

Today, we are interested in your perspective and experience on prioritizing agricultural policy options and your thoughts on the BNs model and outputs that we've shared with you. There are no right or wrong answers, and we are not taking a particular position on the utility of the model. We're interested in your personal views and how they relate to your professional role.

If you agree to the interview or to submit responses via email, all identifying information (your name, your institution, your role) will be removed from your responses and we will only include information on your sector (government, research, development) and gender in the final dataset. These anonymized interviews will be used for research outputs and will potentially influence future research.

Questions for Open Response

Are the model outputs useful for evaluating the ability of ASDPII to address climate resilience in Tanzania? Why or why not?

Does the model adequately capture how a policy option can impact climate resilience? What is not needed? What is missing?

Can you imagine using a model like this in your work? Why or why not?

What information is most needed, in your opinion, for prioritizing policy options to build climate change resilience into agricultural development?

Closing

Thank you for taking the time to answer these questions. Your feedback is incredibly valuable, as the overall goal is to make a tool that is useful for decision makers in general, or could be used to support the development of an ACRP II specifically. If you have any further questions, please contact us.