Data, Economics and Computational Agricultural Science

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My goal in this address is to discuss how computational agricultural science – the application of advances in data infrastructure, data science and computation to agricultural sciences and to economics and related behavioral and social sciences – can accelerate the transformation towards sustainable agricultural systems. As the recent report by the National Academy of Sciences (2018) demonstrates, the scientific community now recognizes the need to transcend the reductionist paradigm in science in order to understand and predict the behavior of complex systems that cannot be subjected to controlled experimentation, but can be modeled and studied using observational data and simulation experiments. Analysis of climate change impacts is the most obvious example, but the same problems pervade all forward-looking efforts at technology design and evaluation. Advances in disciplinary science are needed, as well as trans-disciplinary integration to understand and predict complex system behavior. To identify sustainable development pathways for agricultural systems, data and models are needed that can predict their performance under current conditions, but more importantly, under future conditions that cannot

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be observed in historical data (Brown et al. 2015; Antle and Stöckle 2017). Meeting this challenge raises fundamental methodological issues for all sciences. The challenge is particularly daunting for economics and related disciplines involving human behavior that have favored statistical models estimated with historical data.

In the first section of this address, I discuss some of the actual and potential advances in agricultural systems modeling that provide new ways to link advances in genomics and other fields of science with better biological and physical data to accurately predict crop and livestock productivity. Because these models are largely mechanistic and process-based, in principle they are capable of predicting agricultural production system performance within the range of observable variation of existing systems, as well as the behavior of modified or new systems in new environments. These process-based models are being improved through better data and through more rigorous evaluations and model inter-comparisons, combined with advances in disciplinary science such as soil microbiology, plant pathology and entomology that provide the basis for improved understanding of processes. However, an important limitation of these models is that they do not incorporate human decision making. In the second section I describe methodological challenges to the specification and estimation agricultural system models that include the behavior of farm decision makers, building on insights from the econometrics and statistics literatures on causal inference. These challenges involve the estimation of counterfactuals, accounting for unobserved heterogeneity, and modeling new technologies, and thus all relate to the observability of relevant phenomena.

A common theme that emerges from both the agricultural systems science and economic-behavioral sciences is that improved acquisition and use of data is a critical constraint on agricultural research and its successful application, both for on-farm production system management and for technology and policy decision making. In the third section of this address I present a prototype scheme for acquiring better data that can support advanced computational methods and models, and discuss the economic, technical, legal and institutional challenges to better data. In the final section I summarize and reiterate the case for the high potential return on public investment in better data and computational methods in the agricultural sciences.

Towards Computational Agricultural Science

Experimentation has been the basis of agricultural improvement since at least the 17th Century. The recognition of the public good value of systematic investigation and dissemination of knowledge in the late 19th and early 20th Centuries led to the development of public research and extension systems, as exemplified by the U.S. Land Grant University experiment station system. This system exploited key breakthroughs in statistical methodology in the early 20th Century, based on the application of new mathematics to formalize the central role of randomization in experimental design and hypothesis testing. R.A. Fischer's *Design of Experiments* published in 1935, based largely on data from the Rothamstead Experimental Station in the United Kingdom, was a landmark in these developments.

Along with various other advances in relevant sciences, the systematic use of the experimental paradigm in agronomy and animal science has accelerated advances in agricultural technology, but the process remains a slow one, constrained by the rates of plant and animal growth, their reproductive cycles, and the annual climate cycle. The experimental method also is constrained by the large number of factors that can affect crop or animal growth and other characteristics associated with its genetics, environment and management. In evaluating agricultural systems performance, additional dimensions of environmental and social sustainability further increase the dimensionality problem in experimental design.

Another consequence of these limits to the experimental method is that science-based management recommendations, such as planting date and fertilizer application rates, are based on experiments carried out at a limited number of sites, and thus must be made uniformly across widely varying conditions. Not surprisingly, farm survey data show widely varying management practices that reflect variation in location-specific conditions, farmers' knowledge and experience, and other factors.

Understanding farmers' decision making behavior remains another complicating factor. The research community continues to debate whether farmers' behavior is "economically rational" or driven by other motivations or constraints, but given the inability of "expert" recommendations to take farm-specific conditions into account, farmers appear to rationally deviate from standard recommendations. To varying degrees, new technologies such as mobile sensors on farm machinery are enabling "precision management," but it is unclear what criteria are being used or should be used for management algorithms. As yet the economic and environmental benefits of these technologies remains to be demonstrated (Castle 2016; Schimmelpfennig 2016). Even in technologically advanced countries, most farmers cannot effectively utilize the data becoming available from new digital technologies, in part because useful predictive models are not readily available (Antle et al. 2017b; Leonard et al. 2017).

Agricultural System Models

The production function is a central concept of neoclassical and modern economics, and the earliest empirical applications were mostly statistical (e.g., Cobb and Douglas 1928; Marshak and Andrews 1944). Chenery (1949) provided a formalization and empirical illustration of production functions derived from engineering data that include technical specifications of inputs in addition to quantities. The engineering approach was largely ignored by early empirical economists (Wibe 1984), perhaps because detailed firm-level data were not available whereas new more aggregate data were becoming available for analysis of aggregate relationships such as market supply and demand and aggregate productivity growth. Early statistical estimation of yield response functions in agriculture also seems to have led to econometric approaches instead of engineering ones in agriculture, as exemplified by Heady (1961), and further encouraged by the applied duality theory literature of the 1970s and 1980s, and the production risk literature inspired by Just and Pope (1978). Some economists attempted to develop dynamic production function models to mimic the stages of crop growth (e.g., Antle and Hatchett 1986), but such approaches were hampered by the lack of intra-seasonal input data.

Agronomic researchers began to develop mechanistic crop growth simulation models beginning in the 1960s, encouraged by improved understanding of the relevant processes of crop growth. Initially used to embody process understanding in quantitative terms, researchers combined these models with experimental data and exploited the capabilities of new digital computers to develop simulation models (Jones et al. 2017a). Models that began as crop growth models have evolved into larger and more complex system models with various capabilities and are now used for many research, analytical and decision support purposes, representing individual crops, multi-crop systems, and crop-livestock systems, at scales ranging from an individual point in space (i.e., an experimental field), to global crop yield simulations using gridded soils and climate data for climate impact assessment. A global community of science, the Agricultural Model Inter-comparison and Improvement Project (AgMIP), now supports collaborative research on data, software and model improvement for agricultural systems models (Rosenzweig et al. 2013; 2017).

These mechanistic agricultural simulation models are essentially biological engineering production functions for crops and livestock. They have both strengths and limitations for use in economic impact assessments (Antle and Stöckle 2017). Here I will emphasize the potential for the models to predict out-of-sample in situations where model parameters estimated statistically with historical data are invalid. This can occur, importantly, when new technologies are introduced, or when systems move to regions of the model parameter space not observable in historical, especially when nonlinearities or discontinuities are involved (Antle and Capalbo 2001). For example, Antle and Capalbo (2002) describe the difficulty of using observational data to model the nonlinear response of potato yield to fungicides used to control the late blight disease. In econometric terms the key idea is that, for some purposes, mechanistic models are better suited to represent the model structure needed to predict out-of-sample.

Advances in Data and Modeling

Despite the substantial progress that has been made, current mechanistic models have many limitations, and are in need of significant improvement before they are capable of being sufficiently reliable for use to predict management practices on a field or for use in policy analysis (Holzworth et al. 2015; Jones et al. 2017b; Antle et al. 2017b; Antle and Stöckle 2017). For example, important biological processes such as the soil microbiome are not well understood or represented, the effects of pests and diseases are not represented well in most models, and crop rotations and inter-crops and crop-livestock interactions are not adequately represented. Models have been developed for major annual cereal crops, but many minor crops, horticultural crops, and perennial crops have not yet been modeled. Although some models represent effects of tillage, these biological models do not incorporate human labor, and most importantly, management decision making is beyond the scope of these models.

Despite these limitations, crop growth models do appear to perform well in representing some of the most important elements related to crop management, including response to water and nitrogen. Recent research shows that mechanistic and statistical models perform comparably under near-term conditions (Liu et al. 2016; Lobell and Asseng 2017). However, statistical models are not capable of predicting out-of-sample phenomena such as the effect of increased atmospheric CO2 on crop yields and quality. Recent studies have also shown that gene-based models can provide better out-of-sample predictions that statistical models (Cooper et al. 2016). Moreover, new data and computational methods are leading to substantial improvements in model performance, such as recent advances in modeling crop response to temperature (Maiorano et al., 2017; Wang et al. 2017). Recent research has also demonstrated the use of model ensembles to improve yield prediction, paralleling earlier developments in climate modeling (Martre et al. 2015). In part, these developments have been possible through the collaborative model of science that is emerging through organizations such as AgMIP.

Advances in genomics and crop growth models are creating the possibility of linking genetic information to crop model parameters (Hwang et al. 2017). New gene-based crop models offer the potential of predicting crop performance using advances in genomics, phenomics (phenotyping), and computational technologies that can represent the complex interactions among genotype, environment, and management. For example, new DNA sequencing technologies have increased the number of genetic markers for identifying genes associated with phenotypic traits. Large-scale phenotyping methods such as the use of unmanned aerial vehicles (UAVs), robotics, and sensor technologies are reducing costs and time for collecting field phenotype measurements. Also, new computational and statistical tools are rapidly advancing the capability to identify genes and environmental factors that affect crop traits (Technow et al. 2015; Cooper et al. 2016; Hwang et al. 2017).

But even with these promising developments, do agricultural systems models work well enough to be used for on-farm management prescriptions, for economic assessment of new technologies and policies, or analysis of climate change impacts? The answer today appears to be yes for some purposes and no for others. My personal experience from working with these models and modelers for over 25 years is that the models remain complex and are not user-friendly. A recent study of “next generation” models concluded that a major limitation of agricultural systems models is the difficulty faced by potential users to obtain and interpret model outputs (Antle, Jones and Rosenzweig 2017; also see Holzworth et al. 2015).

Economic Analysis of Agricultural Systems

I now consider the economic paradigm for impact evaluation, in the context of agricultural systems analysis. I will identify key methodological challenges, and then propose “hybrid” production models – the combination of mechanistic and empirical production models – as the best approach to address these challenges.

Economic Impact Evaluation

To facilitate discussion, consider the following stylized representation of an agricultural system. Define: Q = output, economic welfare measure or other impact indicator; X = choice variables such as input types and quantities; A and B are random variables representing covariates and stochastic factors in each of these relationships; α and β are parameters. In general, all can be vectors and can vary in time and space.

(1) $X = X[A, \alpha]$ (decision maker behavior, or the assignment of “treatment”)

(2) $Q = Q[X, B, \beta]$ (technology, welfare metric or impact indicator)

Combining (1) and (2) gives the reduced form:

(3) $Q = S[A, B, \alpha, \beta]$.

Note that *X* represents decisions made before at least some of the realizations of *B* are observable by the farmers. The structure depends on assumptions made about the decision making process of the farmers, such as how expectations are formed and the timing of decisions in relation to the realization of elements of *B* such as rainfall or pest infestations. Thus, in an explicitly dynamic model such as Antle and Hatchett (1986), the model has a recursive stochastic structure. Moreover, equation (2) represents output realizations; the farmer's decision making may depend on some function of *Q*, as in a typical model of expected profit maximization.

For example, in the conventional micro-economic model, we can interpret *Q* as profit and the expectation of $Q[X, B, \beta]$ as the expected profit equation embedding the production function, output price and cost of production. *X* is a vector of variable inputs such as seed variety and fertilizer, *B* represents exogenous variables that can include prices, soil, weather and other biotic and abiotic factors affecting production; β is production function parameters.

A key point is that conventional representations of production functions express some elements of *A* and *B* as "error terms," but some of the factors attributed to the error term are observable in principle. For example, most production function specifications attribute the random error term to weather, but with available weather data, weather distributions can be characterized for modeling *ex ante* decision making, and can be observed and included in the model as an explanatory variable for modeling output realizations. Indeed, in mechanistic crop growth simulation models, weather is a key input variable. Similarly, the random variation in the behavioral equation (1) across farms or over time could be attributed to differences across individuals in psychological attitudes such as risk aversion, experience or knowledge, but in principle with appropriate data each farmers' risk attitudes, experience or knowledge could be quantified and included explicitly as an explanatory variable. Further, as I discuss below, process-based behavioral decision models could be developed and used in place of economists' typically simplistic behavioral assumptions such as expected profit maximization.

With the additional behavioral assumption that X is chosen to maximize expected profit, A contains the elements of B that are known to the decision maker at the time X is determined, and α embeds β and the parameters of the random variables in Q, such as the output price and weather. In this case, the reduced-form production function (3) is the conventional supply function. However, other behavioral models do not lead to the conventional dual relationships between the production function and the input demand and output supply functions. An example is a farm using advisory services to choose some components of X. In this case, the farmer's objective could be increasing in profit and decreasing in management effort (a component of X), but the choice of some elements of X by the advisory service may maximize the advisor's income rather than the farmer's profit, as in a principal-agent model.

This type of model also can be extended by adding an additional welfare metric that depends on elements of Q and X. An example is a semi-subsistence household production model where Q could include nutritional outcomes of farm family members that depend on consumption of farm production as well as income obtained from producing non-food cash crops. Environmental impacts also can be added to the analysis as a function of X and environmental factors captured in B. Other generalizations are also possible, for example, to account for system dynamics (Antle and Stoorvogel 2006).

The Evaluation Paradigm and Agricultural System Modeling

I noted in the introduction that a key challenge is to predict the behavior of agricultural systems outside the range of historical observation. This problem is similar to the policy evaluation problem studied by economists and statisticians. However, it goes beyond conventional out-of-sample inference problems in econometrics and statistics because it involves more fundamental structural changes in agricultural systems that cannot plausibly be addressed with strictly empirical models.

Heckman (2010) argues that "economic policy evaluation" can be defined in terms of three types of problems:

P1: evaluation of implemented interventions in the environment where they are observed (the problem of internal validity in *ex post* evaluation);

P2: evaluation of interventions in a different but observable environment (the problem of external validity in *ex post* evaluation)

P3: evaluation of new interventions in environments *never historically observed* (the *ex ante* evaluation problem).

Heckman argues that in order to solve all three of these problems, structural models satisfying "Markshak's Maxim" are needed, meaning models with sufficient structure to represent the effects of the intervention not only in the environment in which the parameters are estimated, but also in other environments and responses to new kinds of interventions. For example, consider a randomized-controlled trial that randomizes a treatment T = (0,1) among a set of individuals with observable characteristics Z, and let ε represent independent errors, and let γ be a parameter vector. The analyst estimates:

(4) $\quad Q = R[T, Z, \gamma, \varepsilon]$.

Interpreting the relevant measure of impact as the change in the dependent variable of the function (2), Heckman argues the Neyman-Rubin potential outcomes approach to impact evaluation can address P1 by estimating equation (2) to obtain an estimate of the average treatment effect equal to the mean of Q for T=1 minus the mean of Q for T=0. However, this type of analysis cannot address P2 or P3, because the potential outcomes approach does not use theory to define the structure of the system needed to predict the effects of policy interventions in alternative (out-of-sample) environments or the effects of new policies in historically novel environments. Thus, lacking theory to relate *Z* to *X*, *B* and *A*, it follows that γ embeds elements of these variables in a way that is specific to the sample data, and thus cannot be generalized to other environments and does not satisfy Marshak's Maxim for evaluation of interventions in other environments. Additionally, since the behavioral equation (1) is not estimated, it is not possible to identify the relevant range of behavior and estimate other relevant "treatment effects" such as the effect on those individuals who choose to adopt a new technology (treatment effect on the treated), or the effect over a policy-relevant range of a behavior (what Heckman calls the policy-relevant treatment effect).

In contrast, suppose (1) and (2) represent a structure satisfying Marshak's Maxim, e.g., to evaluate a policy that would change incentives to use *X*. To evaluate P2, observations of *A* and *B* are needed in the environment that is distinct from the one used to estimate the parameters. For the estimates of α and β to be unbiased and stable across environments, the description of *A* and *B* must be correct and observations of them must be accurate. Thus, the availability of suitable observational data is a critical part of solving P2, and these data must be available for the estimation environment and for the out-of-sample environment.

Solving P3 involves evaluation of as-yet unobserved interventions in novel environments. A novel environment can be the same location I the future, as in climate change assessments, or a different location with different conditions, or both. This type of analysis requires predicting *A* and *B* into the novel environment. If the new intervention involves a change in technology, the functions in (1) and (2) must endogenize the technological change. For example, some aggregate models specify rates and biases of technological changes as functions of prices. Other research has attempted to incorporate estimate rates of yield improvement through the development of scenarios with input from crop breeders and other experts, e.g., as in Valdivia et al. (2015).

I now consider further the methodological challenges posed by these three problems. My goal is to consider the possibility of implementing the requisite analyses with experimental and non-experimental data and improved computational methods.

The Identification Problem

A basic issue is whether model parameters can be identified and estimated without biases large enough to alter hypothesis tests or predictions. In this section I will argue that non-experimental data involving observations of purposeful (one might say, "rational") behavior are likely to violate the common support conditions required to reliably estimate counterfactuals in *ex post* impact evaluations. The availability of better data and models could make it possible to replace the conventional approach to counterfactual estimation using observational data with a computational approach.

Originally, "identification" in econometrics referred to the problem of being able to uniquely estimate the structural parameters, i.e., α and β in equations (1) and (2) above. But more recently, the recognition (one might say, the "re-discovery") of the experimental design problem in the econometrics literature has led to the use of the term “identification” or “identification strategy” to refer to the problem of distinguishing “control” observations from “treatment” observations to obtain unbiased estimates of γ in equation (4) with non-experimental data – e.g., see the discussion in Angrist and Pishke (2010).

In the problem P1, with experimental data in which the “treatment” X is randomly assigned and independent of random elements in the outcome equation (2), there is no structural identification problem, and an unbiased estimate of the average treatment effect can be obtained. With non-experimental data X is determined by equation (1), and as discussed extensively in the statistics and econometrics literatures, unbiased estimation becomes much more challenging, particularly when stochastic factors determining X are not independent of stochastic elements in the outcome equation (2), and even more challenging when the effect of X on Q is itself heterogeneous and not independent of X. Wooldridge (2010) summarizes many of the methods currently in use, most of which rely on the use of panel data to account for selection behavior and unobserved heterogeneity.

The point I want to emphasize is that with non-experimental data, the properties of the data are determined by the behavior of the economic agents, i.e., in the paradigm of discrete choice models, the properties of the data are determined by the selection behavior of the agents. This basic fact has profound implications for empirical analysis. If indeed economic agents are aiming to achieve a goal such as to maximize profitability or other systematic behavior, then their behavior is likely to lead to choices that do not span the entire range of possible values of X. Consequently, it will not be possible to statistically estimate parameters associated with sub-optimal behavior. In the context of attempting to solve problem P1, this means that the “common support” condition required for identification of a counterfactual is likely to be violated

(Wooldridge 2010). In the case where *X* is a discrete variable such as the choice between a non-hybrid and hybrid maize variety, the formal condition is stated as the probability of *X* conditional on *A* falling strictly between zero and 1. But what is required in practice is that a sufficient number of observations of both choices are observed, conditional on exogenous covariates, for parameter estimation to be reliable.

To illustrate the practical importance of this issue, consider the problem of understanding the adoption and economic impact of hybrid maize varieties in Kenya and Tanzania. Maize yields are very low throughout Tanzania, and are in a similar range in the agro-ecological zones of Kenya that are not favorable to maize. Thus, one of the most important issues facing agricultural scientists aiming to improve maize productivity in these countries is to estimate the productivity potential of hybrid seed *in the areas where it is not now widely used.* Table 1 shows data on patterns of hybrid maize use from the two countries for farms that are permanent users or non-users of hybrid maize varieties, and for farms that are observed to switch between hybrid and non-hybrid varieties. Two striking features of the data are apparent: very few farms use hybrid seed in the low productivity zones; and virtually all farms in the high productivity zones use hybrid. Thus, it is not possible in the low zone to use statistical procedures such as matching, or to estimate structural models of unobserved heterogeneity, because observations of hybrid users are simply not available. Attempting to do so will produce unreliable inferences; attempting to use observations from outside the low zone will likely produce biased estimates. Likewise, it is not possible in the high zone to estimate the productivity of hybrid because there are few observations of non-hybrid seed being used.

Thus, the overlap or common support problem is a problem of what is observable. If observations of non-experimental data are often inadequate to identify counterfactuals because of the economic (selection) behavior of farmers, what is the alternative? Below I argue that an alternative solution is to use mechanistic models that are valid "out of sample" to simulate counterfactuals. In other words, a crop model could be used to estimate the productivity of the hybrid maize variety in the low-productivity zones where it is not observed to be used, and thus could be combined with observations of non-hybrid farms to estimate the return to adopting hybrid for those non-adopters.

Unobserved Heterogeneity

The early literature on production function estimation recognized the problem of unobserved heterogeneity. Today this is recognized as one of the fundamental problems in the use of non-experimental data. Mundlak (1961) referred to this as the problem of "management bias" and proposed the use of a fixed-effects estimator, anticipating by many decades the recent literature on methods to address unobserved heterogeneity, e.g., the application of the Chamberlain-Mundlak mechanism and related panel data methods (Wooldridge 2010). Here I argue that there are two distinct but related problems associated with statistical estimation of production system models that are caused by the observability of relevant variables in a production system. One is the bias problem identified by Mundlak due to the fact that the econometrician does not observe the same phenomena as the farm decision maker. The other is the bias problem due to the fact that the econometrician does not observe accurately all of the appropriate elements of X and B in equation (2).

To illustrate, I use the example of estimating a crop yield function based on the system (1) and (2) presented above. Define Y_{it}^{s} as the yield for a crop produced by farm i in period t using technology s. Following the notation in (2), let $B_{it} = (B_{it}^{f}, e_{it})$, where B_{it}^{f} is the set of biotic (e.g., soil microorganisms) and abiotic (e.g., soil properties) factors and farm characteristics (e.g., fixed capital) that affect production, and e_{it} is the set of random factors that cannot be controlled by the farmer (pest infestations, weather). X_{it}^{s} is a vector of input and management decisions made by the farmer that are specific to this technology. Thus the production function is

(5) $Y_{it}^{s} = f^{s}[X_{it}^{s}, B_{it}, e_{it}, \beta]$

Following (1), define A_{it} as the farmer's information set used to determine X_{it}^{s} that includes B_{it}^{f} as well as output and input prices, and other relevant information such as past production experience, weather forecasts, etc. Thus management decisions are a function of this information, $X_{it}^{s}(A_{it}, \alpha)$.

As long as the unobserved random effects are statistically independent of management decisions, unbiased estimation of the production function parameters β is possible. The unobserved heterogeneity problem arises, following Mundlak (1961), because elements of A_{it} contain or are related to elements of e_{it}, thus violating the independence of X_{it}^{s} and e_{it}. For example, soil quality varies across farms, and thus some farms apply more or less fertilizer due to their knowledge of their soils. In many cases, accurate soil information is not available to an econometrician estimating a production function, giving rise to biased parameter estimates. To the degree that this effect is time invariant, a fixed-effects estimator could eliminate this bias. However, many such unobserved effects, such as soil moisture at planting, are not time-invariant, so a fixed-effects estimator does not solve the unobserved heterogeneity problem. Obviously, better observational data, e.g., from automated soil moisture sensors, could provide this type of site-specific and time-specific data.

While the bias problems caused by unobserved heterogeneity may be important, my experience working with farm survey data suggests that a much more important problem is incomplete and inaccurate data. There has been some discussion of output measurement problems, but input measurement is much more challenging. Anyone who has carried out farm surveys, or worked with farm survey data, knows the difficult problems caused by the diversity of purchased inputs (e.g., seed varieties, nutrient components, pesticides), labor (hired, family, differing by age and gender), various types of tools and mechanical implements, and so on. Additionally, as the example of soil moisture at planting time illustrates, accurate site-specific and time-specific data on soils and weather are also a major challenge. As illustrated by Mundlak's management bias concept, the characteristics of the farm decision maker are also not easily quantified.

What this means is that the econometrician observes a set of variables Z_{it}^s that is typically an inaccurately measured subset of X_{it}^s and B_{it}. It follows that the yield distribution estimated by the econometrician is a biased estimate of the true yield distribution. The mean production function is:

(6) $$Y_{it}^s = m^s[X_{it}^s(A_{it}), B_{it}^f, \beta] + v_{it}^s, E\left[v_{it}^s \middle| A_{it}\right] = 0,$$

where $m^s[X_{it}^s(A_{it}), B_{it}^f, \beta] \equiv E[f^s(X_{it}^s, B_{it}^f, e_{it}, \beta)|A_{it}]$ and E is the expectations operator. By the assumption that A_{it} does not contain e_{it}, we can conclude that unbiased estimation of β is possible with accurate observations of X_{it}^s and B_{it}^f. However, if the econometrician's available data is $Z_{it}^s \neq (X_{it}^s, B_{it}^f)$, the mean function estimated by the econometrician is

$$Y_{it}^s = E[Y_{it}^s|Z_{it}^s] + u_{it}^s, E[u_{it}^s|Z_{it}^s] = 0, E[Y_{it}^s|Z_{it}^s] \equiv E[f^s(X_{it}^s, B_{it}^f, e_{it}, \beta)|Z_{it}^s].$$

Defining $\Delta E\left[Y_{it}^{s}\middle|A_{it}, Z_{it}^{s}\right] \equiv E[Y_{it}^{s}|Z_{it}^{s}] - E\left[Y_{it}^{s}\middle|A_{it}\right]$, the econometrician estimates

(7) $$Y_{it}^{s} = E[Y_{it}^{s}|Z_{it}^{s}] + u_{it}^{s} = m^{s}[X_{it}^{s}(A_{it}), B_{it}^{f}, \beta] + \Delta E_{it}^{s} + u_{it}^{s}$$

Thus ΔE_{it}^{s} is a component of the error term in a production function model, and it is not generally statistically independent of X_{it}^{s} and B_{it}^{f}. It follows that the production function parameter estimates are likely to be biased due to incomplete and inaccurate measurement of inputs and farm-specific conditions.

Evaluating Novel and Future Systems Using Hybrid Structural Models

Problem P3 is the most challenging but also most important problem in agricultural systems analysis because it requires, first, parameterization of a model with sufficiently "deep" structure to endogenize the changes in the technology (2) and associated behavior (1); and second, it requires projection of exogenous variables *A* and *B* into the future. My basic message is that better data and mechanistic models, coupled with better data and econometric models, are likely to provide the best solution to the structural modeling of agricultural systems. The solution to the second problem is the use of participatory scenario methods like the ones that are currently in use for climate impact assessment. This aspect is beyond the scope of this address; I refer the reader to Valdivia et al. (2015) and Antle et al. (2017a) for applications of scenario methods in agricultural systems modeling.

Antle and Capalbo (2001) proposed "econometric-process" simulation models as a way to combine mechanistic crop growth models with econometric production models to simulate agricultural systems "out of sample," i.e., to address problems P2 and P3. Antle and Stöckle (2017) argue that this type of model – which they describe as hybrid structural models – satisfy Marshak's Maxim in the context of climate impact assessment. These hybrid models are composed of a bio-physical process-based production system model that embodies the relevant bio-physical parameters and variables, and an economic-behavioral model that embodies the relevant socio-economic parameters and variables.

However, to date none of the existing models has accomplished a full integration of bio-physical and economic-behavioral models. There are both conceptual and computational difficulties in implementing this kind of integration, for example crop simulation models typically work on a daily time step whereas economic decision making may be made on a longer time step according to operations such as land preparation, planting, irrigation, cultivation and harvest, as well as on longer time horizons involving inter-seasonal dynamics of crop rotations and long term capital investment decisions. To effectively achieve close coupling, it will most likely be necessary to create modular crop and economic models so that different components can be linked in a "plug and play" system (Antle and Stoorvogel 2006).

While full integration of crop simulation and economic models is a desirable goal in principle, researchers thus far have used various methods to achieve a "loose coupling" of models as illustrated in the following discussion. A limitation of this type of modeling is that it cannot represent the dynamics associated, for example, with bio-physical processes such as soil carbon dynamics, or learning by the decision maker. Instead, the productivity component is implemented with assumed management, which may be historically observed values or ones projected into the future using scenarios.

To illustrate the issues that arise when models are not fully integrated, we consider the approach developed by Stoorvogel et al. (2004) and used for technology impact and climate impact assessments such as Valdivia, Antle and Stoorvogel (2012, 2017). Their goal was to replace the usual *ad hoc* inclusion of some bio-physical variables in econometric models with an approach that would incorporate the effects of soil, climate and the genetic characteristics of crops and livestock in a way that is consistent with the process-based knowledge in crop and livestock simulation models. Similar procedures have been utilized in modeling systems in studies of European agriculture (Ewert et al. 2014).

Theoretically, soil and climate conditions define the potential productivity of a location that, combined with a plant type, management practices, and weather conditions, leads to a realized output. Following (5), let a crop growth simulation model can be represented as a function $Y_{it}^s = f^s[X_{it}^s, B_{it}, e_{it}, \beta]$. We can use the crop growth simulation to calculate a yield Y_{it}^* for a specified management X_{it}^* (e.g., average observed management) and stochastic variables e_{it}^* as $Y_{it}^* = f^s[X_{it}^*, B_{it}, e_{it}^*, \beta]$. Stoorvogel *et al.* (2004) refer to this yield estimate as the *inherent productivity* of the site, to distinguish it from an estimate of actual yield, and interpret this quantity as representing what an informed farmer knows about the productivity of the site based on knowledge of its soils and climate. Partition $B_{it} = (B_{it}^a, B_{it}^b)$ where B_{it}^b is the subset of variables used in the crop growth model. Using (6), the mean production function can be written

(8) $$Y_{it}^s = m^s[X_{it}^s(A_{it}), B_{it}^a, Y_{it}^*, \beta] + v_{it}^s = m^s[X_{it}^s(A_{it}), B_{it}^a, f^s[X_{it}^*, B_{it}^b, e_{it}^*, \beta], \beta^X] + v_{it}^s,$$

where β^X is the set of parameters relating X_{it}^s, B_{it}^a and Y_{it}^* to Y_{it}^s. Thus, this procedure produces a special case of the production function in which the bio-physical variables B_{it}^b and e_{it}^* are weakly separable from the management inputs.

This form of the production function implies that the behavioral equations (output supply, input demand) depend on the bio-physical factors through inherent productivity, and thus induces an economic-adaptive response to the bio-physical variables B_{it}^b and e_{it}^* (e.g., changes in soils, climate, etc.). However, in this form, the management variable X_{it}^* is held constant, so a feedback from economic behavior to inherent productivity is not incorporated. A simpler approach that can be interpreted as a special case of the inherent productivity model makes the assumption of strong separability between crop model variables and management inputs, leading to the production function

(9) $$Y_{it}^{s} = m^{s}[X_{it}^{s}(A_{it}), B_{it}^{a}, \beta^{X}]\, f^{s}[X_{it}^{*}, B_{it}^{b}, e_{it}^{*}, \beta] + v_{it}^{s}.$$

There are at least two ways to implement this type of model. Stoorvogel et al. (2004) describe incorporating simulated yields as an explanatory variable in an econometrically estimated production model to account for the effects of B_{it}^{b}. Another approach is to replace the absolute yield Y_{it}^{s} in the derivation of (9) with the relative yield $R_{it}^{HF} = f^{F}[X_{it}^{F}, B_{it}^{F}, e_{it}^{F}, \beta] / f^{H}[X_{it}^{H}, B_{it}^{H}, e_{it}^{H}, \beta]$, and interpret $m^{H}[X_{it}^{H}(A_{it}^{H}), B_{it}^{H}, \beta^{X}]$ as the historically observed production function, so that future yield is predicted to be $Y_{it}^{F} = m^{H}[X_{it}^{H}(A_{it}^{H}), B_{it}^{H}, \beta^{X}]\, R_{it}^{HF}$. This relative yield method can be used to simulate yields for analysis of climate impact and adaptation (Antle et al. 2017c), but more generally can be applied to any analysis involving a new system in a new environment.

A Hybrid Model Example

To illustrate the application of these concepts, and to provide some insight into the capability of current agricultural system models, I elaborate an out-of-sample test of the hybrid structural model discussed in Antle and Stöckle (2017). This example uses data from the main winter wheat producing region of the Pacific Northwest. The study region includes areas where a winter wheat – fallow rotation (WWF) is the predominant cropping system due to low precipitation (fallow restores soil moisture). In areas with higher precipitation, winter wheat is grown in an annual rotation with other crops without fallow (WWA).

The simulation experiment presented here is designed to test the out-of-sample prediction of the CropSyst model (Stöckle, Donatelli and Nelson 2003) combined with the Tradeoff Analysis Model for Multi-dimensional Impact Assessment (TOA-MD; Antle, Stoorvogel and Valdivia 2014), illustrating analysis with elements of both P2 and P3 defined above. In this experiment, the reference system is WWF used by farmers in the WWF region, and the "treatment" is the WWA system. The goal is to test if the models can predict the observed proportion of farms using the WWA system in the WWF region. In the 2007 data used for this test, about 23% of the farms were using WWA in the WWF region, reflecting the lower productivity of the WWA system on average in the WWF region.

In this experiment, the CropSyst model was used to project relative yields for both WWF and WWA in the WWF region on a 4 km grid. These relative yields were then combined with farm-level data from the 2007 agricultural census to parameterize the TOA-MD impact assessment model. The TOA-MD model uses the logic of the Roy model in the econometric policy evaluation literature (e.g., as in Heckman 2010), to simulate economic, environmental and social impacts of exogenous factors including technology and climate. The TOA-MD model uses the difference between expected economic returns to the two systems to simulate farmers' choices between systems (or climate impacts in the case of climate impact experiments). The TOA-MD model requires estimates of the parameters of the distribution of the difference in expected returns between the two systems (mean and variance, assuming normality), which can be calculated from the means, variances and covariance of the expected returns to each system. The relative yields are used to translate the observed wheat returns of farms using one system into the counterfactual returns of the other system.

The CropSyst simulations show, as expected, that the simulated WWF yield distribution in the WWF region has a much higher mean (about 50 bu/ac) than the simulated WWA yield distribution (about 31 bu/ac) in the WWF region. The resulting relative yield distribution indicates that about 88 percent of the relative yields (WWA/WWF) are less than 1 (Figure 1).

Figure 2 shows the results of the TOA-MD simulation for adoption of WWA in the WWF zone by commercial-scale farms averaging about 3700 acres per farm. Because the returns to the two systems are correlated, the marginal treatment effect (MTE) is non-linear, and is zero at a value of about 20 percent, which is equal to the predicted adoption rate of WWA. This compares favorably to the observed adoption rate of 23 percent, confirming that the hybrid model can predict well out of sample. Figure 2 also shows an average treatment effect (ATE) of about –$28 per acre, implying an average loss of this amount if all farms were to use the WWA system in this region instead of the WWF system. The average treatment effect on the treated (ATT) at the predicted adoption rate shows the average gains to those sites that are better off with the WWA system, about $18 per acre. The average treatment effect on the untreated (ATU) is about -$51 per acre and indicates the average losses that farms using WWF would bear if they were to use WWA.

Towards Better Data and Models

The preceding discussion of agricultural system models, as well as a comprehensive review of agricultural systems science and the potential for “next generation” models is that improved acquisition and use of data is a critical constraint on agricultural research and its successful application for on-farm production system management and for technology and policy decision making (Antle, Jones and Rosenzweig 2017). Better data are needed to further improve crop and livestock models in ways that are useful for both on-farm management decision making and for use in research to develop and test new technologies, and to evaluate their productivity and sustainability.

My discussion of the evaluation paradigm and its application to agricultural systems analysis demonstrated that better observational data, and the utilization of both mechanistic and empirical production models, could help address the key analytical challenges in assessing the productivity and sustainability of agricultural systems. Valid mechanistic models could be used for counterfactual identification; better observational data could address bias problems caused by unobserved heterogeneity and inaccurate and incomplete data; and the combination of mechanistic and empirical production system models could improve the analysis of new technologies.

A Prototype Private-Public Data System

A prototype of what is possible is presented in Figure 3, which provides an overview of the features of farm-level data and decision tools, landscape-scale data and analytical tools that support policy analysis, and their interrelationships. Both farm-level decision making and landscape-scale analysis depend on private data (site- and farm-specific characteristics of the land and the farm operation, and the site- and farm-specific management decisions that are made) as well as public data (weather, climate and other physical data describing a specific location, and prices and other publicly available economic data). A key question for the design of the agricultural data infrastructure is how both types of data can be collected, managed and utilized efficiently and securely.

The left-hand side of Figure 3 presents the generic structure of farm-level decision tools the data they use as inputs, and the outputs that are generated. The right hand side of Figure 3 shows the general structure of the data and models needed to carry out landscape-scale research and policy tradeoff analysis. There are three broad categories of regional data: publicly available biophysical data, including down-scaled climate and soils data; publicly available economic data, including prices and policy information; and the confidential site- and farm-specific data obtained from producer- and industry-generated databases.

Capalbo, Antle and Seavert (2017) provide an example of decision support tools that could be used to enable this type of data system at the farm level, and be linked to cloud-based data that could in turn be used for scientific research and policy decision making. However, various issues would have to be addressed to implement this type of system. One issue is how to encourage growers to provide accurate data. This issue would presumably resolved if the data are being entered into a management tool. To translate data into a generic format that would be FAIR (findable, accessible, interoperable and reusable; Wilkinson 2016), translators from commercial management tools into the generic format could be used. A key issue for most farmers is data confidentiality. This issue poses a critical challenge to be addressed if researchers are to be able to obtain the location-specific information needed to link economic and management data to bio-physical data such as weather and soils.

The Current State of Private and Public Agricultural Data

Today we are far from realizing a data infrastructure like the one portrayed in Figure 3. Private data and related soft and hard infrastructure are being developed by a growing array of management advisory and technology companies. Data generated by individual producers or by private firms selling data or advisory services are not public and thus not findable or accessible, often even by farmers themselves. There are no established data standards being used, and thus data are not interoperable even when findable and accessible.

There are also many limitations of currently produced public data. Some of the data identified as public in Figure 3, such as some weather, price and crop yield data, are open access or available for fees. However, many of the data related to agricultural production are collected for various government administrative purposes and are not intended to be used for research or for private decision-making. For example, much of the data collected by the National Agricultural Research Service are findable but are not easily accessible in a timely manner, and then only available in summary or aggregated form. Some of these data, such as Agricultural Census and Agricultural Research Management Survey, can now be accessed at the respondent level, but without location identifiers that are needed for many research purposes. Also, most data fail the interoperability standard, and thus must be processed by users to put in a form that can be usable by analytical software or models. A major shortcoming of the available production data is in terms of management data and cost of production data. For example, the census collects cost of production at the whole farm level, so it cannot be disaggregated to individual production activity (e.g., crop) level. Another major shortcoming is that none of the available data can be used to construct longitudinal data for multiple proximate growing seasons or years. The census data can be used to construct a panel, but is only carried out every five years.

Various efforts are underway to address these data challenges. For example, the international agricultural research centers' Big Data Initiative is working to develop data ontologies for agricultural systems data. The Global Open Data for Agriculture and Nutrition initiative is supported by a number of governmental organizations. In the United States, the National Institutes for Food and Agriculture is supporting the Food and Agriculture Cyberinformatics and Tools grant program. Coble et al. (2018) provide an overview of big data in agriculture and the contributions that economists can make to its use in research and technology implementation.

The Economics of Data and Data Infrastructure

Data are increasingly recognized as a scarce resource, used as inputs into production and decision making processes, and outputs produced by various types of activities. If data were private goods with well-defined property rights and could be produced and used without externalities we would expect markets to arise for their efficient production and utilization. However, it is evident that many types of data are not private goods, as their use is non-rival, but may be excludable, hence may be considered club goods or public goods (Figure 4). Moreover, as yet, property rights are not well-defined. Thus, as noted in the previous section, the current state of the "data market" is disarray. There are various efforts underway to better define data property rights and related legal and institutional rules and arrangements, but as yet there are many unresolved issues, as evidenced by recent events involving personal data by social media firms has illustrated. Likewise for individual farm agricultural data, there are ongoing efforts to define property rights but as yet no general policies have been established. For example, the Farm Bureau has promoted a set of "privacy and security principles for farm data," and the Agricultural Data Act of 2018 was proposed to in the U.S. Senate to address some of the issues related to making government data accessible for research.

Similar points can be made about data infrastructure. This issue has already arisen with the development of the internet, and indeed one of the key limitations to the development of better agricultural data and "soft infrastructure" is the lack of high-speed internet access by many farmers, even in the technologically advanced regions of the world. Various developments in sensor technologies create possibilities for on-farm data infrastructure, and one of the key economic questions is the extent to which it will pay farmers to invest in such infrastructure. An important element of the data system envisaged in Figure 3 is that such on-farm infrastructure could have both private and public benefits if a viable system were in place to enable the public utilization of private data for public good purposes such as research and policy decision making.

The Need for Collaboration and Institutional Innovation

It is now widely acknowledged that to advance agricultural systems science in order to achieve goals of agricultural system sustainability, there is a need for collaboration among disciplines to understand and analyze complex systems (National Academies of Science 2018). The growing capabilities of mobile sensor technologies, unmanned aerial vehicles, cloud computing and other emerging technologies, shows the need to include the data, engineering and computer sciences into the group of relevant disciplines for the further development of agricultural systems science.

A key question is how to organize and incentivize these new collaborations. One answer is for public funding of related research and development, as envisaged by NIFA's Food and Agriculture Cyberinformatics and Tools program. Following ideas taken from the pharmaceutical industry, Antle et al. (2017b) propose the development of "pre-competitive spaces" for public-good-related research, and "competitive spaces" for development of knowledge products in the private sector. To support the pre-competitive development of models and data, advances in collaborative research are also needed. For example, AgMIP has demonstrated the power and value of global teams developing data for model inter-comparisons that have led to substantial model improvement.

Conclusions

In this address I have discussed some of the actual and potential advances in agricultural systems modeling that promise new ways to link advances in genomics and other fields of science with better biological and physical data to accurately predict crop and livestock productivity. These mechanistic, process-based models are capable, at least in principle, and increasingly in practice, of predicting agricultural production system performance within the range of observable variation of existing systems, as well as the behavior of modified or new systems in new environments. Although they continue to be improved through better science and data, a critical limitation of these models is that they do not incorporate human behavior. Thus, I also describe key methodological challenges to specifying and estimating models that include the behavior of farm decision makers, including the estimation of counterfactuals, accounting for unobserved heterogeneity, and modeling new technologies. A common theme that emerges from both the agricultural systems science and economic-behavioral sciences is that improved acquisition and use of data is a critical constraint on agricultural research and its successful application, both for on-farm production system management and for technology and policy decision making. I present a prototype scheme for acquiring better data that can support advanced computational methods and models, and discuss the economic, technical, legal and institutional challenges to better data.

A remarkable fact is that, thus far, agriculture lags virtually every other major industry in the use of digital technology (Ghandi, Khanna and Ramaswamy 2016). One explanation is that agriculture involves highly diverse, complex systems operated by relatively small businesses. These factors make it more difficult to utilize data science technologies that depend on standardized "big" data to enable automation, artificial intelligence and machine learning, and more difficult to exploit scale economies. Combined with the potential value of computational science to accelerate research and development, and the “disarray” in the market for data, these facts suggest that there is a high potential return on public investment in better data and data infrastructure, in computational methods in the agricultural sciences, and in technologies for farm decision making.

Table 1. Permanent and Transitory Hybrid Maize Users and Non-users, Tanzania 2009-2013 and Kenya 1997-2010 (percent)

	Permanent		Transitory	
	Users	Non-users	Users	Non-users
Tanzania	4.5	52.3	16.7	26.5
Kenya - Low	2	25.3	28.4	44.3
Kenya - Medium	58.2	4.5	22.2	15.1
Kenya - High	75.2	0.4	17.5	6.9

Note: Author's calculations based on World Bank Living Standards Measurement data (Tanzania) and Tegemeo Institute Rural Household Survey data (Kenya). Tanzania data are for 850 maize-producing households. Kenya data are for 1161 maize-producing households in Low (294), Medium (493) and High (258) productivity agro-ecological zones.

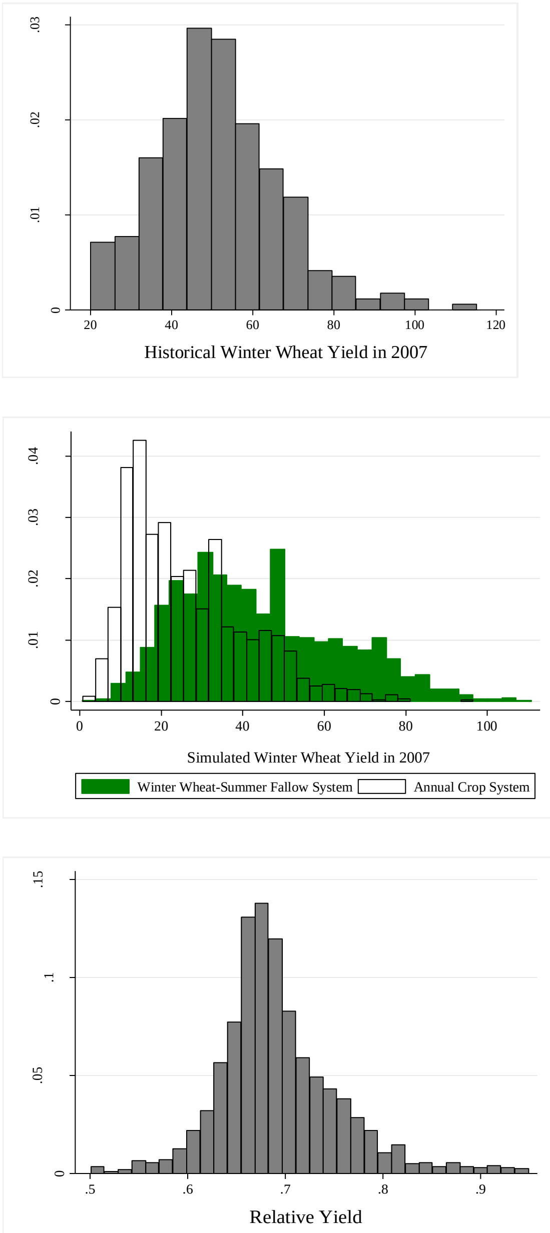

Figure 1: U.S. Pacific Northwest Historical Winter Wheat Yield Distribution for 2007 (top panel); CropSyst Simulated Winter Wheat Yield Distributions for WWF and WWA Systems in the WWF region (middle panel); CropSyst simulated Relative Yield Distribution for Annual Winter Wheat in the Winter Wheat Fallow region.

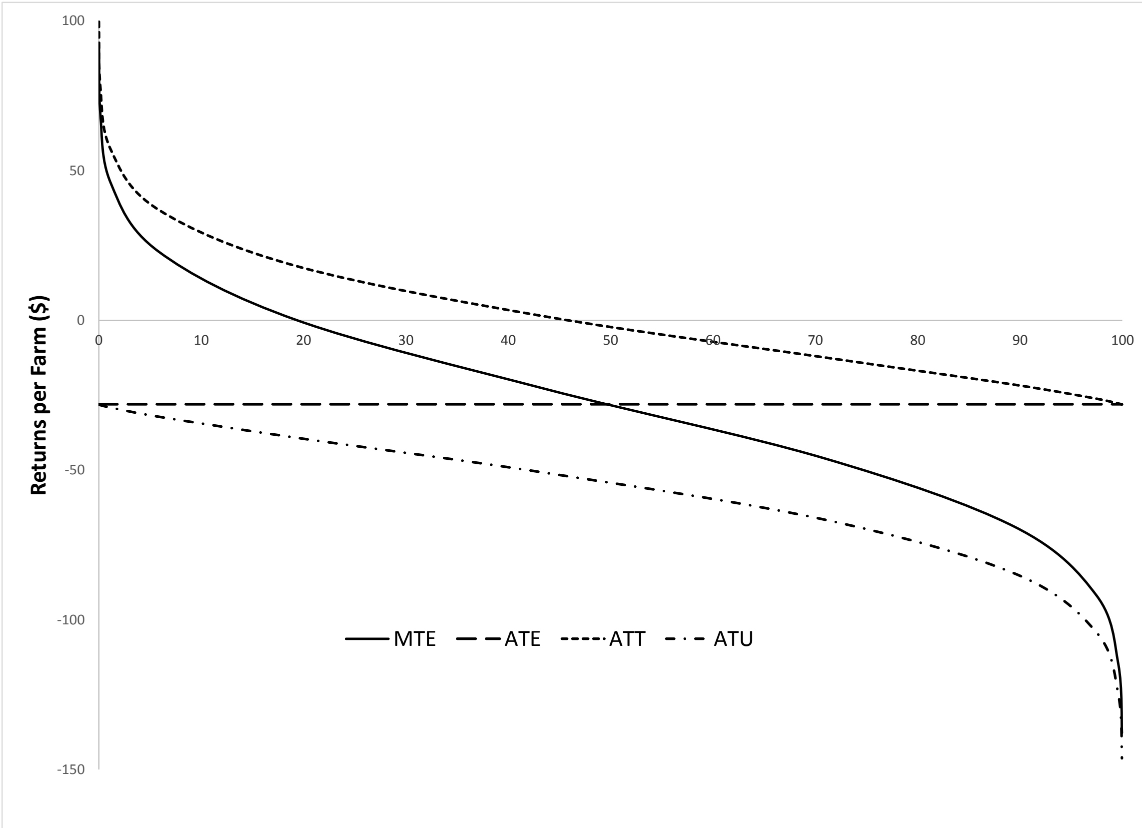

Figure 2. Treatment Effects from a Simulation Experiment for Use of the Annual Winter Wheat system in the areas where the predominant system is Winter Wheat Fallow, Commercial Scale Wheat Farms in the U.S. Pacific Northwest, 2007. The observed use of the annual cropping system in this region is 23 percent, the predicted rate of use is 20 percent. The simulations are based on relative yields from the CropSyst Model (Figure X), and the TOA-MD Model parameterized with agricultural census data. Note: horizontal axis is the percent of farms. MTE = marginal treatment effect; ATE = average treatment effect, ATT = average treatment effect on the treated, ATU = average treatment effect on the untreated.

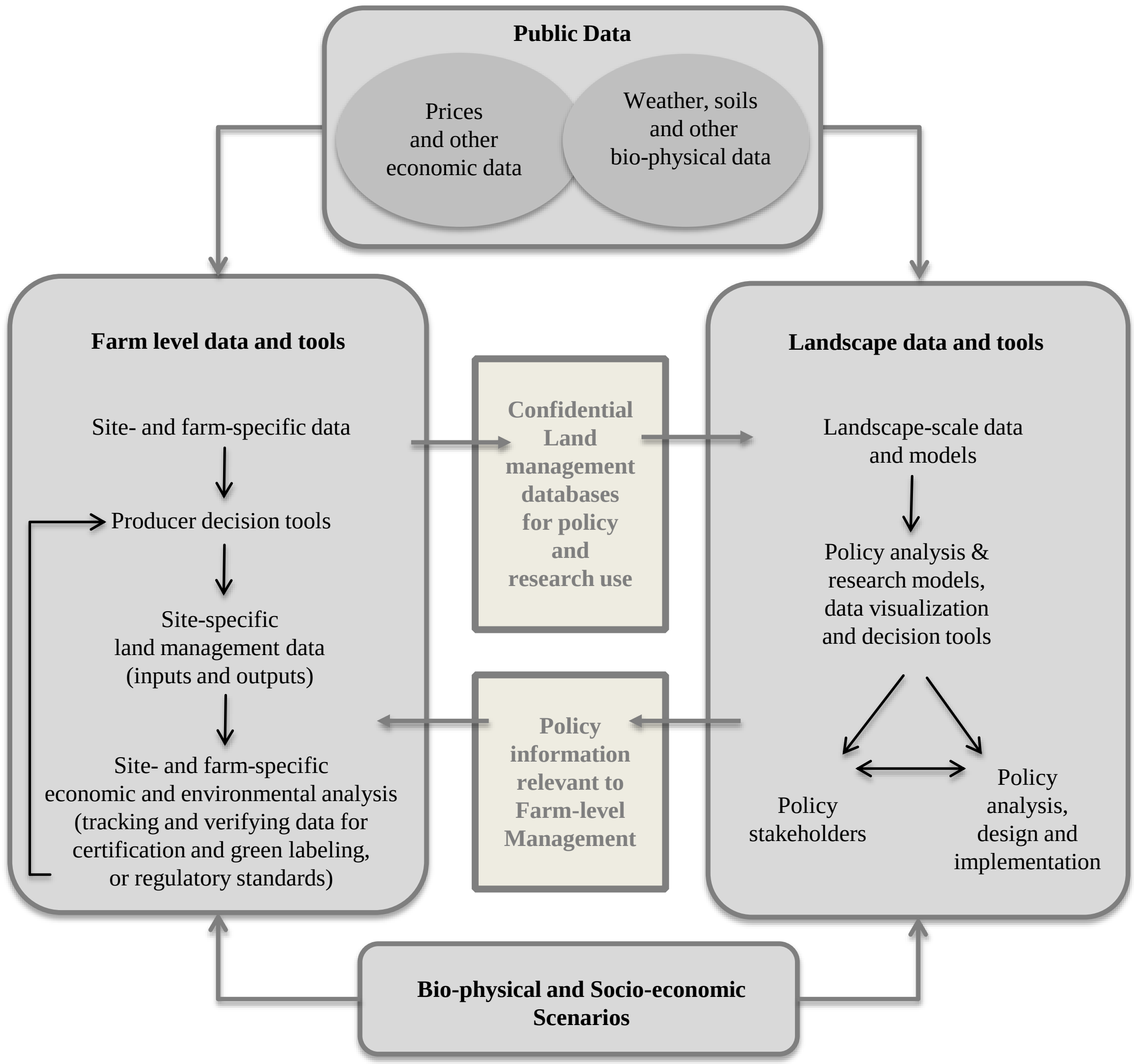

Figure 3. Linkages between Data and Decision Tools at Farm and Landscape Scales (source: Capalbo, Antle and Seavert, 2017).

	Excludable	Non-Excludable
Rival	Private Data and Infrastructure (private good)	Public Infrastructure (open access good)
Non-Rival	Protected Data (club good)	Public Data (public good)

Figure 4. Data and Infrastructure as Private and Public Goods

References

Angrist and Pishke (2010): "The Credibility Revolution in Empirical Economics: How Better Research Design is Taking the Con out of Econometrics." *Journal of Economic Perspectives* 24(2):3-30.

Antle, J.M. and S.M. Capalbo. (2001). "Econometric-Process Models for Integrated Assessment of Agricultural Production Systems." *American Journal of Agricultural Economics* 83(2):389-401.

Antle, J.M. and S.M. Capalbo. (2002). "Agriculture as a Managed Ecosystem: Policy Implications." *Journal of Agricultural and Resource Economics* 27(1):1-15.

Antle, J.M. and S.A. Hatchett. (1986). "Dynamic Input Decisions in Econometric Production Models." *American Journal of Agricultural Economics* 68(4):939-949.

Antle, J.M. and J.J. Stoorvogel. (2006). "Incorporating Systems Dynamics and Spatial Heterogeneity in Integrated Assessment of Agricultural Production Systems." *Environment and Development Economics* 11(1):39-58.

Antle, J.M., J.J. Stoorvogel and R.O. Valdivia. 2014. New Parsimonious Simulation Methods and Tools to Assess Future Food and Environmental Security of Farm Populations. *Philosophical Transactions of the Royal Society B* 369:20120280.

Antle, J.M. and C.O. Stöckle. 2017. Climate Impacts on Agriculture: Insights from Agronomic-Economic Analysis. *Review of Environmental Economics and Policy* 11(2): 299–318. https://doi.org/10.1093/reep/rex012

Antle, J., J. Jones and C. Rosenzweig. 2017. Next Generation Agricultural System Data, Models and Knowledge Products: Synthesis and Strategy. *Agricultural Systems* 155: 179-185.

Antle, J., J. Mu, H. Zhang, S. Capalbo, P. Diebel, S. Eigenbrode, C. Kruger, C. Stöckle, J.D. Wulfhorst. 2017a. Design and Use of Representative Agricultural Pathways in U.S Pacific Northwest Wheat-Based Systems. *Frontiers in Ecology and Evolution.* Published online. doi: 10.3389/fevo.2017.00099.

Antle, J.M., B.O. Basso, R.T. Conant, H.C.J. Godfray, J.W. Jones, M. Herrero, R.E. Howitt, B.A. Keating, R. Munoz-Carpena, C.E. Rosenzweig, and T.R. Wheeler. 2017b. Towards a New Generation of Agricultural System Data, Models and Knowledge Products: Design and Improvement. *Agricultural Systems* 155: 255-268.

Antle, J.M., H. Zhang, J. Mu, J. Abatzoglou and C.O. Stöckle. 2017c. Methods to Assess Between-System Adaptations to Climate Change: Dryland Wheat Systems in the Pacific Northwest United States. *Agriculture, Ecosystems and Environment.* published online. https://doi.org/10.1016/j.agee.2017.03.017

Brown, M.E., J.M. Antle, P. Backlund, E.G. Carr, W.E. Easterling, M.K. Walsh, C. Ammann, W. Attavanich, C.B. Barrett, M.F. Bellemare, V. Dancheck, C. Funk, K. Grace, J.S.I. Ingram, H. Jiang, H. Maletta, T. Mata, A. Murray, M. Ngugi, D. Ojima, B. O'Neill, and C. Tebaldi. 2015. *Climate Change, Global Food Security, and the U.S. Food System*. 267 pages. Available online at http://www.usda.gov/oce/climate_change/FoodSecurity.htm .

Capalbo, S.M., J.M. Antle and C. Seavert. 2017. Next generation data systems and knowledge products to support agricultural producers and science-based policy decision making. *Agricultural Systems* 155: 191-199. http://dx.doi.org/10.1016/j.agsy.2016.10.009

Castle, M. H. “Has the Usage of Precision Agriculture Technologies Actually Led to Increased Profits for Nebraska Producers?” M.S. Thesis. University of Nebraska-Lincoln Department of Agricultural Economics. December 2016. Available at: http://digitalcommons.unl.edu/agecondiss/35/.

Cobb, Charles W., and Paul H. Douglas. 1928. “A Theory of Production.” American Economic Review, Papers and Proceedings of the Fortieth Annual Meeting of the American Economic Association, 18(1, Supplement): 139–65

Coble, K.H., A.K. Mishra, S. Ferrell and T. Griffin. 2018. Big Data in Agriculture: A Challenge for the Future. *Applied Economic Perspectives and Policy* 40:79-96.

Cooper, M., F. Technow, C. Messina, C. Gho, and L. Radu Totir. 2016. Use of Crop Growth Models with Whole-Genome Prediction: Application to a Maize Multienvironment Trial. *Crop Science* 56:2141–2156 (2016).

Ewert, F. , R.P. Roetter, M. Bindi, H. Webber, M. Trnka, K.C. Kersebaum, J.E. Olesen, M.K. van Ittersum, S. Janssen, M. Rivington, M.A. Semenov, D. Wallach, J.R. Porter, D. Stewart, J. Verhagen, T. Gaiser, T. Palosuo, F. Tao, C. Nendel, P.P. Roggero, L. Bartosova, S. Asseng. 2014. Crop modelling for integrated assessment of risk to food production from climate change. *Environmental Modeling and Software.* http://dx.doi.org/10.1016/j.envsoft.2014.12.003

Ghandi, P, S. Khanna and S. Ramaswamy. 2016. “Which Industries are the Most Digital (and Why?). *Harvard Business Review*. April 1. https://hbr.org/2016/04/a-chart-that-shows-which-industries-are-the-most-digital-and-why

Heady, E.O. 1961. *Agricultural Production Functions.* Ames, IA, Iowa State University Press.

Heckman, J.J. (2010): “Building Bridges between Structural and Program Evaluation Approaches to Evaluating Policy.” *Journal of Economic Literature* 48: 356-398.

Holzworth, D.P., et al., 2015. Agricultural production systems modelling and software: Current status and future prospects, Environmental Modelling and Software. 72: 276-286.

Hwang, C., M.J. Correll, S.A. Gezan, L. Zhang, M.S. Bhakta, C.E. Vallejos, K.J. Boote, J.A. Clavijo-Michelangeli, and J.W. Jones. 2017. Next generation crop models: A modular approach to model early vegetative and reproductive development of the common bean (Phaseolus vulgaris L). Agricultural Systems 155: 225–239.

Jones, J.W., J.M. Antle, B.O. Basso, K. Boote, R.T. Conant, I. Foster, H.C.J. Godfray, M. Herrero, R.E. Howitt, S. Janssen, B.A. Keating, R. Munoz-Carpena, C. Porter, C.E. Rosenzweig, and T.R. Wheeler. 2017a. A Brief History of Agricultural Systems Models. *Agricultural Systems* 155: 240-254.

Jones, J.W., J.M. Antle, B.O. Basso, K. Boote, R.T. Conant, I. Foster, H.C.J. Godfray, M. Herrero, R.E. Howitt, S. Janssen, B.A. Keating, R. Munoz-Carpena, C. Porter, C.E. Rosenzweig, and T.R. Wheeler. 2017b. Towards a New Generation of Agricultural System Models, Data, and Knowledge Products: State of Agricultural Systems Science. *Agricultural Systems*. 155: 268-288.

Just, R.E. and R.D. Pope. 1978. Stochastic Specification of Production Functions and Economic Implications. *Journal of Econometrics* 7: 67-86.

Leonard, E. (Ed), Rainbow, R. (Ed), Trindall, J. (Ed), Baker, I., Barry, S., Darragh, L., Darnell, R., George, A., Heath, R., Jakku, E., Laurie, A., Lamb, D., Llewellyn, R., Perrett, E., Sanderson, J., Skinner, A., Stollery, T., Wiseman, L., Wood, G. and Zhang, A. (2017).

Accelerating precision agriculture to decision agriculture: Enabling digital agriculture in Australia. Cotton Research and Development Corporation, Australia.

Lobell, D.B., and S. Asseng. 2017. Comparing estimates of climate change impacts from process-based and statistical crop models. Environmental Research Letters 12.

Maiorano, A., P. Martre, S. Asseng et al. 2017. Crop model improvement reduces the uncertainty of the response to temperature of multi-model ensembles. Field Crops Research 15:5-20.

Marschak, J. and W. H. Andrews, Jr. 1944. Random Simultaneous Equations and the Theory of Production. *Econometrica* 12: 143-205

Martre, P., D. Wallach, S. Asseng, F. Ewert, J.W. Jones, R.P. Rötter, K.J. Boote, et al. 2015. Multimodel ensembles of wheat growth: many models are better than one. Global change biology 21: 911-925.

Mundlak, Y. 1961. "Production Function Estimation Free of Management Bias." *Journal of Farm Economics XXX.*

National Academies of Sciences, Engineering, and Medicine. 2018. *Science Breakthroughs to Advance Food and Agricultural Research by 2030.* Washington, DC: The National Academies Press. doi: https://doi.org/10.17226/25059.

Rosenzweig, C., J.W. Jones, J.L. Hatfield, A.C. Ruane, K.J. Boote, P. Thorburn, J.M. Antle,G.C. Nelson, C. Porter, S. Janssen, S. Asseng, B. Basso, F. Ewert, D. Wallach, G. Baigorria, and J.M. Winter. 2013. The Agricultural Model Intercomparison and Improvement Project (AgMIP): Protocols and Pilot Studies. *Ag. For. Meteor*. 170:166-182.

Rosenzweig, C., A.C. Ruane, J.M. Antle, et al. 2017. Coordinating AgMIP data and model across global and regional scales for 1.5° and 2.0° C assessments. Philosophical Transactions of the Royal Society A. 2018 May 13;376(2119). doi: 10.1098/rsta.2016.0455.

Stöckle, C.O., M. Donatelli and R. Nelson. 2003. CropSyst, a cropping systems simulation model. *European Journal of Agronomy* 18:289–307.

Stoorvogel, J.J., J.M. Antle, C.C. Crissman, and W. Bowen (2004), The tradeoff analysis model: integrated bio-physical and economic modeling of agricultural production systems. *Agricultural Systems* **80**: 43–66.

Schimmelpfennig, D. "Farm Profits and Adoption of Precision Agriculture." ERR-217, U.S. Department of Agriculture, Economic Research Service, October 2016. Available at: https://www.ers.usda.gov/publications/pub-details/?pubid=80325.

Technow F, Messina CD, Totir LR, Cooper M (2015) Integrating Crop Growth Models with Whole Genome Prediction through Approximate Bayesian Computation. PLoS ONE 10(6): e0130855. https://doi.org/10.1371/journal.pone.0130855

Valdivia, R., J.M. Antle and J. Stoorvogel. 2012. "Coupling the Tradeoff Analysis Model with a Market Equilibrium Model to Analyze Economic and Environmental Outcomes of Agricultural Production Systems." *Agricultural Systems* 110: 17-29.

Valdivia, R.O., J.M. Antle, C. Rosenzweig, A.C. Ruane, J. Vervoort, M. Ashfaq, I. Hathie, S. Homann-Kee Tui, R. Mulwa, C. Nhemachena, P. Ponnusamy, H. Rasnayaka and H. Singh. (2015). Representative Agricultural Pathways and Scenarios for Regional Integrated Assessment of Climate Change Impact, Vulnerability and Adaptation. C.

Rosenzweig and D. Hillel, eds. *Handbook of Climate Change and Agroecosystems: The Agricultural Model Intercomparison and Improvement Project Integrated Crop and Economic Assessments, Part 1.* London: Imperial College Press.

Valdivia, R., J.M. Antle and J. Stoorvogel. 2012. "Coupling the Tradeoff Analysis Model with a Market Equilibrium Model to Analyze Economic and Environmental Outcomes of Agricultural Production Systems." *Agricultural Systems* 110: 17-29.

Valdivia, R.O., J.M. Antle and J.J. Stoorvogel. 2017. Designing and Evaluating Sustainable Development Pathways for Semi-Subsistence Crop-Livestock Systems: Lessons from Kenya. *Agricultural Economics.* Volume 48(S1): 11–26. DOI: 10.1111/agec.12383.

Wang, E., P. Martre, Z. Zhao, F. Ewert, A. Maiorano. 2017. The Uncertainty of Crop Yield Projections is Reduced by Improved Temperature Response Functions. *Nature Plants* 3:17102.

Wibe, S. 1984. "Engineering Production Functions: A Survey." *Economica*

51: 401-411.

Wilkinson, M.D., et al. 2016. The FAIR Guiding Principles for Scientific Data Management and Stewardship. *Scientific Data* 3, article number 160018.

Wooldridge, J.M. (2010): *Econometric Analysis of Cross Section and Panel Data.* Cambridge, Mass., MIT Press.