RTI Press

Developing Climate-Smart Agriculture Policies: The Role of Economic Modeling

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RTI
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Suggested Citation

Crouch, L., Lapidus, D., Beach, R., Birur, D., Moussavi, M., and Turner, E. (2017). *Developing Climate-Smart Agriculture Policies: The Role of Economic Modeling*. RTI Press Publication No. OP-0034-1701. Research Triangle Park, NC: RTI Press. http://doi.org/10.3768/rtipress.2017.op.0034.1701

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Abbreviations

AgMIP	Agricultural Model Intercomparison and Improvement Project
BMP	Best Management Practice
CBA	Cost-Benefit Analysis
CEA	Cost-Effectiveness Analysis
CGE	Computable General Equilibrium (modeling)
CSA	Climate-Smart Agriculture
DSSAT	Decision Support System for Agrotechnology Transfer
EPIC	Economics and Policy Innovations for Climate-Smart Agriculture
FAO	Food and Agriculture Organization of the United Nations
GACSA	Global Alliance for Climate-Smart Agriculture
GHG	Greenhouse Gas
IMPACT	International Model for Policy Analysis of Agricultural Commodities Trade
MAC	Marginal Abatement Cost
MCA	Multi-Criteria Decision Analysis
NRM	Natural Resource Management
PE	Partial Equilibrium (modeling)
TOA-MD	Tradeoff Analysis–Minimum Data (modeling)

Abstract

There has been growing interest in climate-smart agriculture among many national governments and the international donor community. An array of policies and programs could potentially be considered climate smart, but for the purposes of this paper, we define climate-smart agriculture as an approach that strives to meet the following criteria: (1) increase agricultural productivity in a sustainable manner, (2) improve the resilience of agricultural production and food systems to environmental change, or (3) reduce net greenhouse gas emissions associated with the agriculture and forestry sectors. This definition encompasses, but goes beyond, the traditional agricultural development policy concerns of increasing incomes and reducing rural poverty, thus increasing the complexity of the policy agenda and modeling that supports policy-making. The goal of the paper is to provide policymakers and program designers with an overview of the primary types of economic models that could be used to inform policy design and implementation. The most specific audience for the paper is international development practitioners who design projects, pilots, and other efforts to advance climate-smart agriculture, and who may wish to inject modeling sensibilities and approaches into such efforts. The readership of the paper is assumed to be subject matter specialists and generalists who are not economists but may need to consume the results of economic modeling. We describe alternative economic modeling approaches relevant for analyses of climate-smart agriculture approaches and provide general principles for selecting an approach for a specific application.

Introduction

As global populations and economies grow, less land is available to meet the rising demand for food, fiber, forestry products, energy, and ecosystem benefits such as carbon sequestration. Yield growth on existing agricultural lands is not as fast as in previous decades. In addition, we face the present and future threats posed by climate change. Recent manifestations of this new reality include food price spikes and price volatility and the increasing frequency of extreme weather events (Porter et al., 2014). Some projections show global yield declines for major agricultural commodities, more pests and diseases, and higher commodity prices (e.g., Brown et al., 2015). The food and agriculture paradigm is changing and will disproportionately affect the world's poorest populations—those least able to cope with shocks.

Accordingly, food security and agriculture, including climate-smart or sustainable approaches, have received more attention and funding from the international community in recent years, including the finalization of the United Nations' Sustainable Development Goals, with specific reference to food and agriculture in late 2015. The Malabo Declaration, passed in 2014, was an unprecedented commitment of African leaders to improve agricultural productivity and reduce hunger. It calls on the use of data and analysis to "develop mechanisms to enhance Africa's capacity for knowledge and data generation and management to strengthen evidence based planning and implementation." The Malabo declaration renewed a commitment to the Comprehensive Africa Agriculture Program as a means to transform African economies through agriculture (originally adopted in Maputo in 2003).

Food security and agriculture also featured prominently in the United Nations process that led to the Paris Climate Agreement, adopted in December 2015. The agreement includes language that speaks to promoting climate resilience and low greenhouse gas (GHG) emissions in "a manner that does not threaten food production." As part of the agreement, each country developed "intended nationally determined contributions" (INDCs) that include emission reduction targets as well as broader climate change mitigation and adaptation strategies. Of the 188 countries that submitted INDCs, 94 percent of them include the agriculture sectors in their mitigation strategies, adaptation contributions, or both. Developing countries put a particularly strong emphasis on the agricultural sector within their INDCs (Food and Agriculture Organization of the United Nations [FAO], 2016).

Climate-smart agriculture (CSA) has emerged as the dominant paradigm for agricultural development that incorporates climate considerations. The Global Alliance for Climate-Smart Agriculture (GACSA), hosted by the FAO, already has more than 100 members, including 22 countries.[1] The three top-line aspirational outcomes of GACSA are

- sustainable and equitable increases in agricultural productivity and incomes,

- greater resilience of food systems and farming livelihoods, and

- reduction or removal of GHG emissions associated with agriculture (including the relationship between agriculture and ecosystems), where possible.

As implied in the "sustainable" wording in the first aspirational outcome above, CSA programs are typically concerned with other environmental sustainability aspects that may not be encompassed the second two outcomes, such as soil erosion, soil degradation, agricultural runoff, and eutrophication of water bodies. Other CSA-related efforts tend to have overall goals that are very similar to GACSA, although not identical.

The CSA paradigm is in its early stages, but as programs and policies are developed, there is a great need for appropriate economic policy tools to help guide this decision-making. Issues related to sustainable agriculture, sustainable food systems, and sustainable value chains are not new, but the simultaneous consideration of both the impact of

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[1] See Global Alliance for Climate-Smart Agriculture (GACSA) (2016).

climate change on agriculture and the contributions of agriculture to climate change add additional layers of complexity. Climate change necessitates consideration of long-term outcomes and resilience of agricultural investments to a changing climate.

There are several major challenges in identifying effective CSA solutions. Agricultural practices and related forestry and natural resource management (NRM) practices are diverse and context-specific. Compounding the complexity is the fact that climate-smart investments can have feedback effects, and producer decision-making is sometimes poorly understood or predicted. A practice deemed effective on a research plot could have low replicability or scalability in farm conditions. Alternatively, a productivity-enhancing practice may have unintended impacts on output prices when widely adopted, reducing farmer profit and ultimately limiting the area of cropland on which the practice can be profitably adopted.

CSA is not restricted to cropping actions and solutions; it involves the whole value chain for commodities produced by agriculture and other land-based sectors, such as food, fuel, fiber, forest products, and feed. This breadth of concerns involves options for sustainably producing pre-farm inputs as well as post-farm processes such as post-harvest handling, storage, processing, aggregating, packaging, and adding value. All aspects of the post-farm processes harken back to the whole food system.

Lack of quality data further bedevils decision-making around agricultural policies. Despite recent improvements in agricultural data collection and availability, high-quality data remain difficult to access, aggregate, and process, particularly for developing countries. Efforts to reduce the costs of data collection while increasing the standardization and accessibility of agricultural sector data present a major opportunity to expand and improve the available base of knowledge used for policy modeling and decision making. One of the best ways to organize data and make the data tell policy stories is to do so around modeling efforts. Modeling forces discipline in the sorts of data to gather, and in how

to put the data together in a meaningful way. At the same time, those doing the modeling must be cognizant that modeling efforts should not necessarily put extra pressure on data producers to come up with more data, unless the situation truly warrants it.

Another challenge is related to the nature of policy making. As in other sectors, agricultural policy makers often respond to short-term pressures in ways that do not account for the all potential consequences (e.g., shutting down food exports in response to a domestic food security crisis, not accounting for loss in income to farmers and the potential of higher prices to stimulate investment and production). They are often unable to quantify the trade-offs associated with alternative policy actions, or of the trade-offs between satisfying particular groups versus the overall welfare of the general public. Although policies are partly the result of complex political machinations and messy consensus-building, policy-making is not entirely bereft of rational and systematic analysis. Economic modeling can help inform decisions by illustrating the trade-offs between goals, the unintended impacts of policies on various groups, and the long-term dynamics unleashed by policies aimed at resolving short-term problems.

The additional complexity of bidirectional climate impacts requires more sophisticated modeling and analysis. Tools exist that can incorporate this complexity, but the modern analytical techniques may not be readily accessible to CSA decision makers who are not specialists in modeling. Thus, this paper provides a "consumer's guide" to help the nonspecialist understand some of the applications, pros, and cons of the array of modeling techniques available. In particular, we focus on economic models that will help policy makers pursue the three aspirational outcomes of the CSA: sustainable productivity improvements, resilience, and mitigation of GHG emissions.

Use of Economic Models

General Motivation for Model-Based Analysis

The agricultural agenda of the 1950s through 1990s, increasing production and fighting poverty, was complicated and often fraught with inefficient policies. Incorporating food security and climate considerations only further complicates policy making. Understanding the effects of agricultural policies and programs can be greatly aided by the use of modeling and similar analytical techniques because models are a simplified and controlled version of reality in which to experiment. Real-world experimentation is expensive and risky for populations who may experience unintended consequences. Models represent a means to predict intended and unintended consequences of policy and project interventions ex ante (or in some cases concurrently or ex post). Table 1 shows a few illustrative examples of policies that could be aided by modeling.

Modeling is often viewed simultaneously as both too simplistic and too complex. Models are simplified versions of reality and, by nature, cannot account for every detail, yet they are operated using complicated mathematical equations that can be opaque to nonexperts. George Box's aphorism that "Essentially, all models are wrong, but some are useful" (Box & Draper, 1987) is a good clue to this dichotomy. Models are indeed useful precisely because they simplify, but this also makes them "wrong" in some sense. A model can be viewed like a map: with as much detail as reality, it would be useless. Yet with too little or too much detail, or the wrong detail, it would likewise not be useful. Consumers of modeling should ask of those carrying out the model, as one would ask a cartographer, "Does the model have the appropriate level of complexity, and does it focus on the right things?"

Table 1. Policies, possible effects, and modeling response

Common agricultural policy	Intended effects	Unintended (potential) effects that could be assessed and quantified with modeling
Promote farmer adoption of climate-smart crops or practices through training and demonstration	• Increased profits • Reduced crop loss from extreme climate events • Reduced or avoided GHG emissions • Increased farmer resilience	• Low adoption because of perceived or real risk or lack of complementary inputs, and lack of knowledge of which complementary inputs matter most • Lower yields or profits when scaled up • Certain policies oriented at farmer income in short-run may lead farmers to adopt cropping patterns or practices that are not climate-smart because they reduce net GHG emissions or decrease resilience
Input subsidies (e.g., seeds, fertilizers)	• Improved productivity	• Reduced agricultural diversification, leading to lower resilience • Reduced diet diversity • Higher GHG emissions (either aggregate or net) depending on the technology being subsidized
Trade barriers during food crises (e.g., restricted exports)	• Lower domestic prices for consumers	• Lower prices for producers, which fails to stimulate production • Net loss of welfare
NRM improvements through demonstration and education	• Improved environmental stewardship without having to rely on subsidies and payment for ecosystem services	• Low uptake of practices because of high upfront investment and transaction costs or lack of analysis as to which new practices are the most profitable
Incentives and subsidies for NRM or Reduced Emissions from Deforestation and Degradation+ (REDD+)	• Improved environmental stewardship and NRM through subsidies or direct payments	• Land-use changes, including less land available for food, leading (possibly) to higher food prices and expansion of agricultural area outside the project area, which will impact net GHG emissions reductions provided by NRM or REDD+

Finally, modeling is not the only deep analytical technique useful for advising CSA policy. Although the focus of this paper is modeling, certain questions about farmer or resource manager behavior and barriers to behavior change (e.g., adoption of climate-smart practices) may be better addressed through multidisciplinary techniques based on ethnography or economic anthropology. Furthermore, in understanding the effect size of specific interventions, impact evaluations using experimental or quasi-experimental designs may be more appropriate than modeling, although modeling can help one understand the "how" aspects and supplement the "how big" aspects and the causal attribution that experiments can produce. Experimental approaches can work with or without modeling. A simple approach to impact evaluation might only consider whether there is an impact rather than using modeling or other techniques to determine why the impact occurred. Thus, modeling has its place in the arsenal of the CSA policy analyst, particularly when it comes to analyzing likely consequences before large, complex, and often irreversible actions are taken, or in understanding ex post facto why certain consequences occurred.

Key Principles to Consider in Choosing a Model or Designing an Approach

In this section, we outline the key factors to consider when selecting a modeling technique or analytical approach to CSA policy formulation.

Type of intervention. Policy makers or practitioners may be interested in assessing the degree to which an agricultural intervention may be climate smart, or whether an intervention intended to be climate smart achieves the climate-smart objectives. Three main categories of potential interventions are as follows:

1. **Policy changes.** Governments may consider policy shifts to encourage greater production, more-resilient agriculture, or lower emissions (or emissions intensity). Such policy shifts may include providing credit, subsidies, or incentives for certain kinds of crops or technologies; allowing carbon offsets from the agricultural or forestry sectors; passing trade restrictions for crops important to food security; or subsidizing the production of maize or sugar cane for biofuels.

2. **Direct farmer support programs.** Programs aimed at improving farmer productivity, income, resilience, or emission reductions through interventions such as farmer education, training, technological transfer, agricultural extension on new management practices, or crop or livestock insurance. Interventions in this category would also incorporate the promotion of practices such as conservation agriculture, cover cropping, intercropping, or planting drought-resistant seeds.

3. **Infrastructure investments.** This category includes traditional infrastructure investments such as building a dam, an irrigation system, or micro-hydro infrastructure to increase access to water; improving storage or warehousing; building infrastructure to reduce post-harvest waste; or building waste treatment facilities. Note that modeling is most useful when such interventions are made at a large scale.

The category of intervention under consideration will determine both the appropriate type of model and the level of complexity required. Interventions through subsidies and price signals tend to necessitate greater complexity because of feedback loops and interactions. Modeling can help analyze how much climate issues interact (e.g., GHG emissions and resilience) with intensified agricultural production; what consequences these interactions have for whom; and whether subsidies, taxes, or the creation of new environmental markets are the most efficient way to optimize possible trade-offs. Analysis of discrete infrastructure developments tend to be simpler, typically requiring relatively straightforward analysis of costs and benefits.

Data availability. For small, targeted studies, or for urgent actions, reliance on existing data will be a constraint. For larger, more-complex studies, or ones that will require large investments and significant policy changes, a specific household or farm survey may be justified. Some models and model types, such as trade-off analysis–minimum data [TOA-MD] and Bayesian models, require less data or can operate on the basis of expert opinion, and can be updated as more data come in. Local partner organizations will often have access to data or subject matter experts that can sometimes provide the minimum data necessary for conducting an analysis.

Externalities. Are there any third parties and stakeholders that would be affected by the project or policy? In addition to GHG emissions (which are explicitly covered by CSA), other externalities such as air quality, water quality, or ecosystems may be affected by an intervention. For example, if water is being diverted through the development of a dam to address water availability, how should the people and ecosystems downstream be factored into the analysis? Or, if a productivity-enhancing policy subsidizes fertilizers, what is the cost in terms of eutrophication of water bodies, and who should bear that cost? What incentives (e.g., payments for environmental services) are required to induce farmers to provide environmental services such as enhanced biodiversity or to contribute to improved water quality, air quality, or both by using lower-impact inputs or reducing the use of certain inputs (e.g., fertilizer, pesticides) to socially optimal levels, accounting for externalities associated with their use?

CSA priorities. Which CSA outcomes—sustainable productivity, equity, resilience, and mitigation of emissions—are most important to the decision maker? For interventions that improve productivity and resilience but increase GHG emissions, should those emissions be considered in terms of net emissions, emission intensity, or some other way? For interventions that improve productivity and mitigate greenhouse emissions, how will resilience be measured? Simple models cannot incorporate all of these aspects simultaneously (see next section), so the policy maker must select which to consider explicitly, which to consider implicitly, and which to exclude from the analysis, based on the issue at hand.

Consideration of feedback loops. What important feedback loops are generated by the policy or intervention? For example, if the project is focused on a particular best management practice (BMP) or set of BMPs that increases productivity, improves resilience, or mitigates emissions, how does that affect the price of the commodity and thus future participation in the program? Some good ideas can be self-limiting if too successful. If there is a chance that the BMP increases labor demand (e.g., conservation agriculture, or alternate wetting and drying for rice),

how will the cost and availability of labor increase or decrease when the BMP is rolled out? Feedback loops, if explicitly taken into account, can help one anticipate and mitigate this kind of issue.

Scale of impact. The larger the anticipated scale of impact, the greater the responsibility to consider externalities, distributional effects, and impacts on general welfare before the policy is enacted. For systemic policy interventions that cannot be analyzed through techniques such as randomized trials, the only way to predict effects is through simulation modeling. Although a larger modeling effort will have a greater cost, it may be justified relative to the size of the intervention.

Spatial scale. Is the policy or program likely to affect a polity or jurisdiction (national economy, province, or state) or a geographical catchment area? Policy reforms tend to have broader, country-wide scales, whereas specific farmer support programs or infrastructural investments will more likely affect circumscribed geographies or agro-ecosystems. Issues affecting determined agro-ecological zones or watersheds are often amenable for CSA analysis, as they encompass areas that share certain biophysical characteristics such as temperature, precipitation, soil characteristics, and pest patterns.

Temporal scale. For programs of 3–5 years' duration, models should consider projected economic growth or commodity prices during that time frame. For policies aimed at long-term impacts, such as 20–30 years or more, climate scenarios or different emission pathways will be key for testing sensitivity levels.

Time and budget. Time and budget are often the most obvious and practical constraints to conducting any analysis. As the size and impact of the analysis increases, the relative cost of the analysis (relative to size of the issue or intervention) will likely decrease and have greater relevance.

Once the above factors are identified, it becomes much easier to identify an appropriate model. The next section addresses classification of different kinds of economic concepts and models that can be used to address CSA issues.

Which Models for What Purposes?

Economic Modeling Approaches and Examples Pertaining to CSA

A wide range of economic models and economic modeling approaches have been applied generally to agriculture. There are many different ways of classifying them, and each model has relative strengths and weaknesses depending on the question being posed and the factors outlined in the previous section. In addition, different modeling approaches may be combined to address different kinds of questions. Here we classify some economic modeling approaches that have been applied to or could be used to assess CSA policies, primarily in an international development context. We then describe each model type and reference some examples and, where possible, how these models have been used to inform policies or design programs.

The modeling approaches we focus on in this section include multicriteria decision analysis (MCA), statistical models of individual or firm behavior (e.g., econometric models), Bayesian networks, optimization (e.g., farm or regional/sector-scale models, linear or non-linear, positive mathematical programming), partial equilibrium (PE), computable general equilibrium (CGE) and TOA-MD, and agricultural system models (combination of biophysical and economic models). Table 2 is intended to aid the reader in selecting appropriate models by aligning the models to the principles described in Section 2. For a description of the three types or levels of analysis in column 1, see the beginning of section 2.2, Key Principles to Consider in Choosing a Model or Designing an Approach. Infrastructural investments are typically not subjected to modeling as discussed in that section, unless the investments are very large.

Table 2. Comparing typical uses of economic models and their relationship to climate-smart agriculture (CSA)

	Type of intervention[a]	Interactions/ feedback loops	Data requirements: stringency and sources	Ability to model ecological systems in detail	Complexity of approach	Can address all three pillars of CSA simultaneously?
Multicriteria Decision analysis	P, R, I	No interactions; project specific	Low—Expert opinion can work, but can be improved greatly with survey or agronomic or natural systems information	Not typically	Low	Yes
Statistical models of individual behavior	P, R	No or few interactions	High—Surveys	Not typically	Medium	No
Bayesian network models	P, R	No interactions or feedbacks	Low—Expert opinion can work, but can be improved greatly with information from surveys or agronomic or natural systems information	Would depend on the application	Low–medium	Yes
Farm or regional optimization models	P, R	Typical farms, explicit interactions	High—Surveys, experiment station data, close farm observation	Yes, if they include biophysical features	Medium–high	Yes
Partial equilibrium (PE) models	P, R	Explicitly integrates feedback loops, but only for selected markets	Medium—Surveys of cost and demand, production analysis of farms	Not typically	Medium–high	No

Table 2. Comparing typical uses of economic models and their relationship to climate-smart agriculture (CSA) *[continued]*

	Type of intervention[a]	Interactions/ feedback loops	Data requirements: stringency and sources	Ability to model ecological systems in detail	Complexity of approach	Can address all three pillars of CSA simultaneously?
Computable general equilibrium (CGE) models	P, R but less likely	Explicitly integrates feedback loops for whole economy	High, depending on the level of aggregation and detail desired—surveys, national income accounts data, farm and firm engineering data	Not typically, but could depend on whether they include biophysical features or link to a biophysical model	High	To some degree, depending on how much complexity the consumers or producers of the modeling exercise can tolerate
Trade-off analysis—minimum data (TOA-MD)	P, R, I	Implicit	Medium—Surveys, experiment station data, expert opinion	No	Medium–high	Yes
Agricultural system models	P, R, I	Depends on the type of economic model linked to the biophysical model	Medium to high, but depends on model	Yes	High	Yes

[a] I = infrastructure; P = policy; R = program level.

Multicriteria Decision Analysis

Description. MCA is a relatively simple analytical approach to facilitate a choice between discrete options to achieve common objectives using agreed-upon criteria. Take a situation where the objectives are to increase farmer incomes, improve women's access to income-generating activities, and reduce greenhouse emissions. MCA can weight those criteria equally or differently. For example, in one country, the goal of improving farmers' incomes may be weighted more heavily than the goal of reducing emissions, but in another country, the weighting could be the opposite. In this respect, MCA is very flexible and transparent. Options to address those objectives could include legal changes, farmer education, subsidies, and so on. Each option is scored in terms of its effect on each criterion. This then leads to a solution that maximizes the weighted sum of the criteria, such as, for example, a decision that maximizes the weighted sum of increases in farmers' income, reduction in GHG emissions, and reduction in farmer resilience due to climate change.

Because MCA is so flexible, it may be the ideal tool for considering issues that are sometimes hard to handle with precise models, such as issues related to youth in agriculture and generational renewal of the labor force, the fact that certain schemes may work well technically but require strong governance or political economic changes that may be unlikely, the impact on nutrition or within-family nutritional distribution, and so on. Hard data on these factors are difficult to obtain. MCA can mix quantitative data with softer informed opinion. Information can also be derived from surveys or the outputs of the other modeling approaches described below. Weighting of criteria and scoring the impact of various options on the criteria can also be done by groups, which stimulates discussion and dialogue. For example, if productivity and resilience are higher priorities than reducing GHG emissions within a given stakeholder group, interventions with greater impact on productivity can be given a higher score when that group develops their rankings.

In general, MCA is a less formal and less expensive modeling approach, but it can be a practical, collaborative, and useful way to stimulate dialogue around complex decisions with relatively little formal data. One big advantage is that because MCA can be based largely on expert opinion, it can incorporate a great variety of concerns (options for dealing with a problem, such as making an infrastructure investment or using price signals to induce farmer behavior, and criteria to judge those options, such as whether farmer incomes are increased, farmer resilience is reduced, or GHG emissions are reduced) for which there may not be much hard data, such as gender-differentiated impacts. That is, of course, also a disadvantage, given the old adage of "garbage-in, garbage-out." Whether the expert opinion is solid and sufficiently tight, in terms of consensus, to drive serious policy decisions, is a matter of professional judgment and consensus amongst professionals and stakeholders.

Examples. Some climate change adaptation approaches and case studies have used this methodology to help communities choose between discrete adaptations options. The paper "Assessing the Costs and Benefits of Adaptation Options" (UNFCCC, 2011) provides a number of different case studies for how MCA was used to assess the value of different climate change adaptation options in Bhutan, Yemen, and the Netherlands. It has also been used to identify and prioritize adaptation options in Ethiopia (see The Federal Republic of Ethiopia, 2007), Rwanda (see Republic of Rwanda, 2006), and Bangladesh (see Haque et al., 2010).

The previous examples focus primarily on adaptation options, but MCA could also be used to assess options according to broader criteria such as agricultural productivity, mitigation of emissions, and resilience. The CSA Prioritization Framework, developed by the International Center for Tropical Agriculture, analyzes outcomes in terms of food security, adaptation, and mitigation (Corner-Dolloff et al., 2015). Although the framework is technically not presented as a model, it weighs CSA outcomes and prioritizes CSA options along several different criteria similar to how an MCA would work. It allows practitioners to analyze different CSA options but

does not explicitly include feedback effects between them.

Statistical Models of Individual Behavior

Description. Statistical models of behavior (e.g., econometric models) are typically based on observation of large numbers of individuals and use of multivariate techniques to study the effect of key variables on a behavior (e.g., estimation of the effect of age, education, income, access to credit, and provision of extension services on adoption of a CSA management practice or technology). These models typically estimate whether relationships are statistically significant and, if they are, make statements such as "X extra amount of farmer training leads to Y percent extra adoption of new practices," or "as climate variability increases, farmers are more likely to adopt drought-resistant seeds or conservation agriculture practices." This kind of modeling can be used to estimate varied reactions by gender, age, level of education, or any other factor that may influence the object of study. For instance, more-educated but younger farmers may react more readily to extension advice, farm size may relate to the likelihood that farmers will adopt a certain technology, or female farmers may be more likely than male farmers to join a microcredit institution. In randomized controlled impact evaluations and quasi-experimental designs (e.g., matching farms participating in some project to nonparticipating farms), analysts typically employ such approaches to evaluate differences between farmer populations where an intervention was implemented versus where it was not. Results are typically useful in targeting farmers or other actors for certain practices, or may help in understanding why certain practices do not spread.

Examples. Statistical modeling for agriculture probably has the most examples in the literature (compared to other forms of modeling in agriculture), although like many of the other models described below, it is not always clear how the results from these models are used in the conceptualization of policies and programs. One prominent example of a program that specializes in using econometric analysis to analyze CSA issues is the FAO Economics and Policy Innovations for

Climate-Smart Agriculture (EPIC) project and associated literature (see FAO, 2016b). Recent studies from EPIC have analyzed the impact of climate-smart agricultural practices on crop yields in Zambia; the effect of climate variability on the adoption of climate-smart agricultural practices in Ethiopia; and factors affecting adaptation strategies in Malawi (Arslan et al., 2015; Asfaw et al., 2014; Asfaw et al., 2015). Similarly, statistical approaches have been used to analyze factors that affect farmers' use of adaptation strategies (Nhemachena & Hassan, 2007) and to design index-based insurance contracts (Chantarat et. al, 2012). Because statistical and econometric models can show predictive relationships, they can be used to support and justify using a particular biophysical indicator (e.g., the Normalized Difference Vegetation index, precipitation, temperatures) to trigger an insurance payment based on an indicator of farmer loss (e.g., livestock mortality, crop failure). In Fafchamps & Minten (2012), the authors conducted a randomized controlled experiment in 100 villages in Maharashtra, India, to econometrically estimate the benefits that farmers derive from market and weather information delivered to their mobile phones. The effects were found to be minimal, and this contributed to the World Bank deciding not to invest funds in distributing the service to all extension agents in India (M. Fafchamps, personal communication, September 16, 2015).

Bayesian Networks

Description. A Bayesian network can be represented (putting it colloquially) as a sort of flow chart without feedback loops, in which the key nodes are probabilities. A conditional probability distribution quantifies the effect of variables on each other. To illustrate, the simple model shown in Figure 1 states the following: *the farming yield is affected by farmer's knowledge and investment*; *knowledge and incentives affect investment in the farm*. The probability calculus of the network allows estimation of the probability of any variable taking a value using the values of some or all of other variables in the network. For example, given observations about a certain average farmers' knowledge and incentives, the model allows users to predict the likelihood that the farmers' yields would be high or low. Bayesian networks offer several

Figure 1. Bayesian network of farming yields, farmer's knowledge, farmer's investment, and farmer's incentives
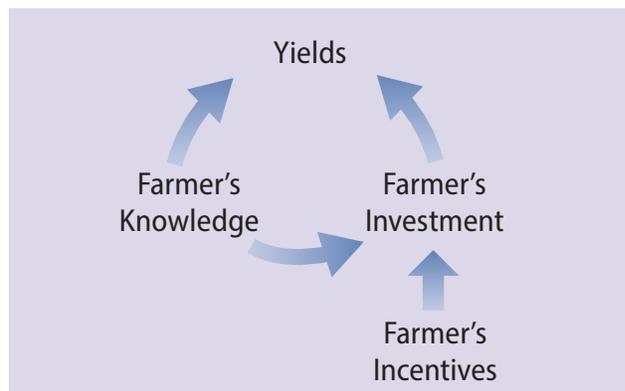
advantages over other data-analysis techniques, such as multivariate statistical modeling. Bayesian networks can handle incomplete datasets and facilitate the combination of experts' domain knowledge and research data. These networks also allow for learning about causal relationships from the data. In addition, because of Bayesian networks' modular structure, one can represent prior causal knowledge and encode the strength of those relationships with probabilities. This enables prediction in the presence of an intervention even when no experiments about the effect of the intervention are available. Finally, the modeling itself is graphical and acyclic (that is, there are no feedback loops), which makes the logic of the model easy to follow and allows for the model to be easily explained to decision-makers. This is hard to do with models that are highly recursive or contain feedback loops, such as general equilibrium models or farm or system optimization models. Bayesian network models, like multicriteria decision analyses, can be estimated without extensive empirical methods such as surveys or agronomic studies, and can depend on expert knowledge. The better the knowledge, the more reliable the results.

Examples. To our knowledge, Bayesian network models have not been applied directly to CSA efforts, but could be, given their applications in other contexts. For example, a Bayesian network model was applied to climate change adaptation research within the South East Queensland Climate Adaptation Research Initiative. Participatory workshops involving 66 stakeholders led to conceptualizations

and development of 22 alpha-level Bayesian Belief Networks (Richards et al., 2012). The outcomes of the initial systems modeling exercise successfully allowed researchers to select critical determinants of key response variables related to adaptive capacity for in-depth analysis (Richards et al., 2012).

In other research, the potential of Bayesian network models was evaluated for the task of managing GHG emissions in the British agricultural sector (Perez-Minana et al., 2012). Case study farms typifying the British agricultural sector were input into the Bayesian network model to provide understanding of how the tasks carried out on a farm impact the environment through the generation of GHG emissions.

Furthermore, the World Agroforestry Centre has proposed using a Bayesian analysis framework to help program designers assess risk to improve agro-ecosystem intervention design in data-scarce environments (Shepherd, et al., 2014). The approach they cite is based on Applied Information Economics (Hubbard, 2014), and where survey data do not exist, the approach can rely on subject matter experts to develop probability estimates and generate risk-return analyses of different interventions.

Farm- or Regional-Scale Optimization

Description. Farm- or regional-scale optimization models attempt to maximize or minimize a variable of interest, such as a typical farmer's income, or environmental variables, such as GHG emissions, subject to constraints (e.g., amount of credit, land, and inputs at hand; amount of tree cover and investment in reforestation in the watershed). At a landscape or watershed scale, these models can be used to compare how adoption of different agricultural technologies would maximize general welfare or minimize environmental pollution while holding input costs constant. These models can also help identify the most binding constraints to achieving certain outcomes on farms or through forest management (is it credit, farm family labor availability, education and knowledge?). CSA approaches sometimes assume that unless all inputs and conditions are improved, the results will not improve. On the flip side, some CSA approaches

might assume that liberating just one constraint (e.g., farmer education) will lead to improved results.

Linear programming and other similar optimization models often highlight the existence of binding constraints (e.g., water, fertilizer, credit) that limit production regardless of other interventions. For example, without water, educating farmers, increasing fertilizer use, and increasing access to credit might not impact productivity. Thus, these kinds of models can help project or policy designers get a better understanding of which constraints are most critical and have to be lifted before results will improve, and which constraints might not matter so much. At a watershed scale, hydro-economic optimization modeling can demonstrate how water can be distributed to maximize welfare across rural populations and agricultural and domestic uses. Hydro-economic modeling is useful in regions experiencing increasing water scarcity as global temperatures rise.

Optimization models also allow a very detailed assessment of the interactions between agronomic issues and environmental issues. The relationship between tillage, fodder for cattle, cattle productivity, soil conditioning, and the variety of crops used, and how of these relate to credit availability, income, and GHG emissions, can all be modeled and analyzed, as can any similarly complex set of issues. These models help researchers identify the most binding constraints and understand trade-offs, such as trade-offs between feeding cattle and leaving crop residues on or in the soil.

Examples. Optimization modeling has been applied to the agriculture sector in the United States and other countries for decades (McCarl et al., 1977; Thorbecke & Hall, 1982; Crouch & Siam, 1982; Hildebrand & Cabrera, 2003), but more recently, there has been a rapid spread of farm optimization models across the world. Robertson et al. (2012) reviewed 53 studies on agricultural systems over a period of 6 years, including whole-farm models in the context of developing countries. The study reviewed the typology of these models, validation, and how farmers cope with risk. Fowler et al. (2015) provides a recent example of using an optimization technique in CSA. Those authors use the Farm Process

Version 2 of the MODFLOW model (MODFLOW-FMP2) simulation tool developed by the US Geological Survey (Schmid and Hanson, 2009), which extensively models hydrological and farming processes, to evaluate a case study on planting decisions of farmers experiencing water stress. The results from optimization indicated feasible planting scenarios for farmers and policy makers during the water-stressed phase. Another recent example of a simple linear optimization model related to CSA and developed under the Enhancing Capacity for Low Emission Development Strategies (EC-LEDS) program involved the adaptation of the TAURUS feed ration formulation software to estimate methane emissions from beef cattle associated with different feed rations in Vietnam (see University of California, Davis, Department of Animal Science, 2016). The model maximizes animal nutrition and minimizes methane emissions for a given ration of feed and fodder available in Vietnam.

Partial Equilibrium

Description. A PE framework or model is a collection of demand and supply equations focusing on specific markets of interest while holding all other things in an economy constant. This type of model is, perhaps to over-simplify, an empirical application of the typical supply and demand curves of Economics 101, with the ability to actually produce numerical results. PE models are simpler to understand and require less data and time for construction than CGE models, described below. National-level policies in agriculture or trade, such as crop subsidies, support prices, or import tariffs, often target specific commodities. PE models are useful when assessing the impact on the price or traded quantity of that specific crop or sub-sector. For instance, a PE model can predict the impact of a crop-specific subsidy or tax on the production levels and price of that crop.

Though a multicommodity, multiregion PE model could be sufficient to address various policy questions, use of PE models comes with many caveats. A key limitation is that they suppress interactions between the commodity or crop of interest and other commodities that are linked together by substitution and competition. For instance, a subsidy on use of sugar cane for producing energy might result in lands

being withdrawn from other crops, and the price of those other crops might rise. PE models cannot capture this kind of feedback between crops. Thus, although PE models could offer greater depth of analysis because of their focus on finely disaggregated sub-sectors, they are often insufficient, as they do not capture interindustry and macroeconomic implications of a policy. Hertel (1990) illustrates some of the limitations of a PE approach: PE models' failure to acknowledge the finite resource base in the economy; no possibility of tracking the effect of transfers such as subsidies or tax revenue flows on other crops or products; and absence of an explicit budget constraint for households with links between sources and uses of income. Nonetheless, PE models are a good, low-cost first approximation for relatively simple agricultural policy questions.

Examples. There are various PE models focused on agriculture with differing crop-specific details and the capability to handle sectoral dynamics with respect to production, consumption, commodity prices, land use decisions, crop productivity changes, trade, and GHG emissions from the agricultural sectors. Some of the prominent ones that are widely cited in policy analyses are the Forestry and Agriculture Sector Optimization Model (FASOM) (Adams et al., 2005; Beach et al., 2010a); the Food and Agricultural Policy Research Institute model (CARD, 2009); the Global Biosphere Management Model (GLOBIOM) (Havlik et al., 2011); the International Model for Policy Analysis of Agricultural Commodities Trade (IMPACT) (Rosegrant et al., 2008); the Regional Environment and Agriculture Programming model (Johansson et al., 2007); and the Policy Analysis System model (De La Torre Ugarte et al., 2010). Although most of these models have been used to analyze implications of biofuels policies sourcing from agriculture, some of them (FASOM, GLOBIOM, and IMPACT) have also been applied to study the impacts of climate change on agriculture.

The IMPACT model was recently applied in Colombia as part of an analysis of the trade-offs, opportunities, and repercussions of GHG emission reduction policies (De Pinto et al., 2014). This study found that policies that successfully reduced land allocated to pasture would greatly reduce projected

deforestation, increase carbon stock, reduce GHG emissions, and generate higher revenues. This analytical framework can be adapted to any country to explore economic viability and the impact of agriculture-based GHG reduction policies. Miankhel (2015) provides an example in a PE framework focused on Pakistan. The model used historical trade data to reveal that "behind the border" constraints affected the pattern of trade in agriculture and manufactured products, preventing Pakistan from realizing its potential in bilateral trade. ("Behind the border" constraints refer to constraints on trade other than the traditional barriers such as export or import controls, tariffs, and subsidies. These constraints can include poor development of product standards and standardization, poor transport, poor governance of regulatory institutions, and so on.) The study recommended liberalizing trade with neighboring countries to smooth consumption and insulate the country from future regional price shocks. Lastly, a PE model was used to estimate the effects of climate change and adaptation measures in Organisation for Economic Co-operation and Development countries using the IMPACT model (Ignaciuk & Mason-D'Croz, 2014). This study quantifies the potential impacts of climate change on crop yields and prices and outlines possible adaptation strategies and investment required for research and development on new crop varieties and to improve irrigation technologies.

Computable General Equilibrium

Description. General equilibrium models assess what happens to prices and quantities produced and consumed in an economy when a change in policy shifts an economy to a new equilibrium. "Equilibrium" denotes that demand and supply are equal (no oversupply and no excess demand) in all markets at the same time. Given the relative shortcomings of PE models as discussed above, application of a general equilibrium model would be justified when an understanding of broader and more economy-wide outcomes of policy change is desired, and when one wants to assess the impacts of one sector of an economy on other sectors, and on a multiplicity of variables of interest, such as the impact of a subsidy or a technical innovation on

the inequality of income among classes of farmers and nonfarmers. CGE models are comprehensive market models, as they include all the commodities in an economy (even if many are aggregated). A CGE model consists of systems of equations where each equation models a key aspect of economic behavior: supply, demand, production, or price formation. The equations are solved simultaneously to see how the whole equilibrium (e.g., equilibrium of supply and demand, prices of goods and services, incomes) changes if there is some outside shock or policy change (e.g., how do agricultural credit subsidies affect the prices of all goods, including nonagricultural goods).

There are many advantages of using a CGE framework for agricultural policy analyses. As Hertel (1990) highlights, CGE models follow accounting consistency rules to track how a policy shift displaces the economy from one equilibrium (one set of prices, quantities produced, and incomes for different groups) to another. CGE models can track inter-industry linkages, which is particularly important for agriculture in contexts where agriculture drives GDP and employment, but other sectors are also important to the economy. CGE models are particularly useful when one market affects others with complex indirect effects. For example, how does restricting exports of one crop affect incentives to produce that crop, other crops, and even nonagricultural goods? By simulating the whole economy, CGE models can identify who will be affected positively and negatively by a policy change. However, CGE models are complex and time-consuming to implement and depend on consistent and balanced economy-wide data sets. Moreover, the results are highly driven by key behavioral parameters with intrinsic uncertainty. Often, CGE models require higher levels of geographic and sectoral aggregation, leading to loss of country- or commodity-specific details. Despite these limitations, CGE models offer a rigorous quantitative economic tool for policy analyses.

Until the inception of World Trade Organization, not many CGE models focused on agriculture in great depth. In the past couple of decades, researchers have paid more attention to analyzing the impact of agricultural trade policies using CGE frameworks.

Currently, several CGE models offer comprehensive representation of a disaggregated agricultural sector, land use and land cover, and GHGs emissions, which are essential for CSA policy analyses. Some of these prominent CGE models are the Applied Dynamic Analysis of the Global Economy model (Ross, 2009); the Global Trade Analysis Project–based models (Birur et al., 2008; Hertel et al., 2010); the Future Agricultural Resources Model (Darwin et al., 1995; Sands, 2011); the Modeling International Relationships in Applied General Equilibrium model (Bouët et al., 2010); and the Global Dynamic CGE model (Timilsina et al., 2010).

Examples. Most of the CGE models listed above adequately represent agriculture-specific details and are well-suited to analyzing inter-industry and global economy-wide impacts of CSA policies. However, these models would need to be adapted to a developing country context. This has been done in several cases already. In Gebreegziabher et al. (2011), a CGE model was applied to evaluate the effects of climate change on Ethiopia's agricultural sector; in Thurlow et al. (2009), a CGE was used to assess the impact of climate change on economic growth and poverty in Zambia; in Arndt (2010), a dynamic CGE model was used to simulate economy-wide impacts of climate change in Mozambique; and in Bezabih et al. (2011), a countrywide CGE model was used to project the effect of climate change on agricultural productivity over time. For an applied example that relates directly to a policy decision, Diao et al. (2013) used a dynamic CGE model to analyze the impact of maize exports bans in Tanzania imposed because of droughts in the region. Their model-predicted results indicated that a maize export ban had counterproductive impacts on domestic food security, increasing poverty, particularly in previously maize-exporting rural regions of Tanzania. The dynamic nature of the CGE model captured the trade-offs between short-term and long-term effects of the policy. The model also showed that the export ban policy benefited only some of the urban households in the country, not all urban households and not rural households in general. The International Food Policy Research Institute team presented these model predictions to the Tanzania government at a critical time, and the ban was lifted in September

2012. The Prime Minister of Tanzania stated that "the research provided clear and convincing evidence and recommendations on alternative policies to export ban" (Robinson, 2012). As droughts become more frequent with climate change, there is a greater possibility that countries will consider such policies. Thus, CGE models that can model these effects could have greater relevance.

Trade-off Analysis—Minimum Data

Description. The Agricultural Model Intercomparison and Improvement Project (AgMIP) is one of the largest concerted international agricultural modeling efforts to produce improved climate impact projections for the agricultural sector. AgMIP has identified the following core research questions to support informed decision making by various stakeholders:

1. How sensitive are current agricultural production systems to climate change?

2. What is the impact of climate change on future agricultural production systems?

3. What are the benefits of climate change adaptations?

To answer the economics-related aspects of these questions, AgMIP employs the TOA-MD developed by Oregon State University to analyze climate impact, including vulnerability and adaptation analysis. It is the only model listed in this paper that is a specific model, rather than a very general category of models, but we highlight it because of its direct relevance to CSA. The model works by simulating technology adoption and impact in a population of heterogeneous farms. TOA-MD models a farm population or whole farming systems, rather than an individual or representative farm (Antle, 2011; Antle, Stoorvogel, & Valdivia, 2014; Antle & Valdivia, 2006). As described in the paper:

> In the TOA-MD model, farmers are presented with a simple binary choice: they can operate with a current or base production system 1, or they can switch to an alternative system 2. In a technology adoption and impact analysis, the model simulates the proportion of farms that would adopt the new or alternative system, as well as the impacts of the new system by simulating impact indicators defined by the user. (Antle et al., 2014)

The TOA-MD model approach is unique because it requires only empirical evidence on means, variances, and correlations between various variables (e.g., income and costs, observed adoption and technologies used, farmer characteristics) in specific geographies such as microregions and regions. It allows the user to incorporate disparate types of information, including expert judgment, macro conditions, biophysical models, and farm cross-sectional surveys. Those data can then inform the knowledge base about the correlations, means, and variances to derive its results. Because the "database" is a set of joint distributions, one can build it up from any set of observations. For example, a user could start with survey data, but include data from experiment stations and expert judgement. The ease and parsimony of the approach reduces the cost of modeling. The results can range from predictions about the adoption of GHG mitigation practices, analysis of farm income, nutritional status under different climactic conditions. It can include the distribution of those results among types of farmers (e.g., bigger, smaller), and threshold levels for adoption. Examples of how the TOA-MD model has been used can be found on the Oregon State University website (http://tradeoffs.oregonstate. edu/). In the Chingale region of Malawi, for example, TOA-MD was used to simulate the rate of adoption that could be expected if integrated aquaculture-agriculture technologies were made available (Tran et al., 2013). A 59 percent adoption rate was estimated, and it was estimated that the poverty rate among adopters would be reduced by 22 percent. The modeling concluded, interestingly, that subsidization of the fish ponds would not have much impact on rates of adoption. The tool has been used to simulate the carbon sequestration response of farmers in wheat-based farming systems in the Indo-Gangetic Plain to different carbon prices, using low- or no-tillage practices. This allows modeling of how high the price for an eco-system benefit would have to be to get certain levels of the benefit (Grace et al., 2012)

Hybrid Biophysical and Economic

Description. It is often valuable to incorporate detailed biophysical data into economic analyses of CSA options. Biogeochemical crop process models such as the Daily Century, DeNitrification-DeComposition, EPIC, Lund-Potsdam-Jena managed Land, Predicting Ecosystem Goods And Services Using Scenarios, and Decision Support System for Agrotechnology Transfer (DSSAT) models simulate the impacts of alternative climate conditions and production strategies on yield, water use, and GHG emissions. These models use equations based on experimental and field research to represent plant growth, nutrient, water, soil, and GHG dynamics. Although these models are generally designed to work at a site level, they can be scaled up and averaged for use at larger scales. They provide an effective way to quantify the potential impacts of numerous alternative scenarios at a spatially and temporally disaggregated level. There are many additional process models designed to model a single crop, but the models listed above have been calibrated for and applied to multiple crops in many different parts of the world.

Biogeochemical crop process models provide information on the potential changes in productivity and environmental impacts given input assumptions, but do not reflect behavioral adjustments or market equilibria. If one wants to extend the modeling to behavioral and market response issues, the simulated impacts of climate change, alternative management practices, or both are incorporated into economic models of the agricultural sector to reflect producer behavior and market interactions. Impacts are generally included as shifts in the supply or production function associated with each combination of crop, region, and production process. Given the potential changes in the trade-offs faced by producers, defined by the process models as yields, input requirements, and emissions change, it is vital to account for behavioral response. Economic models are combined with the biophysical models to simulate market outcomes and to assess producer adjustments in land cover, crop and livestock mix, and production practices (e.g., tillage, irrigation, fertilizer application) in response to changing incentives.

Examples. A number of biogeochemical process models are being used in combination with economic models to assess both climate impacts and adaptation as well as mitigation policies. These studies have been conducted at a variety of levels of disaggregation. Felkner et al. (2009) simulated the impacts of climate change on rice production in Thailand using DSSAT and a detailed economic model of rice production in the northeastern province of Thailand calibrated to household rice plots. Some of the examples provided above related to CGE models also incorporate biophysical models into their analyses. In addition to a number of studies of individual crops at the sub-regional or national levels, several large studies have linked crop and economic models on a broader scale. Nelson et al. (2010) applied simulation results from the DSSAT model in the IMPACT model to assess the global impacts of climate change on agricultural yields, production, markets, and trade.

In addition, the international AgMIP effort focuses on combining crop models and economic models (see discussion of TOA-MD above) to generate estimates of potential implications of both climate impacts and adaptation and mitigation strategies at a variety of scales, from a small subregion of a country to the global level (Rosenzweig et al., 2013). A set of US Environmental Protection Agency mitigation studies also developed global marginal abatement cost (MAC) curves for agriculture. These studies incorporated results from DAYCENT (a daily version of the CENTURY model) simulations for non-rice crops and DeNitrification-DeComposition (DNDC) simulations for rice with economic data to generate estimates of the costs and potential mitigation associated with a suite of non-CO2 GHG mitigation options for the agricultural sector (US Environmental Protection Agency, 2006; Beach et al., 2008; US Environmental Protection Agency, 2013; Beach et al., 2015).

Nonmodeling Economic Techniques

As discussed above, in conducting economic analyses of CSA options, a broad range of models can be used to support decision making. Some authors and practitioners (UNFCCC, 2011) have compared the MCA model discussed above with

cost-benefit analysis and cost-effectiveness analysis as different approaches that can be used to evaluate climate change adaptation options. Here we make a distinction between MCA, which we view more as a model, and cost-benefit and cost-effectiveness analyses, which we view more as techniques that can be used to either capture the monetary benefits of an activity (cost-benefit analysis) or capture how cost-effective an activity is at achieving a particular CSA goal (cost-effectiveness analysis). Cost-benefit analysis might manifest the return on investment of an activity but typically does not incorporate externalities or broader market interactions. Cost-effectiveness analysis can be a useful technique to assess emissions reduced or resilience gained per dollar of investment in an activity. Although both of these techniques are useful, here we distinguish these techniques from agricultural modeling, which attempts to simplify reality and re-create relationships by weighting, regressing, optimizing, simulating equilibriums, and so on to produce results that can then often be used for, or expressed in terms of, cost-benefit or cost-effectiveness.

In climate change mitigation programming (e.g., low emission development, low carbon development), one popular method for assessing and ranking alternative mitigation strategies based on their relative cost-effectiveness is through the development of marginal abatement cost (MAC) curves. MAC curves order available mitigation options from lowest to highest cost and show the quantity of mitigation available at different levels of incentives for GHG mitigation (usually represented as a carbon price for simplicity). However, MAC curves are very dependent on the assumptions used, sensitive to the discount rate applied, and do not take into account transaction costs or the cost of overcoming barriers to adoption. Thus, it is important for a MAC curve to be only one of several inputs used to prioritize investments, and then only with a full understanding of the assumptions built into the curve (FAO, 2012).

Discussion and Conclusions

The challenge of modeling climate-smart interventions lies at the intersection of climate change modeling and agricultural modeling. Working on this intersection increases complexity. We argue that although the introduction of climate change variables presents additional complexities to traditional agricultural modeling paradigms of the past, it is still both feasible and practicable to apply them. The choices one makes about which model and methodology to choose, however, are highly dependent on the questions facing in-country local decision-makers, or global decision-makers. We would argue that, quite possibly, no given model needs to become much more complex than is currently the case. One could abstract more in certain traditional areas and add more detail in climate-related areas, for instance.

Under the Paris Climate Agreement, more than 90 percent of the countries that submitted INDCs included the agriculture sectors in their mitigation contributions, adaptation contributions, or both. Most of the INDCs provided high-level goals and strategies, and few provided much detail about how they intended to achieve those reductions. In addition, there are important interactions between adaptation, resilience, and mitigation goals that ideally should be considered to increase the efficiency of policy actions selected. To better evaluate the validity, feasibility, and social profitability of these nationally determined contributions, decision-makers in these countries must define which CSA interventions and outcomes they are interested in pursuing and evaluating, and then work closely with technical specialists to pick the right mix of technical methods depending on desired outcomes, budget availability, and contextual factors discussed in Section 2.2.

In the context of the Paris Climate Agreement, there is an unprecedented opportunity for decision-makers to test the validity of their Nationally Determined Contribution goals and assumptions through the development and co-implementation of modeling techniques. Modelers that use abstruse or "black box" methods provide a perhaps unnecessary challenge to policy-makers, because they limit decision-makers' ability to fully understand and evaluate the results of the analysis. It is important for modelers to be as explicit and transparent as possible, and to effectively communicate with nonmodelers and decision-makers. This may require developing easy-to-use tools or displays (such as some of those discussed in this paper), or to work with decision-makers to test each assumption and data source throughout the process. The goal of the paper is not to recommend one type of modeling over another, but to suggest ways to gear a modeling exercise to answer the questions that decision-makers are grappling with.

The Approach to Uncertainty

An important consideration for modeling CSA or any other issue involving climate change is the reflection of uncertainty. Agricultural producers have always faced numerous production and price risks, particularly risks associated with the weather. However, forecasts of more rapid changes in climatic conditions and likely changes in the frequency and severity of extreme weather have raised concerns that these risks will increase and become more difficult to predict and manage. Most studies to date have focused on the long-run impacts associated with mean climate changes for a given global circulation model and scenario, but better characterization of the variability of potential impacts is vital. There is not only variability within a given global circulation model/scenario combination, but also a general lack of agreement on the distribution of potential climate impacts across global circulation models and scenarios. It is also important to improve the modeling of short- to medium-term climate variability and potential adaptation responses. Catastrophic modeling is likely to become increasingly important over time as temperature thresholds for crop germination, growth, and winter chill are likely to be exceeded more often; water availability is expected to become more constrained in certain areas; and extreme events may happen more often. One of the key challenges is developing an accurate picture of how the variability in weather, and therefore crop yields, may change as climate moves outside of recent historical experience.

Relying on historical data implicitly assumes that low-frequency high-loss events are reflected in the available data. However, data series for many crops and regions may not be long enough to capture historical probabilities of these extreme events, let alone account for the potential changes in the probabilities of these events given projected changes in climate.

Although difficulties remain in defining exactly what the future climate may hold, the modeling tools examined in this paper generally can be extended to explore the implications of a given level of climate variability on the distribution of potential economic impacts. For instance, an optimization model can be run multiple times for a series of climate scenarios to develop a set of potential outcomes resulting from different climate conditions. Beach et al. (2010b) applied an optimization model as part of a hybrid biophysical and economic model to explore the potential impacts of climate change on the US crop insurance program by running the model for a series of climate states. This resulted in a distribution of yields, production, and prices that was used to help examine potential changes in the probability of crop losses that would trigger insurance payments. Similarly, PE, CGE, and most of the other types of models can potentially be run many times with different climate scenarios and response parameters to better capture the range and distribution of potential impacts. Statistical models are generally less suited to use for projections far into the future as the historical data on which they are based becomes less and less representative of future conditions, especially when there are major underlying trends such as climate change.

Concluding Remarks

In this paper, we have argued that the programs and policies of both development agencies and governments aimed at supporting CSA can benefit from both ex-ante modeling, before policy decisions are made, and ex-post modeling, to understand the reasons for the impact of past decisions. In this section, we suggest reasonable next steps.

Most reviews of modeling approaches and reports of specific modeling exercises simply describe the models and, to some extent, how each model is or was applied. Few publications describe how modeling has influenced policy or how the modeling effort was (or was not) embedded in a policy dialogue. Papers that describe how modeling skills have been transferred to researchers in developing countries, and how these skills have been institutionalized into policy shaping, are also relatively hard to come by. In short, there is a research agenda in when and how models have been used, in practice, to affect policy. There is also an agenda in documenting their accuracy, data maintenance requirements, and sustainability.

Similarly, there is little research as to how modeling fits or could fit better into the project or policy cycle. Given the time and budget available for project preparation, it may be too much to expect that projects engage in in-depth modeling before project start-up to pick the activities to be emphasized by the project. But if such projects did some modeling at the beginning of the project and modeling or analytics accompanied the project throughout its lifecycle, then the next project at least would benefit from the lessons of the prior one. At the same time, the project can be used to validate the modeling (thus justifying using the modeling conclusions for the next evolution in the project cycle). Because development agencies have intensified financing of CSA projects after 2008, many agencies are still conducting the first project of new project cycles in many countries or have not yet incorporated analytics into the second or so project in a cycle of projects. The time is ripe for building analytics and modeling into the project cycle so that projects could learn from each other.

Modeling skills are scarce and modeling, if done thoroughly, is not inexpensive. However, it is inexpensive in comparison with policy mistakes. CSA presents a more complex policy environment than those of previous decades; thus, analytical tools such as modeling may be even more relevant to analyzing outcomes from policies or project interventions. We have noted that policies or interventions that are complex, large-scale, one-off, irreversible (or difficult to reverse), and have potential impacts

beyond the intended ones are particularly good candidates for modeling support. At the other extreme, small projects, especially if they themselves are pilot projects meant to test an intervention, or are adapting a tried-and-true approach with only minor modifications, are not especially in need of modeling. This paper has described various types of models and provided a discussion, along with examples, of which types of models are best suited for which types of policy interventions.

References

Adams, D. E. (2005). F*ASOM-GHG conceptual structure, and specification: Documentation* [Unpublished paper]. College Station, TX: Texas A&M University.

Antle, J. (2011). Parsimonious multi-dimensional impact assessment. *American Journal of Agricultural Economics, 93*(5), 1292–1311. http://dx.doi.org/10.1093/ajae/aar052

Antle, J., Stoorvogel, J., & Valdivia, R. (2014). New parsimonious simulation methods and tools to assess future food and environmental security of farm populations. *Philosophical Transactions of the Royal Society B, 369*(1639). http://dx.doi.org/10.1098/rstb.2012.0280

Antle, J., & Valdivia, R. (2006). Modelling the supply of ecosystem services agriculture: A minimum-data approach. *The Australian Journal of Agricultural and Resource Economics, 50*(1), 1–15. http://dx.doi.org/10.1111/j.1467-8489.2006.00315.x

Arndt, C., Benfica, R., Tarp, F., Thurlow, J., & Uaiene, R. (2010). Biofuels, poverty, and growth: a computable general equilibrium analysis of Mozambique. *Environment and Development Economics, 15*(01), 81–105.

Arslan, A., McCarthy, N., Lipper, L., Asfaw, S., Cattaneo, A., & Kokwe, M. (2015). Climate smart agriculture? Assessing the adaptation implications in Zambia. *Journal of Agricultural Economics, 66*(3), 753–780.

Asfaw, S., Coromaldi, M., & Lipper, L. (2015). Adaptation to climate risk and food security: *Evidence from smallholder farmers in Ethiopia*. Rome, Italy: FAO.

Asfaw, S., McCarthy, N., Lipper, L., Arslan, A., Cattaneo, A., & Kachulu, M. (2014). *Climate variability, adaptation strategies and food security in Malawi* (ESA Working Paper No. 14-08). Rome, Italy: FAO.

Beach, R., Adams, D., Alig, R., Baker, J., Latta, G., McCarl, B., & White, E. (2010a). *Model documentation for the Forest and Agricultural Sector Optimization Model with Greenhouse Gases (FASOM-GHG)*. Washington, DC: Project Report Prepared for U.S.US Environmental Protection Agency.

Beach, R. H., Creason, J., Ohrel, S. B., Ragnauth, S., Ogle, S., Li, C., Ingraham, P., & Salas, W. (2015). Global mitigation potential and costs of reducing agricultural non-CO_2 greenhouse gas emissions through 2030. *Journal of Integrative Environmental Sciences, 12*(sup1), 87–105.

Beach, R. H., DeAngelo, B. J., Rose, S., Li, C., Salas, W., & DelGrosso, S. J. (2008). Mitigation potential and costs for global agricultural greenhouse gas emissions. *Agricultural Economics, 38*(2), 109–115.

Beach, R. H., Zhen, C., Thomson, A. M., Rejesus, R. M., Sinha, P., Lentz, A. W., … McCarl, B. (2010b, May). *Climate change impacts on crop insurance*. Prepared for U.S. Department of Agriculture, Risk Management Agency.

Bezabih, M., Chambwera, M., & Stage, J. (2011). Climate change and total factor productivity in the Tanzanian economy. *Climate Policy, 11*(6), 1289–1302.

Birur, D., & Hertel, T. T. (2008). *Impact of biofuel production on world agricultural markets: A computable general equilibrium analysis*. West Lafayette, IN: Purdue University.

Bouët, A., Dimaranan, B., & Valin, H. (2010). *Modeling the global trade and environmental impacts of biofuel policies*. Washington, DC: International Food Policy Research Institute.

Box, G., & Draper, N. (1987). E*mpirical model building and response surfaces*. New York, NY: John Wiley & Sons.

Brown, M. E., Antle, J. M., Backlund, P., Carr, E. R., Easterling, W. E., Walsh, M. K., & Tebaldi, C. (2015). *Climate change, global food security, and the US food system.* Washington, DC: US Department of Agriculture Office of the Chief Economist, the University Corporation for Atmospheric Research, and the National Center for Atmospheric Research. Retrieved December 2, 2016, from www.usda.gov/oce/climate_change/FoodSecurity2015Assessment/FullAssessment.pdf

CARD. (2009). *An Analysis of EPA renewable fuel scenarios with the FAPRI-CARD International Models.* Washington, DC: Center for Agricultural and Rural Development (CARD), Food and Agricultural Policy Research Institute (FAPRI), Iowa State University.

Chantarat, S., Mude, A. G., Barrett, C. B., & Carter, M. R. (2012). Designing index-based livestock insurance for managing asset risk in northern Kenya. *Journal of Risk and Insurance, 80*(1), 205–237.

Corner-Dolloff, C., Jarvis, A., Loboguerrero, A. M., Lizarazo, M., Nowak, A., Andrieu, N., … Girvetz, E. (2015). *Climate-smart agriculture prioritization framework. Palmira, Colombia.* Retrieved December 2, 2016, from http://hdl.handle.net/10568/68398

Crouch, L. & Siam, G. (1982). *Government policy, farmers' responses, and rural income distribution in Egypt.* University of California, Berkeley: Department of Agricultural and Resource Economics.

Darwin, R., Tsigas, M., Lewandrowski, J., & Raneses, A. (1995). *World agriculture and climate change: Economic adaptations.* Washington, DC: Natural Resources and Environment Division, Economic Research Service, US Department of Agriculture.

De La Torre Ugarte, D., He, L., Jensen, K., & English, B. (2010). Expanded ethanol production: Implications for agriculture, water demand, and water quality. *Biomass and Bioenergy, 34*(11), 1586–1596. http://dx.doi.org/10.1016/j.biombioe.2010.06.006

De Pinto, A. (2014). *Low emission development strategies (LEDS) for agriculture and other land uses: The case of Colombia.* Washington, D.C.: International Food Policy Research Institute.

Debowicz, D., Dorosh, P., Sherman, R., & Haider, S. (2014). *PSSP implications of productivity growth in Pakistan: An economy wide analysis.* Washington, DC: International Food Policy Research Institute.

Diao, X., Kennedy, A., Mabiso, A., & Pradesha, A. (2013). *Economy-wide impact of maize export bans on agricultural growth and household welfare in Tanzania - A dynamic computable general equilibrium model analysis.* Washington, DC: International Food Policy Research Institute.

Fafchamps, M., & Minten, B. (2012). Impact of SMS-based agricultural information on Indian farmers. *The World Bank Economic Review, 26*(3), 383–414.

FAO. (2012). *Developing a climate-smart agricultural strategy at the country level: Lessons from recent experience.* Background paper for the Second Global Conference on Agriculture, Food Security and Climate Change, Hanoi, Vietnam.

Felkner, J., Tazhibayeva, K., & Townsend, R. (2009). Impact of climate change on rice production in Thailand. *American Economic Review, 99*(2), 205.

Food and Agriculture Organization of the United Nations (FAO). (2016a). *The agriculture sectors in the intended nationally determined contributions: Analysis* (Environment and Natural Resources Management Working Paper). Retrieved on August 18, 2016, from http://www.fao.org/3/a-i5687e.pdf

FAO. (2016b). *Economics and policy innovations for climate-smart agriculture.* Retrieved on November 30, 2016, from http://www.fao.org/climatechange/epic/home/en/

Fowler, K., Jenkins, E., Ostrove, C., Chispell, J., Farthing, M., & Parno, M. (2015). A decision making framework with MODFLOW-FMP2 via optimization: Determining trade-offs in crop selection. *Environmental Modelling and Software, 69*, 280–291.

Gebreegziabher, Z., Stage, J., Mekonnen, A., & Alemu, A. (2011). Climate change and the Ethiopian economy: A computable general equilibrium analysis. Retrieved December 2, 2016, from http://www.rff.org/files/sharepoint/WorkImages/Download/EfD-DP-11-09.pdf

Global Alliance for Climate-Smart Agriculture (GACSA). (2016, August). *Members.* Retrieved November 28, 2016, from http://www.fao.org/gacsa/members/en/

Grace, P. R., Antle, J., Aggarwal, P. K., Ogle, S., Paustian, K., & Basso, B. (2012). Soil carbon sequestration and associated economic costs for farming systems of the Indo-Gangetic Plain: A meta-analysis. *Agriculture, Ecosystems & Environment, 146*(1), 137–146.

Haque, A. N., Grafakos, S., & Huijsman, M. (2010). *Assessment of adaptation measures against flooding in the city of Dhaka, Bangladesh* (Institute for Housing and Urban Development Studies, University of Rotterdam, Working Paper 25/10). Retrieved December 2, 2016, from https://www.ihs.nl/fileadmin/ASSETS/ihs/IHS_Publication/IHS_Working_Paper/IHS_WP_025_Haque_AN_Grafakos_S_Huijsman_M_Assessment_of_adaptation_measures_agains_flooding_Dhaka_Bangladesh__2010_.pdf

Havlik, P., Schneider, U. A., Schmid, E., Böttcher, H., Fritz, S., Skalský, R., … Obersteiner, M. (2011). Global land-use implications of first and second generation biofuel targets. *Energy Policy, 39*(10), 5690–5702. http://dx.doi.org/10.1016/j.enpol.2010.03.030

Hertel, T. W. (1990). General equilibrium analysis of US agriculture: what does it contribute? *The Journal of Agricultural Economics Research, 42*(3), 3–9.

Hertel, T., Tyner, W., & Birur, D. (2010). The global impacts of biofuel mandates. *The Energy Journal, 31*(1), 75–100.

Hildebrand, P. E., & Cabrera, V. E. (2003). *Modeling and analyzing small farm livelihood systems with linear programming*. Gainesville, FL: University of Florida, Institute of Food and Agricultural Sciences, Food and Resource Economics Department.

Hubbard, D. (2014). *How to measure anything. Finding the value of "intangibles" in business* (3rd ed.). Hoboken, NJ: John Wiley & Sons, Inc.

Ignaciuk, A., & Mason-D'Croz, D. (2014). *Modelling adaptation to climate change in agriculture*. Paris: OECD Publishing. http://dx.doi.org/10.1787/5jxrclljnbxq-en

Johansson, R., Peters, M., & House, R. (2007). *Regional environment and agriculture programming model*. Washington, DC: United States Department of Agriculture.

McCarl, B., Candler, W., Doster, H., & Robbins, P. (1977). Experiences with farmer oriented linear programming for crop planning. *Canadian Journal of Agricultural Economics, 25*(1), 17–30. http://dx.doi.org/10.1111/j.1744-7976.1977.tb02862.x

Miankhel, A. (2015). *Pakistan's potential trade and behind the border constraints*. Washington, DC: International Food Policy Research Institute.

Nelson, G. C., Rosegrant, M. W., Koo, J., Robertson, R., Sulser, T., Zhu, T., … Magalhaes, M. (2010). The costs of agricultural adaptation to climate change. *Development and Climate Change Discussion Paper, 4.*

Nhemachena, C., & Hassan, R. (2007). *Micro-level analysis of farmers' adaptation to climate change in Southern Africa*. IFPRI Discussion Paper 00714. Washington, DC: International Food Policy Research Institute.

Perez-Minana, E., Krause, P., & Thornton, J. (2012). Bayesian Networks for the management of greenhouse gas emissions in the British agricultural sector. *Environmental Modelling & Software, 35*, 132–148.

Porter, J., Xie, L., Challinor, A., Cochrane, K., Howden, S., Iqbal, M., … Travasso, M. (2014). Food Security and food production systems. In C.B. Field, V. R. Barros, D. J. Dokken, K. J. Mach, M. D. Mastrandrea, T. E. Bilir, … L. L. White (Eds.), *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 485–533). Cambridge, UK, and New York, NY, USA: Cambridge University Press.

Republic of Rwanda. (2006). *National adaptation programmes of action to climate change*. Retrieved December 2, 2016, from http://www.preventionweb.net/files/8564_rwa01e.pdf

Richards, R., Sano, M., Roiko, A., Carter, R., Bussey, M., Matthews, J., & Smith, T. (2013). Bayesian belief modeling of climate change impacts for informing regional adaptation options. *Environmental Modelling & Software, 44*, 113–121.

Robertson, M., Pannell, D., & Chalak, M. (2012). Whole-farm models: A review of recent approaches. *Australian Farm Business Management Journal*, 13–26.

Robinson, S. (2012, September 10). *Tanzania looks for investment in agriculture sector*. Retrieved from http://www.foodworldnews.com/articles/2124/20120910/tanzania-looks-investment-agriculture-sector.htm

Rosegrant, M. (2008). *International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT): Model description*. Washington, DC: International Food Policy Research Institute.

Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P., … Asseng, S. (2013). The agricultural model intercomparison and improvement project (AgMIP): Protocols and pilot studies. *Agricultural and Forest Meteorology, 170*, 166–182.

Ross, M. (2009). *Documentation of the Applied Dynamic Analysis of the Global Economy (ADAGE)*. Research Triangle Park: RTI International.

Sands, R. (2011). *Interaction of agriculture and energy in global greenhouse gas mitigation scenarios*. Presented at the Forestry and Agriculture Greenhouse Gas Modeling Forum, Shepherdstown, WV.

Shepherd, K., Luedeling, E., de Leeuw, J., Rosenstock, T., Fenton, N., Neil, M., . . . Millar, M. (2014, April). *Concept note: A novel decision analysis and risk assessment framework for improving agro-ecosystem interventions*. Nairobi, Kenya: World Agroforestry Center (ICRAF).

The Federal Democratic Republic of Ethiopia. (2007). *Climate change National Adaptation Programme of Action (NAPA) of Ethiopia*. Ministry of Water Resources, National Meteorological Agency. Retrieved December 2, 2016, from http://unfccc.int/resource/docs/napa/eth01.pdf

Thorbecke, E., & Hall, L. (1982). *Agricultural sector analysis and models in developing countries*. Rome: Food and Agricultural Organization of the United Nations.

Zhu, T., Diao, X., & Thurlow, J. (2009). *The impact of climate variability and change on economic growth and poverty in Zambia*. Retrieved December 2, 2016, from http://www.ifpri.org/publication/impact-climate-variability-and-change-economic-growth-and-poverty-zambia

Timilsina, G., Beghin, J., van der Mensbrugghe, D., & Mevel, S. (2010). *The impacts of biofuel targets on land-use change and food supply: A global CGE assessment*. Washington, DC: The World Bank, Development Research Group, Environment and Energy Team. http://dx.doi.org/10.1596/1813-9450-5513

Tran, N., Crissman, C., Chijere, A., Hong, M. C., Teoh, S. J., & Valdivia, R. O. (2013). *Ex-ante assessment of integrated aquaculture-agriculture adoption and impact in Southern Malawi*. Retrieved December 2, 2016, from http://aquaticcommons.org/10942/1/WF_3453.pdf

University of California, Davis, Department of Animal Science. (2016, June 30). *Animal Science Cooperative Extension software*. Retrieved February 26, 2016, from http://animalscience.ucdavis.edu/extension/software/

United Nations Framework Convention on Climate Change (UNFCCC). (2011). *Assessing the costs and benefits of adaptation options: An overview of approaches*. Bonn, Germany: UNFCCC.

US Environmental Protection Agency (USEPA). (2006). *Global mitigation of non-CO_2 greenhouse gases* (EPA Report 430-R-06-005). Washington, DC: US Environmental Protection Agency.

US Environmental Protection Agency (USEPA). (2013). *Global mitigation of non-CO_2 greenhouse gases: 2010–2030* (EPA Report 430-R-13-011). Washington, DC: US Environmental Protection Agency.